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The impact of artificial intelligence on audit quality

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This research report is submitted in partial fulfilment of the requirements for the degree of Master of Commerce at the University of the Witwatersrand, Johannesburg.

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The Head of the School of Accountancy

Dear Sir

I hereby declare that this research report is my own unaided work and that all the sources have been reported and acknowledged. It is submitted in partial fulfilment of the degree of Master of Commerce by Coursework and Research Report at the University of the Witwatersrand, Johannesburg.

This research has been carried out according to the ethical policies of the University of the Witwatersrand and has not been submitted elsewhere for the purpose of being awarded another degree or for examination purposes at any other university.

Yours sincerely,



Signature of student

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Abstract

Audit firms are under pressure to complete high-quality engagements to re-establish the legitimacy of the profession, following several audit failures and the growing repercussions of subpar audit quality. Considering this, firms have started incorporating artificial intelligence technologies into their resource mix to enhance audit quality. Research on the effect of the use of AI on audit quality is limited, despite the growing use of AI technologies in the audit process. This study explores how artificial intelligence (AI) features can improve audit quality in order to address this problem. A mixed-method approach is used in this study, combining correspondence analysis and content analysis. Preliminary links between audit quality themes and AI features were established by conducting a content analysis to analyse the body of literature on audit quality and the use of AI in the auditing process. Following that, a correspondence study was carried out to gather opinions from auditing professionals regarding the perceived impact of AI on audit quality. A correspondence table that linked AI features to audit quality measures was given to the research participants to complete. Using the correspondence table, forty auditing experts shared their viewpoints. The correlation between AI themes and audit quality attributes was evaluated through the analysis of the responses. The results show that the use of AI will have a positive impact on multiple key audit quality elements and enhance overall audit quality. It was discovered that auditors can use AI to analyse all of the available data and do comprehensive risk assessments. Additionally, by automating repetitive audit duties, respondents indicated that AI would free up audit teams to concentrate on more important and high-risk areas that call for professional judgement. It is recommended that audit firms adopt AI to increase the capacity of their resources and the firm's ability to deliver quality audits. However, while there is a favourable correlation between the use of AI and audit quality, there are some risks and concerns that companies must address before using AI to execute engagements. As one of the first interpretive insights into how AI affects the key audit quality factors, the research contributes to the body of literature on the impact of using AI on audit quality.

Keywords: Audit quality, Audit evidence, Artificial intelligence, ISQM1, Machine learning, Deep learning, International Standards on Auditing

Contents

I: List of abbreviations and acronyms 1
II: List of referenced auditing standards 1
1. Introduction 2
1.1: Context of the study 2
1.3: Contribution 7
1.4: Limitations and delimitations 7
2. Literature review 8
2.1 Audit Quality 8
2.1.1: Acceptance, continuance and resources 10
2.1.2: Ethical requirements, governance, and leadership 11
2.1.3: The firm's risk assessment process 13
2.1.4: Engagement Performance 15
2.1.5 Monitoring and Remediation Process 19
2.1.6: Information and communication 19
2.2: Artificial intelligence 20
2.2.1 Subsets of AI 21
2.2.2 Categories of AI 23
2.2.3: Types of artificial intelligence 24
2.2.4 Possible application of AI to audits 25
2.3 Potential drawbacks of AI in auditing 34
3. Data and method 39
3.1: Methodological paradigm 39
3.2 Content analysis: developing rows and columns for the correspondence analysis 39
3.3 Correspondence analysis 40
3.4: Sample 41
3.5: Data collection and management 42
3.6: Data analysis 42
3.7: Validity and Reliability 43
3.8: Assumptions 44
4. Results 45
5. Discussion 52

6. Conclusion 66
References 74
Appendix A: Audit quality characteristics 83
Appendix B: Participant Information Sheet 85
Appendix C: Consent form for participants in the research study 86
Appendix D: Data collection instrument: Correspondence table 87
Appendix E: Statistics for audit quality traits 89
Appendix F: Statistics for Artificial Intelligence themes 90

I: List of abbreviations and acronyms

Abbreviation/Acronym	Description
AI	Artificial Intelligence
FRC	Financial Reporting Council
IAASB	International Auditing and Assurance Standards Board
ISA	International Standard on Auditing
ISQC	International Standard on Audit Quality control
SEC	Securities and Exchange Commission
PwC	PricewaterhouseCoopers
VBS	Venda Building Society

II: List of referenced auditing standards

Standard	Description
ISQM 1	Quality Management for Firms that Perform Audits or Reviews of Financial Statements, or Other Assurance or Related Services Engagements
ISA 200	Overall objectives of the independent auditor and the conduct of an audit in accordance with international standards on auditing
ISA 230	Audit Documentation
ISA 315	Identifying and assessing the risks of material misstatement through understanding the entity and its environment
ISA 320	Materiality in Planning and Performing an Audit
ISA 330	The auditor's response to assessed risks
ISA 500	Audit Evidence
ISA 520	Analytical Procedures
ISA 530	International Standard on Auditing: Audit sampling
ISA 700	Forming an opinion and reporting on financial statements

1. Introduction

1.1: Context of the study

South Africa has experienced several high-profile corporate collapses and audit failures in the last five years, including, for example, Steinhoff, Tongaat, the Venda Building Society (VBS) Mutual Bank and African Bank Jaffer et al. (2019). The international community has also experienced auditing scandals such as the collapse of Carillion, a public contractor in the United Kingdom (Peterson, 2019). One key outcome is that the reputation of the auditing profession has been undermined (Coffee, 2019; Holm & Zaman, 2012; Pong et al., 2009; Rezaee, 2004; Ryan, 2019).

Regulators have also increased their monitoring role over audit firms to restore the legitimacy of the profession (Dikuua et al., 2023). Additional monitoring goes hand-in-hand with significant increases in the number and amount of financial penalties imposed on audit firms (FRC, 2019).

The Independent Regulatory Board for Auditors (IRBA) recently increased the value of monetary fines to be imposed for improper audit conduct (IRBA, 2023). The IRBA has the authority to choose any business and any engagement for inspection; nevertheless, the selection process tends to be risk-based (Logie & Maroun, 2021). Given that engagements are chosen using a risk-based methodology, those that are more likely to be of lesser quality will typically be selected (Logie & Maroun, 2021). As a result of subpar audit quality or inadequate quality management systems at their companies, auditors may be subject to a disciplinary investigation (Logie & Maroun, 2021). Sanctions may include disbarment in addition to monetary fines (Logie & Maroun, 2021).

Several solutions are being pursued by audit companies to enhance their audit process and audit efficiency in response to the numerous audit scandals, audit failures, and increases in punishments issued by audit authorities (Bowling & Meyer, 2019; Raphael, 2015). The improvement of auditing techniques is necessary to keep up with the rapidly expanding digital economy, in addition to the concerns about audit quality (Chiu et al., 2018). More sophisticated operating and accounting systems are being used by audit clients, necessitating the use of sophisticated auditing systems (Noordin et al., 2022).

Businesses are increasingly integrating artificial intelligence into their accounting and financial reporting processes (Sreseli, 2023). AI is being used by businesses to handle and process

massive amounts of data accurately and efficiently (Sreseli, 2023). AI for businesses has the potential to enhance management's decision-making process through the automation of tasks such as the analysis of financial data and the generation of reports (Sreseli, 2023). According to Sereseli (2023), AI reduces the amount of time that finance professionals need to spend on tasks like data analysis, report generation, and reconciliation.

AI also offers the benefit of minimising human errors which may occur with manual data processes, as data capture and the generation of reports can be automated (Sreseli, 2023). The predictive analysis models of AI can be used to make predictions under various business scenarios to support management decisions (Sreseli, 2023). The AI algorithms are useful in determining anomalies and potential fraud (Sreseli, 2023). Furthermore, as businesses are exposed to fraud risk, AI's pattern analysis capabilities can be used to identify anomalies, and fraudulent transactions and alert businesses to areas of fraud (Fedyk et al., 2022).

A survey conducted by KPMG revealed that 65% of finance executives have adopted AI in their finance functions (KPMG, 2023). Almost half of the respondents expected that auditors would utilise AI (KPMG, 2023). The results of the study also indicated that various financial statement users expect the use of AI to improve the quality of audits (KPMG, 2023). Businesses expect that AI's data analyses and prediction models will enhance the auditor's abilities to ask the right questions and challenge management's estimates (KPMG, 2023). The use of data analysis will enable the auditor to obtain better insights and, in turn, be able to add value to the business by providing relevant suggestions for improvements (Ken, 2022).

Similarly, AI's functional abilities, including predictive analysis and the ability to analyse full data sets have the potential to increase the identification of fraud, and misstatements and improve communication with those charged with governance (Fedyk et al., 2022). Consequently, a study conducted by PwC revealed that 57% of executives consider audit firms' ability to utilise AI when selecting audit firms (PwC, 2021).

Firms have started incorporating artificial intelligence (AI) into their audit methodologies to enhance their audit processes (Greenman, 2017; Kokina & Davenport, 2017). AI models are used in the risk assessment phase of an audit to identify risks through examining prior financial data and detecting potential audit issues (AICPA 2019). These predictive algorithms help auditors prioritise high-risk areas and concentrate their efforts on crucial issues throughout an audit (AICPA, 2019). For example, PwC employs AI-powered tools to evaluate audit risks by analysing client data and identifying potential areas of concern, allowing auditors to focus their attention on high-risk areas (AICPA, 2019).

AI techniques such as sentiment analysis are used to evaluate text data from a range of sources, including company reports and social media posts (Li & Li, 2020). This can provide auditors with insight into the tone and attitude of corporate governance of an auditee, helping them to identify potential management and internal control concerns (Li & Li, 2020). Audit firms, for example, employ AI-based sentiment analysis tools to monitor corporate governance issues by assessing reports, media stories, and other textual data for indicators of possible audit risk (Li & Li, 2020).

AI technologies are also being utilised by audit firms in the execution phase of an audit to extract and process enormous amounts of data from financial documents such as invoices, contracts, and financial statements (Leary, 2013). These solutions automate the examination and extraction of data, saving manual work and enhancing audit efficiency (Leary, 2013). For example, KPMG developed a tool called "Clara" that leverages AI to automate data extraction from contracts and invoices during the audit process, allowing auditors to focus on higher-value duties (Leary, 2013).

AI, specifically machine learning algorithms, is used to detect anomalies or fraudulent activity in financial transactions (Chen & Liao, 2020). These algorithms can detect patterns of behaviour in financial data and flag transactions that differ from expected patterns, which may be an indication of fraud or errors (Chen & Liao, 2020). Deloitte, for example, utilises AI algorithms to analyse financial data and detect fraudulent transactions by spotting outliers or patterns that indicate irregular behaviour (Chen & Liao, 2020).

AI is transforming the auditing profession by automating routine tasks, improving data analysis, detecting fraud, and facilitating more efficient risk assessments (Cao & Lin, 2022). AI integration into auditing operations not only increases audit accuracy and efficiency but also provides auditors with the tools they need to produce more timely and informative results (Cao & Lin, 2022). The continued growth of AI technologies promises to increase the quality and breadth of auditing procedures in the future (Cao and Lin, 2022).

As AI becomes more prominent in auditing, the skill set required of auditors' changes (Cao & Lin, 2022). While technical knowledge in data analytics, machine learning, and programming is becoming increasingly important, auditors must still possess traditional skills such as professional judgement, critical thinking, and communication (Cao & Lin, 2022).

Auditors' duties are evolving as AI automates onerous and regular tasks (Glover et al., 2017). Auditors are shifting their attention away from traditional tasks like data entry and transaction

testing and towards higher-level activities such as judgement, decision-making, and value-added insight (Glover et al., 2017). The increasing reliance on AI for routine tasks requires auditors to revise their roles to monitoring AI operations and reviewing the results produced by these systems (Glover et al., 2017). With AI performing more analytical and data processing tasks, auditors have more time to focus on complex areas like risk assessment, checking the quality of AI-generated insights, and providing strategic audit recommendations to the auditees (Glover et al., 2017).

The use of AI in auditing necessitates a transformation in auditor capabilities (Cao & Lin, 2022). While traditional auditing abilities such as financial reporting knowledge and auditing standards remain important, auditors must also be proficient in data analytics, machine learning, and artificial intelligence (AI) (Cao & Lin, 2022). Furthermore, auditors must be capable of assessing AI-generated data, which requires a combination of technical expertise and professional judgement (Cao & Lin, 2022). Auditors are increasingly being taught in data analytics and programming languages like Python, enabling them to work effectively with AI systems and understand complex datasets (Cao & Lin, 2022).

The use of AI in auditing also raises regulatory concerns (Kogan and Vasarhelyi, 2014). Audit standards and processes have historically relied on human decision-making, and it is uncertain how AI will fit into these existing systems (Kogan & Vasarhelyi, 2014). Regulators must develop new rules that account for AI's capabilities and limitations in auditing practice (Kogan & Vasarhelyi, 2014). Furthermore, there are concerns about the security and privacy of the data used by AI systems, particularly in jurisdictions with strict data protection regulations (Kogan & Vasarhelyi, 2014).

The application of AI to increase audit accuracy and speed may have an impact on client-auditor interactions by increasing transparency and confidence (Li & Li, 2020). However, the adoption of AI technology may raise concerns about the potential loss of auditors' human judgement and insight, which has traditionally been a crucial part of the relationship between auditors and their clients (Li & Li, 2020).

AI has the potential to improve audit quality by increasing data analysis and enabling more accurate risk assessments (Chen & Liao, 2020). However, the use of AI tools raises the prospect that auditors would over-rely on automated processes and overlook their professional judgement, possibly jeopardising audit quality (Chen & Liao, 2020). Ensuring that AI technologies supplement, rather than replace, human expertise is critical for audit quality and integrity. While AI can assist in detecting anomalies and fraud, human auditors must still

use their discretion to evaluate these findings and assess their importance in the greater context of financial reporting (Chen & Liao, 2020).

While there are concerns about job losses, some study suggests that AI's involvement in auditing may help to create jobs in other industries (Glover et al., 2017). As AI tools automate basic tasks, auditors may be able to focus on more value services, including advising, risk management, and strategic recommendations (Glover et al., 2017). This change may provide opportunities for auditors to obtain expertise in specific areas such as data analysis, cybersecurity, and AI-powered business insights (Glover et al., 2017).

AI will not necessarily result in large-scale job losses, but it will alter the types of duties that auditors perform (Glover et al., 2017). Auditors will increasingly focus on activities that need human judgement, interpretation, and strategic thinking, leading to opportunities for more skilled and senior positions in the profession (Glover et al., 2017). AI has the potential to improve various auditing processes (Gopal, 2023). EY has invested $1.4 billion in an AI platform, evidencing that audit firms realise the potential and return to be gained from the use of AI (EY, 2023). On the other hand, KPMG makes use of AI technologies to facilitate the analysis of huge quantities of data at a faster pace to better understand their clients and provide valuable feedback (Lee, 2016).

Innovation in the audit profession through AI enables auditors to apply the more critical skills of professional judgement and scepticism (Raphael, 2017). The results of a survey conducted by KPMG on financial executives revealed that almost half of the respondents expected auditors to utilise AI to perform data analysis (KPMG, 2023). The results of the survey also indicated that various financial statement users expect the use of AI to improve the quality of audits (KPMG, 2023).

Given the increasing use (Greenman, 2017) and unique functional abilities of artificial intelligence technologies (Kokina & Davenport, 2017), this study is concerned with whether audit quality is improved by AI. While there is research on audit quality attributes (DeAngelo, 1981; Francis, 2011; Kilgore et al., 2011; Watkins et al., 2004) and current uses of artificial intelligence in the audit process (Bowling & Meyer, 2019; Dickey et al., 2019; Greenman, 2017), researchers have not explored the impact of AI on audit quality in detail. The auditing literature has not yet examined auditor professionals' perspectives on how AI influences audit quality (Noordin et al., 2022). Furthermore, global research on artificial intelligence (AI) and its application in auditing is limited, and the studies that are currently available do not extensively investigate how AI affects audit quality (Noordin et al., 2022).

1.2: Research question

- How do the functionalities of AI contribute to potential improvements in audit quality?

1.3: Contribution

The study explores the key indicators of audit quality which may be impacted by audit firms' use of AI. These indicators can be used by audit firms, regulators, and oversight bodies to perform informed assessments regarding the quality of audit engagements. It is of particular importance for audit firms to understand what factors contribute to the quality of the audit engagements they perform, as regulators have increased their monitoring role over audit firms to restore the legitimacy of the profession and not performing quality audits may result in sanctions and financial penalties against the firms (Dikuua et al., 2023).

Furthermore, the study contributes to the understanding of artificial intelligence and how it can be applied within the auditing function to aid in the auditing processes. Given the increasing expectation of auditors to use AI, auditing firms need to understand how they can utilise AI to perform audits and the particular areas of the audit processes they stand to benefit from the most by using AI.

Lastly, the study investigates how the application of AI affects audit quality. Auditing firms are under pressure to perform high-quality engagements in order to restore the legitimacy of the profession (Bowling & Meyer, 2019; Dikuua et al., 2023). As a result, understanding how the use of AI impacts the quality of audit engagements performed by the firms is important. Auditing firms have started incorporating AI into their auditing resources (Kokina & Davenport, 2017). Audit firms can use and apply artificial intelligence technology more effectively if they know how AI influences audit quality.

1.4: Limitations and delimitations

Only auditing experts are engaged to complete the correspondence table to ensure that respondents comprise only individuals who are well-versed in the subject matter which enhances the reliability of the study. The approach is considered appropriate given that the objective of the research is not to provide results which are broad and the study is only exploring the subject matter (Maroun, 2014). A risk that responses from participants are biased exists as this is the case with many qualitative studies (Ram et al., 2016). This risk has been

mitigated in this study by maintaining the anonymity of respondents during the data collection process.

The results are not stratified based on the job title of the respondents in this study (Ram et al., 2016). The correspondence analysis is an exploratory tool and cannot be used for hypothesis testing as it deals with subjective opinions. Consequently, the purpose is not to reach a quantitative conclusion (Maroun, 2014).

The following section explores the literature on audit quality and artificial intelligence functional abilities.

2. Literature review

In this section, the characteristics of audit quality are identified and presented as rows in the correspondence analysis (see Appendix F). Similarly, the characteristics of artificial intelligence are identified and detailed. These serve as columns in the correspondence table (see Appendix F) which is the basis for the finalised correspondence analysis and plot.

2.1 Audit Quality

Audit quality is described in terms of elements that are likely to result in high-quality audits; it cannot be covered by a single metric (Neri & Russo, 2014; Sulaiman, 2018; Wooten, 2003). A firm's duty to create policies that address the quality of engagements the firm executes is emphasised by the International Standard on Quality Management 1 (ISQM 1) (IAASB, 2022).

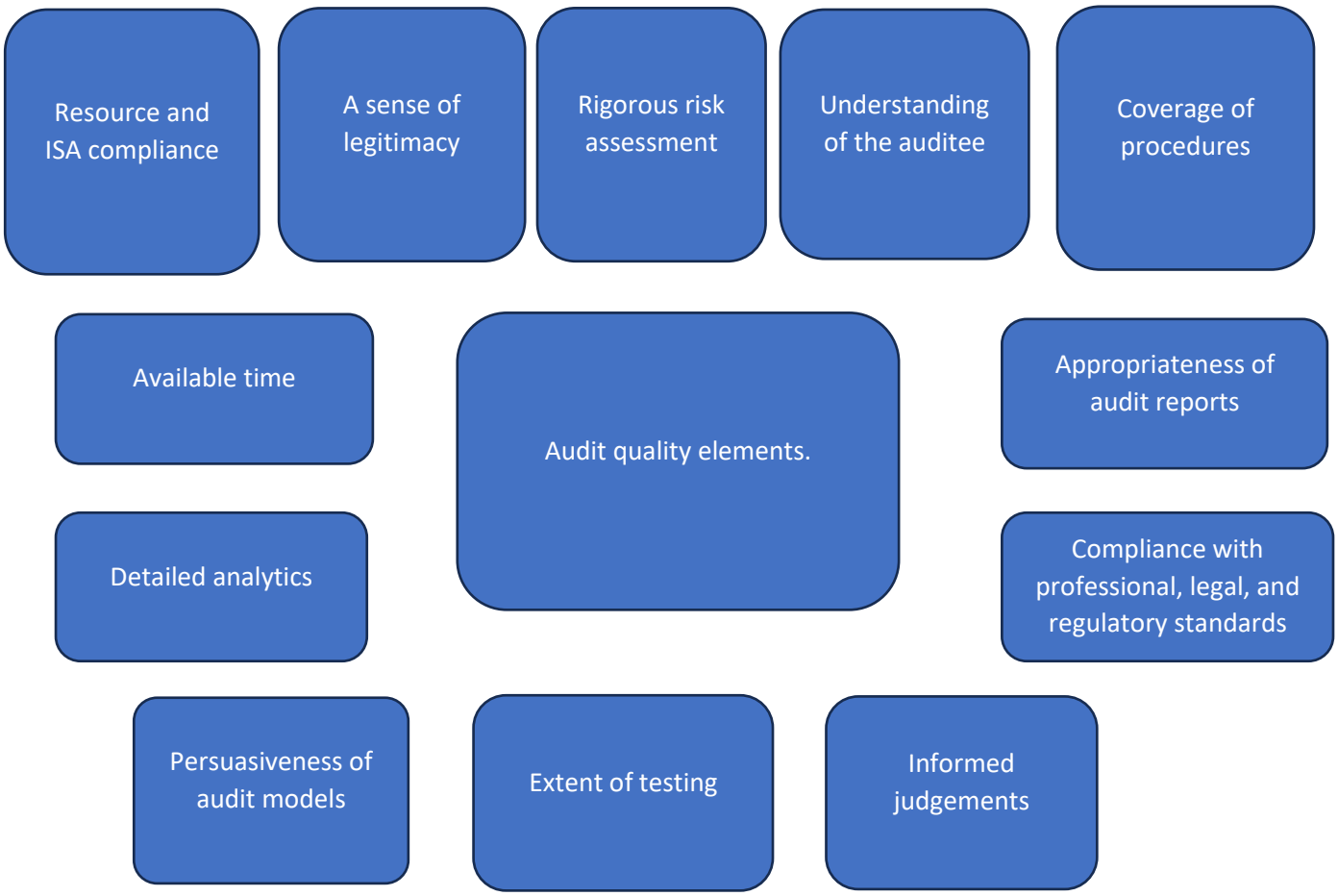
To facilitate the constant performance of quality engagement by organisations, the standard mandates them to set up a quality management system in compliance with its guidelines (IAASB, 2022). The firm's risk assessment process, governance and leadership, adherence to pertinent ethical requirements, acceptance and continuation of client relationships and specific engagements, engagement performance, resources, information and communication, monitoring and remediation process are among the quality elements of ISQM 1 (IAASB, 2022).

The ISQM 1 quality criteria serve as the foundation for audit quality for this research. The firm's capacity to organise, carry out, and report on engagements in compliance with the relevant legal and regulatory obligations, as well as professional standards, is fundamental for quality engagements in terms of ISQM 1 (IAASB, 2022). As part of the standards that auditors must follow, International Standards on Auditing (ISA) specify the purpose of an audit and the duties

of auditors when carrying out engagements. They also offer direction on engagement performance.

Since over 100 jurisdictions have either approved or incorporated ISAs as the foundation for conducting audit engagements, auditing standards are widely used and applied (IAASB, 2006). Before being implemented, the standards must pass stringent peer review and consultation (Maroun, 2015). Because of this, the study defines audit quality as the auditor's capacity to implement ISA guidelines. To determine the essential characteristics of audit quality, the elements emanating from ISAs that indicate audit quality are examined and deliberated. The literature that has been examined has been summarised and structure in the form of a concept matrix (Table A). The elements that have been identified are shown in Figure 1 below.

Figure 1: Elements of audit quality



2.1.1: Acceptance, continuance and resources

Engagement quality holds great significance in terms of ISQM 1. Accordingly, ISQM 1 (IAASB, 2022) recommends the creation and usage of explicit client acceptance procedures. Before agreeing to an appointment, a company must determine if it can accept the client's request for services (IAASB, 2022). As such, companies must evaluate as part of the assessment if they can adhere to professional standards when providing the service (IAASB, 2022). Having the right resources to complete the audit affects the firm's capacity to adhere to professional standards (IAASB, 2022).

Audit companies are unable to assess if they have the time and resources needed to handle audit issues that may occur throughout the audit in the absence of appropriate acceptance and continuance procedures (AFRC, 2023). This could lead to the auditor accepting subpar audit work to meet deadlines for the audit, including those for releasing audited results for auditees listed on the stock exchange (AFRC, 2023).

Considering the degree of expertise and experience needed for the firm's engagements, employers should select, train, and retain staff members who possess the necessary skills to consistently carry out high-quality engagements (IAASB, 2022). Workers should show by their actions and attitudes that they are committed to quality (IAASB, 2022). Businesses should hold employees responsible and acknowledge their contributions through performance reviews and rewards (IAASB, 2022). Given that the industry is labour-intensive, the firm's human resource procedures are just as important as its resources and expertise. According to Francis (2011) and Lennox & Wu (2018), human capital is crucial for delivering quality engagements.

Similarly, in terms of King IV, human capital is one of the six capitals as it is one of the key inputs required for the success of a business. King IV recommends that a firm’s remuneration policy should achieve the objective of attracting, motivating, and retaining human capital and promoting positive outcomes. It is evident from the above that there is a consensus between ISQM1 and King IV regarding how vital human resource practises are to ensuring quality (Maroun, 2014).

The necessary skills, resources and ethical standing are of essence for the engagement team to effectively carry out their professional duties (IAASB, 2009f; IFA, 2006). An audit team that has the appropriate skill set and experience is more likely to perform audits to the highest quality standards (IAASB, 2015). There is a risk that firms will not carry out their professional responsibilities in terms of the service they have been contracted to provide if their resources do not have the necessary level of competence required for the engagement (Maroun, 2014).

The competence of the engagement team and audit quality have been found to be positively and significantly correlated by several studies (Arief Himmawan et al., 2019; Dewi, 2023). According to Christensen et al. (2015), auditors believe that higher audit quality is correlated with compliance with auditing standards, yet business investors believe there is a substantial association between the audit team's competence and audit quality. In light of the aforementioned, the correspondence table includes the following factors:

> **C1: Acknowledging the importance of resources and competency of the engagement team as well as the need for full compliance with ISA.**

2.1.2: Ethical requirements, governance, and leadership

In addition to ensuring that they have the right resources to carry out engagements, firms should assess whether those resources are capable of satisfying their obligations pertaining to the applicable ethical standards (IAASB, 2022). Consequently, in performing their duties, auditors are expected to uphold the following core principles: objectivity, integrity, professional competence and due care, confidentiality, and professional behaviour (IESBA, 2021). The auditor may encounter situations which could create a threat to one or more of the fundamental principles resulting in the auditor being compromised (IESBA, 2021).

Previous research (Beckett, 2020; Decker Jeff 2016; Dikuua et al., 2023) emphasises the significance of assessing variables that may indicate threats to the tenets of the fundamental principles and developing safeguards to reduce the threats. When there are serious threats and insufficient safety measures, the auditor should decline or resign from the engagement (Beckett, 2020; IESBA, 2021).

The evaluation of compliance with ethical requirements should include specific assessments relating to the firm's and engagement team's ability to remain independent from the auditee (IAASB, 2022). This is because auditors bear the dual responsibility of fulfilling their professional commitments to clients and maintaining public trust (Wolfe & Sterna, 2020). Auditors act as independent collaborators of the information produced by management which the public relies on and therefore are viewed as agents acting in the public interest (Ardelean, 2013).

Accordingly, the credibility of the audit profession depends on their reports accurately reflecting the company's financial situation (Ardelean, 2013). As a result, auditors must provide an opinion that is impartial and unaffected by conflicts of interest (Ardelean, 2013). Conflicts of interest make it difficult for the auditor to maintain their integrity and function as dependable agents (Ardelean, 2013). Thus, the credibility and confidence of the auditing profession depend on the auditor's professionalism and independence (Carrington, 2010). Based on the above, the following theme of audit quality has been included.

C2: A sense of legitimacy in the eyes of the informed public.

In order to serve the public interest, the firm's governance and leadership structure should demonstrate a commitment to quality by cultivating a culture that encourages completing quality engagements (IAASB, 2022). Additionally, the company culture needs to uphold moral principles and professional demeanours (IAASB, 2022). Since the firm's financial and

operational priorities may have an impact on its commitment to quality, the importance of quality should be integrated into the firm's strategic focus and priorities (IAASB, 2022).

The firm may inappropriately accept engagements to realise audit fees even in situations where it will be unable to fulfil its obligations relating to the pertinent ethical, professional, legal, and other regulatory standards due to its financial priorities, which include realising profits through audit fees (IAASB, 2022). Leadership should be responsible and accountable for quality and quality evaluations (IAASB, 2022). The ISQM 1 governance and leadership element is synonymous with King IV principles (Institute of Directors Southern Africa, 2016). King IV also emphasises that the governing body should lead in a manner that is ethical and effective (Institute of Directors Southern Africa, 2016). In terms of King IV, the governing body should also promote an ethical culture and assume responsibility for corporate governance in the organisation (Institute of Directors Southern Africa, 2016).

2.1.3: The firm’s risk assessment process

Since conducting audit engagements exposes audit firms to audit risks, such risks should be considered as part of the firm's risk assessment. According to ISA 200, audit risk is the possibility that an audit opinion would be provided that is deceptive and does not accurately reflect the financial affairs of an auditee (IAASB, 2009f). Identifying audit risk requires a thorough risk assessment. The auditor's goal is to gather adequate and relevant audit evidence in order to reduce audit risk and identify misstatements (Nikolovski et al., 2016).

A prior study indicated that a risk-based audit is key to achieving audit quality (Sardasht & Rashedi, 2018). A thorough risk assessment process is essential for audit quality (Qi & Yuan, 2023). The identification of audit risks is crucial, as the auditor would be unable to respond to risks which they cannot identify (Munter, 2023). As a consequence, the audit opinion would be deemed inappropriate since it is not supported by adequate and relevant audit evidence (AFRC, 2023).

Establishing policies and processes to ensure that businesses produce reliable engagement reports is one of ISQM 1's primary objectives (IAASB, 2022). The auditor is expected to take into account all audit evidence obtained during the risk assessment process in order to reach a conclusion regarding the auditee's risk assessment (IAASB, 2019b). According to (Le et al., 2021) producing a high-quality audit is more likely when audit risk has been thoroughly assessed.

Audit risks are typically discovered during the audit planning phase, which is a process that considers numerous aspects of the auditee (Gartland, 2017). Audit planning includes considerations about the industry, laws and regulations and the nature of the auditee's operations. There is a consensus that audit planning is essential for quality audits (Azizi & Muliartha, 2018; Brant E. Christensen, 2016; Christensen et al., 2015; Dresdner & Fischer, 2020; Pardo, 2023). The AFRC (2023) and Pardo (2023) encourage audit firms to embrace a culture of thorough and timely audit planning in order to produce high-quality audit results.

Assessing the risk of material misstatement per ISA 315 requires the auditor to gain a thorough understanding of the entity and the environment in which it operates (IAASB, 2009b). One important characteristic of a high-quality audit is the auditor's report's credibility and usefulness, which is influenced by how thorough the risk assessment process is (Francis, 2011; FRC, 2008; Nelson & Tan, 2005).

C3: A rigorous risk assessment process has been followed.

The auditor is required to have a broader view of the client rather than merely the debits and credits in the ledgers to perform a thorough risk assessment (Gartland, 2017). Furthermore, auditors should be unbiased by obtaining audit evidence from various sources, such as public knowledge about the auditee (IAASB, 2019b). A broader view includes knowledge about the industry, regulations and micro and macro-economic factors to which the auditee is exposed (Gartland, 2017).

The broad view allows the auditor to identify high-risk areas in the audit, which the auditor may prioritise during the audit (Gartland, 2017). The use of automated tools and processes will allow risk assessments to be performed on large amounts of data (IAASB, 2019b). Increased audit effort results in a robust understanding of the auditee, leading to a more accurate and comprehensive risk assessment and the identification of material misstatements (Xiao et al., 2020).

The complexity of the client's operations influences how long it takes the auditor to fully comprehend the client and the risks that the client faces, which in turn affects the auditor's capacity to produce a more trustworthy audit report (Cassell et al., 2020). As a result, companies that can recognise and comprehend the client's primary risk areas can focus more of their attention on those areas, improving the audit's quality (Wooten, 2003). Since these are more likely to lead to substantial misstatements, the auditor should concentrate their efforts

on areas where there is a higher risk of error (Nikolovski et al., 2016). This ensures an efficient audit.

Auditors should identify and pay particular attention to material changes in business operations, non-routine transactions and unusual trends, as these may result in high-risk areas that require more focus (AFRC, 2023; Munter, 2023). Certain facts may arise and circumstances that affect the auditee may change while the execution of the audit has already begun. Auditors are required to regularly update the audit plan, risk assessment and audit procedures to address any subsequently discovered changes (AFRC, 2023; Le et al., 2021).

C4: The auditor's ability to understand the client and the key risks of the client's operations.

2.1.4: Engagement Performance

The risk of significant misstatement influences the type, timing, and scope of audit procedures (IAASB, 2009g). The auditor obtains sufficient and suitable audit evidence in connection to the risks identified by employing various combinations of substantive analytical evaluations, tests of details, and tests of controls (IAASB, 2009g). The market-based probability that an auditor will find anomalies in the client's accounting records and report the irregularities identified was defined by DeAngelo (1981) as audit quality.

When there is a greater chance of significant misstatements, more substantive testing will probably be carried out in addition to any control work that has been done (IAASB, 2009g). More persuasive evidence is obtained by performing tests of detail. Consequently, as more relevant and reliable information is required, the auditor might rely more on tests of detail instead of substantive analytics (IAASB, 2009d).

C5: The extent and coverage of substantive procedures and test of controls.

Audit quality is a broad concept, as auditing standards provide guidance and principles of auditing, however, they do not provide a comprehensive list of procedures for audit gathering tasks and what constitutes adequate and suitable audit evidence (Francis, 2023). The ability to detect material misstatements is affected by how thorough the audit team has been while performing the audit (Wooten, 2003). Considering that auditing standards are founded on principles, auditors frequently have to use their professional judgment to determine what constitutes sufficient and suitable audit evidence (Francis, 2023).

The auditor must create an expectation of the recorded amounts when using analytical processes, and then determine if the expectation is accurate enough to detect an inaccuracy (IAASB, 2009e). Contrary to high-level trend analysis, the expectation developed must be sufficiently refined and defined to detect a misstatement and it cannot be a broad expectation (IAASB, 2009b).

Based on the expected values, the auditor is then required to follow up on differences that deviate from the expected amounts and perform further investigations and testing (IAASB, 2009b). Analytical techniques entail assessing recorded transactions by utilising both financial and non-financial data to analyse logical links (IAASB, 2009e). Consequently, it follows that these procedures can be used to identify trends or relationships in data that are not consistent with other information obtained by the audit team (IAASB, 2009b). According to Kritzinger and Barac (2017), analytical techniques improve the audit's efficacy and value while also boosting its efficiency.

C6: The use of detailed analytics rather than high-level trend analytics.

There is an interrelationship between sufficient and appropriate audit evidence (IAASB, 2009a). Appropriateness refers to the calibre of the audit evidence, whereas sufficiency refers to its quantity (IAASB, 2009d). High-risk audit areas are likely to result in a higher quantity of audit evidence being required because the quantity is influenced by the risk assessment and the quality of the audit evidence (IAASB, 2009d).

In order to be convinced that the audit evidence gathered is sufficient, the audit team needs the ability and time to gather and assess audit evidence. This will allow them to obtain sufficient quantities of audit evidence. Consequently, firms should consider if their staff have sufficient time to be able to produce quality engagements (IAASB, 2022). Time constraints make it more likely that errors will not be detected and therefore jeopardise the quality and quantity of audit evidence (Cassell et al., 2020).

C7: The amount of time available to perform audit evidence-gathering and evaluation tasks.

The accounting records of a business can be examined using a variety of audit processes; nevertheless, in order for the audit team to determine that it has gathered adequate audit evidence, it is necessary to take into account the quality of the evidence (IAASB, 2009d). More assurance is obtained by contrasting management information with information from

independent sources and evaluating if the management information is consistent with the information from other sources (IAASB, 2009a).

Consideration should be given to whether additional procedures are needed to resolve discrepancies between management information and information from other sources, as well as how the discrepancies may affect other audit areas (IAASB, 2009d). Given that they may gather data from several sources, firms that employ sophisticated audit techniques are more likely to detect misstatements and produce compelling audit evidence (Wooten, 2003).

C8: The persuasiveness of the methods used to obtain and evaluate audit evidence.

When planning and carrying out audit procedures, the auditor should take the information's relevance and dependability into account (IAASB, 2009d). This includes questions about whether management information is accurate and complete, and about how precise and detailed the information needs to be to carry out the particular audit procedure (IAASB, 2009d).

The likelihood that material misstatements will be discovered is also dependent on the sampling method used to perform the audit (DeAngelo, 1981), as this has an impact on the sufficiency of the audit evidence obtained. Auditors rely on sampling techniques to select how many samples to test, as due to the amount of available time and the high cost of audit services, it is not practical to test 100% of the financial data of the auditee (Meleshenko & Usanova, 2014). The degree of risk that the auditor is prepared to accept influences the sample size (IAASB, 2009i). When an auditor is unwilling to take on a significant level of risk, a larger number of samples will be selected (IAASB, 2009i).

The use of sampling methods introduces the risk that the auditor may have reached a different conclusion and audit opinion had they tested 100% of the financial information compared to only a sample of the population (Meleshenko & Usanova, 2014). When applying sampling methods, auditors often have to project the sampling errors over the entire population being tested. At times, auditors fail to appropriately extrapolate the errors and are susceptible to bias when evaluating the audit results based on a sample (Elder et al., 2013).

According to (Xiao et al., 2020), putting in more effort during an audit increases the likelihood that misstatements will be found since the auditor can adopt thorough audit methods and gather strong audit evidence. A study by Al-Ansi (2022) that also discovered a positive link between audit effort and audit quality lends additional credence to the claim.

The overall role of auditors is to identify misstatements, propose adjustments and report on remaining material misstatements to deliver an audit opinion that can be relied upon (Xiao et al., 2020). The more audit effort applied, the higher the chances that misstatements will be identified, and audit adjustments will be made to correct the statements, resulting in improved quality of the audited financial statements (Xiao et al., 2020). The extent of testing performed by the audit team, therefore, influences audit quality as it signals greater audit effort.

C9: The extent of testing.

Businesses operate in certain conditions of uncertainty, which results in some accounting treatment being based on accruals and estimates on the financial statements using management's judgment (Francis, 2023). Accruals and estimates are susceptible to misstatements and fraud as they are based on management's judgements and management may be biased to manipulate earnings to meet performance targets (Francis, 2023).

In order to avoid aggressive accounting decisions and management bias, which could lead to material misstatements in the financial statements, the auditor should evaluate the accruals and estimates (Francis, 2023). The auditor's judgement is used to determine if management estimates are conservative or aggressive, which has an impact on the quality of the audit (AUASB, 2022). Engagement teams should exercise professional judgement at all times during the audit, as it is a key element of the proper performance of an audit (IAASB, 2009c).

The auditor's understanding and experience with the engagement's facts and circumstances inform the interpretation of ISAs, ethical standards, and engagement-related judgements (IAASB, 2009f). Assessing the reasonableness of management's estimates requires expert judgement (IAASB, 2009f). The engagement team must use professional discretion in light of the engagement's particular facts and circumstances, as stressed by ISQM 1 (IAASB, 2022). Moreover, professional scepticism improves the calibre of professional decisions made (IAASB, 2022).

The Independent Regulatory Board for Auditors (IRBA) in its 2022 Public Inspection Report, underlined the value of interrogating information provided by management by exercising professional scepticism (IRBA, 2023a). There is a consensus that when an auditor applies more professional scepticism, the quality of the conclusions the auditor makes also improves. Professional scepticism is generally perceived as a vital input towards audit quality (Quadackers et al., 2014). The auditor should maintain presumed doubt on the reliability of

the information provided by management and corroborate such information to be able to rely on it (Puthukulam et al., 2021; Quadackers et al., 2014).

An audit conducted without maintaining professional scepticism is likely to present deficient audit evidence, as no collaborative evidence would have been obtained to substantiate management representations (Quadackers et al., 2014). Effective oversight, guidance, and monitoring for complicated matters requiring high degrees of judgment are also crucial (IAASB, 2009e). The audit work performed and judgements made by less experienced engagement team members should be adequately reviewed by more experienced team members, and appropriate direction and supervision should be given to them throughout the performance of their audit work (IAASB, 2022).

C10: Informed judgements after consultation, supervision and review have been made in reaching the audit opinion.

2.1.5 Monitoring and Remediation Process

Companies must have monitoring and remedial procedures established to provide information regarding the development, execution, and functioning of the quality management system (IAASB, 2022). The procedure also gives the businesses the ability to address any flaws found in the quality system (IAASB, 2022). It is recommended that monitoring activities consider all pertinent information, including any claims regarding the firm's noncompliance with professional standards and any legal and regulatory obligations (IAASB, 2022).

According to ISQM 1, a company can cultivate an internal culture that is quality-oriented by mandating that audit work be carried out and reported following relevant rules and professional standards (IAASB, 2022).

C11: Audit work is performed in compliance with professional standards and applicable legal and regulatory requirements.

2.1.6: Information and communication

The need for relevant and reliable information being communicated with external parties is emphasised by ISQM 1 (IAASB, 2022). One kind of information that companies provide to different users of the financial statements is the audit report. According to ISQM 1, one of the key objectives of a system of quality management is to provide the company with an

appropriate degree of comfort that the audit reports of the company issues are suitable based on the specific observations derived from the performance of the engagement (IAASB, 2022).

Since investors and lenders depend on the company's financial statements to make decisions about the company, an independent audit opinion is essential for these users of financial statements (Dewi, 2023). Consequently, the auditor offers reassurance about the accuracy of the data in the financial accounts, which are used as a foundation for decision-making by various users (Dewi, 2023).

According to Francis (2023), the primary results of an audit are the audit report and the quality of the financial statements, which serve as a pertinent foundation for evaluating the audit's quality. The appropriateness of the audit opinion is an area of concern towards audit quality as material misstatements are identified during inspections of audit files by regulators rendering the issued audit opinions inappropriate (IRBA, 2023a).

Research on the definition of audit quality was done by (Francis, 2023) who contends in his paper that audit quality is made up of two components: the accuracy of the audit findings on the audit report and, by extension, the audited financial statements that the report is based on (Francis, 2023).

Audit quality is influenced by the auditor's ability to accurately provide a judgement regarding the veracity of the data presented in a client's financial statements (Titman & Trueman, 1986). Audit quality is questionable when an auditor has issued an unqualified audit opinion on statements which are subsequently found to contain material misstatements (Titman & Trueman, 1986).

C12: Appropriate audit reports are issued.

The next section explores the use of artificial intelligence in auditing.

2.2: Artificial intelligence

Artificial intelligence has been described in several ways by previous research. According to the study's objective artificial intelligence is defined as the ability of machines to carry out cognitively demanding activities (Adeoye et al., 2023; Basu et al., 2020; Hasan, 2022; Russell et al., 2023; Stuart Russell, 2023). Like humans, machines can observe, reason, and draw

conclusions (Chan et al., 2018). AI also describes a machine's capacity to receive and process information to automate a manual process (Rikhardsson et al., 2022).

AI systems may have defined objectives or implied ones (Stuart et al., 2023). Artificial Intelligence (AI) can be applied to explicit goals when a human developer programmes the software directly, or implicit goals when a developer specifies a set of rules or when the system can adapt to changes and acquire additional objectives (Stuart et al., 2023).

According to Stuart et al. (2023), these systems are capable of reasoning and producing outputs from input data. As explained by Stuart et al. (2023), the output data can take many different forms, such as suggestions, judgements, content, or predictions.

2.2.1 Subsets of AI

This section outlines the most frequently encountered AI components: natural language processing, machine learning, and deep learning.

Machine learning

One aspect of artificial intelligence is machine learning (ML), which is the capacity of AI systems to learn and become adept at performing tasks (Raphael, 2015). The ability of a machine to recognise and apply patterns from data in order to learn is known as machine learning (ML) (Lv, 2023; Shimamoto, 2018). When machines encounter scenarios comparable to those they previously encountered, they can generate predictions through skills which they have learned from exposure to a variety of data sources (Jhawat et al., 2023).

When a computer learns from data, it can perform tasks without explicit programme instructions by using what it has learned (Jhawat et al., 2023; McKinsey & Company, 2023). Through learning, the machine's algorithms improve with time (McKinsey & Company, 2023. The machines are capable of learning in both supervised and unsupervised environments. (Dickey et al., 2019).

When past data is available to forecast future results, supervised learning may be utilised (Castle, 2017). To generate forecasts and draw conclusions, it sorts data and checks for correlations between variables in data sets (OECD, 2021). Conversely, unsupervised learning does not need past data to find patterns; it can do so on its own (Castle, 2017). To analyse the distribution of the data and the relationships between the variables in the data, it only uses

the current data set (OECD, 2021). It then makes judgements based on observations from the current data set without consulting prior assumptions or experiences (OECD, 2021).

Deep learning

A component of machine learning known as "deep learning" uses artificial neural networks and huge data to solve problems (Jhawat et al., 2023; McKinsey & Company, 2023). The term "big data" describes the accumulation of vast amounts of structured and unstructured data that keep growing over time (Jhawat et al., 2023). The function of an artificial neural network (ANN) is comparable to that of the nervous system in humans (Jhawat et al., 2023; McKinsey & Company, 2023).

Neural networks are engineered to function in a way that is similar to the way the human brain does, learning from many (deep) layers of input to recognise intricate patterns, much like neurons communicate with the brain (OECD, 2021). Multiple data sources can be received and processed by them (Jhawat et al., 2023; McKinsey & Company, 2023). The data that is processed by neural networks teaches the machines how to operate effectively (Jhawat et al., 2023; McKinsey & Company, 2023).

Three layers make up an artificial neural network: the input layer, which accepts complex data; the processing layer, also known as the hidden layer, which uses mathematical techniques to process the received data; and the output layer, which presents the results (Jhawat et al., 2023). Based on the volume and complexity of the data, there may be additional hidden layers in addition to the three that make up the program's basic representation (Jhawat et al., 2023).

Natural Language Processing

The branch of artificial intelligence known as "natural language processing" (NLP) studies how well AI systems can understand and process human language. For AI models to comprehend human languages, natural language processing is necessary (Lv, 2023). AI systems can comprehend instructions and produce content that depends on human instructions because of their ability to grasp languages (Lv, 2023). Natural language understanding (NLU) is a subset of natural language processing (NLP) that specialises in tasks such as sentiment analysis and language translation (Samant et al., 2022). According to Samant et al. (2022), NLU can also be used to read, process, and summarise emails.

2.2.2 Categories of AI

This section outlines the commonly encountered categories of AI namely, generative AI, weak, and strong AI.

Generative AI

Diverse forms of artificial intelligence exhibit varying degrees of self-sufficiency and flexibility (OECD, 2021). The term "generative AI" describes a type of AI that can create text and visual information, as well as act autonomously (Lv, 2023; PwC, 2023). Because it operates with straightforward language commands, generative AI is user-friendly (PwC, 2023).

Previous research (Beyan & Rossy, 2023; Newell, 2022; Thurzo et al., 2023) has suggested that the potential of generative AI can be realised using autoregressive models or Generative Adversarial Networks (GANs). Autoregressive models are those that use conditional probability to generate new content based on similar previously generated content (Beyan & Rossy, 2023; Lv, 2023; Newell, 2022; Thurzo et al., 2023).

GANs, on the other hand, replicate cognitive capacities similar to those of humans. They can learn from previous experiences, use complex data sets, and generate new data (Aggarwal et al., 2021; Lv, 2023).

ChatGPT is a type of generative AI that can generate and present data (Lv, 2023). It employs AI technology to scrutinise, interpret, and show detailed information in a variety of ways (Lv, 2023). In principle, generative AI can generate new data independently from a given set of input data (Lv, 2023). It can also employ computer vision to process images and generate content from them (Dihao et al., 2023).

Weak and strong AI

Several researchers have also suggested distinguishing between weak and strong AI (Butz, 2021; Khan, 2021; Liu, 2021). According to (Liu, 2021), computers that replicate human intelligence are examples of weak AI, whereas strong AI refers to machines that have human-like intelligence in the form of cognitive capacities. They can not only learn from processed data, but also grasp and explain the elements, forces, and processes that influence the underlying data used to learn (Butz, 2021; Hassani et al., 2020).

As a result, strong AI refers to machines that can reason and justify their actions (Butz, 2021). Weak AI is also known as narrow AI due to its functional limitations. It is less robust compared to strong AI and can make predictions and conclusions, but it cannot explain the reasons behind its decisions (Khan, 2021). The term Artificial General Intelligence (AGI) is used interchangeably with strong AI, whereas weak AI is often referred to as Artificial Narrow Intelligence (ANI).

Simply put, “weak AI” represents computational systems that exhibit as if they own human intelligence, but they do not. In contrast, “strong AI” represents computational systems that have human intelligence. Strong AI is still a notion, and current AI systems fall under weak AI due to the lack of strong cognitive abilities (Butz, 2021; Fjelland, 2020; Liu, 2021).

2.2.3: Types of artificial intelligence

This section outlines the four forms of AI namely, reactive machines, limited memory, theory of mind and self-aware AI.

Reactive machines

These are computers that are incapable of forming memories or making decisions based on previous experiences (Hintze 2016). (Hassiani et al., 2020). As a result, machines cannot learn from the past and will always react the same way (Hassani et al., 2020; Hintze, 2016). They rely on predetermined logic derived from programming (Khan, 2021).

Limited memory

AIs that have a short-term memory used for storing past experiences are referred to as limited memory AI (Hassani et al., 2020; Lateef, 2020). Contrary to reactive machines, they can learn and make subsequent decisions using the learning from past experiences (Hassani et al., 2020). In addition, past data in the form of facts and occurrences informs future decisions using the machine learning model (Khan, 2021). An example of limited memory AI is self-driving cars as they can observe and make decisions based on what has been observed (Fonseca, 2020). An example of existing limited memory AI is self-driving cars[1] as they can observe and make decisions based on what has been observed (Fonseca, 2020).

[1] Self-driving cars rely on sensors to detect incoming vehicles and lanes and use this information to make smarter driving decisions.

Theory of mind

The phrase alludes to the idea that machines can recognise that humans have ideas and emotions that influence their actions (Hintze, 2016). AIs with the theory of mind capabilities would be able to grasp emotions, mental processes, and beliefs in the same way that people do, allowing them to communicate with humans. AI technologies do not yet display this level of comprehension; nonetheless, development is ongoing (Khan, 2021; Reynoso, 2019).

Self-aware AI

Contrary to the theory of mind AI, self-aware AI does not merely focus on the machine's ability to understand and mimic human behaviour but also has its independent way of thinking and reactions (Reynoso, 2019). Self-aware AIs would be considered the most advanced stage of AI development as they would exhibit common sense and logical abilities (Khan, 2021). However, this is only a concept, as such machines do not yet exist (Hassani et al., 2020; Khan, 2021).

2.2.4 Possible application of AI to audits

This section explores how AI can be used in different parts of the auditing process such as the automation of tasks.

Automation of tasks

Determining materiality involves professional judgement (IAASB, 2009b); nevertheless, AI can use financial data to inform auditors' decisions. AI systems can use an entity's financial data to recommend a set of appropriate audit materiality benchmarks to the auditor (CPA, 2020). AI can gather data from earlier and intermediate financial periods to establish materiality (CPA, 2020).

Auditors must examine the relative volatility of the benchmark when determining whether it is appropriate (IAASB, 2009b). AI can be used to assess the volatility of multiple benchmarks and recommend a suitable one. Materiality fluctuates in response to changes in the benchmark. AI can calculate updated materiality levels when the benchmark changes and establish final materiality (CPA, 2020).

Auditors can also use AI to assess the auditee's performance using ratio and trend analysis (CPA 2020). Auditors are frequently faced with massive data sets to employ for ratio and trend analysis; AI can automatically clean and transform data, as well as do trend and ratio analysis, which auditors can use to analyse how an auditee has performed (IABAC, 2023).

AI also offers predictive modelling capabilities, which allow it to use historical data to predict outcomes and forecast the auditee's future performance (IABAC, 2023). AI's pattern recognition ability may detect complicated patterns and trends that humans may overlook due to their subtlety or frequency. The analysis can be utilised to improve the risk assessment of the auditee.

AI systems can execute audit activities such as data extraction and capture from large data sets faster than traditional auditing techniques, reducing the possibility of human error (Gopal, 2023; Noordin et al., 2022). Auditors must gather and review audit evidence to support the conclusions reached (IAASB, 2009c); the investigated data must be documented in such a way that the investigation may be re-performed (IAASB, 2009a).

This implies that details of the audit evidence that was gathered need to be recorded (IAASB, 2009a). AI can extract data from audit evidence and automatically generate information for use in working papers as proof of completed work (ASA, 2023; EY, 2018). For instance, AI can analyse contract agreements and extract data such as contract number, parties, start date, contract amount, and period, and then populate the extracted data in a working paper if an auditor has decided that contract agreements are the proper audit evidence. A study conducted by Raschke et al. (2018) found that using AI enhances the accuracy of data collected during the audit process and lowers human error, producing more trustworthy results.

Similarly, AI can be applied to assess various types of audit evidence, including delivery notes and invoices. AI can extract invoice dates, amounts, and dates and compare the invoice's information with that of the transaction that has been chosen for audit. Because it saves time and allows auditors to concentrate on more valuable activities during the audit process, this can be especially helpful when auditors are faced with a large number of samples.

As a result, it is anticipated that the auditor's role will become more focused on determining which audit procedures are appropriate to perform and interpreting the results of those

procedures rather than on carrying out the audit procedures, which would involve time-consuming repetitive tasks (Dalwai et al., 2022; Noordin et al., 2022; Shimamoto, 2018).

Based on the above, the following functional ability of AI is included in the correspondence table:

R1: AI systems perform time-consuming repetitive tasks which previously required the auditor's effort.

AI systems can also be utilised to improve junior staff members' audit training and supervision. Members can use Chat GPT, for instance, to ask questions regarding the proper audit methods to carry out to test line items in financial statements (Blake, 2023). This would be in contrast to conventional audit procedures, which caused delays in the audit process by requiring junior members to wait for senior audit members to be available to answer their queries (Blake, 2023).

In essence, auditors can spend less time on duties like determining materiality, analysing ratios and trends, gathering data, assessing audit evidence, and providing training and supervision when they utilise AI. (Munoko et al., 2020; Rao & Verweij, 2017) Auditors can use the time they save to concentrate on tasks that enhance the audit. Liao et al. (2024) also found that by automating repetitive operations, AI gives auditors the tools they need to concentrate on more intricate auditing tasks, which speeds up the production of audit reports.

Risk assessment and response

AI can be used to obtain data, providing the audit team with greater insights regarding the auditee (Al-Sayyed et al., 2021). AI can pull data from various sources, such as newsfeeds and market data, that can be used as part of the risk assessment process (CPA, 2020). In addition to the collection and processing of data, the Natural Language Processing System (NPL) can establish tone and sentiment in the data, which can be used to classify the data into various categories (CPA, 2020).

AI systems can produce detailed reports, which can be used to identify suspicious activities by probing transactions and provide an opportunity for auditors to proactively address areas of high risk and concern (Gopal, 2023). Garbelmen Winslow makes use of artificial intelligence to assess the level of risk of their audit clients' transactions (Bowling & Meyer, 2019). Artificial

intelligence technology can group transactions on a given general ledger based on the level of risk (Bowling & Meyer, 2019).

R2: Identify the level of risks of a given transaction as part of the risk assessment process.

The use of pattern analysis can also direct auditors to areas that are more susceptible to errors or fraud and therefore aid in the risk of material misstatement due to error or fraud (Gopal, 2023; Law, 2020). As a result, auditors can utilise their resources effectively by directing their efforts to areas flagged to possess suspicious patterns by AI that require greater scrutiny (Elliot et al., 2020; Gopal, 2023).

The data handling and processing capabilities of AI also assist with improving the timely and accurate identification of potential risks and aid in the decision-making process (Noordin et al., 2022). The application of AI systems reduces the risk of not detecting areas susceptible to material misstatements and shifts the auditors' focus towards analysing the results for their implications, contrary to obtaining and summarising data (CPA, 2020; Gopal, 2023). Previous literature has found that the utilisation of AI systems results in improved knowledge about the risks associated with the operations of an auditee (Elliot et al., 2020; Law, 2020). Increased knowledge about the risks of the auditee enables the auditors to better plan and allocate more time to areas that have been flagged as higher risks and these require more effort.

R3: Enable auditors to devote their time to identifying and developing an audit approach for high-risk areas.

As part of the risk assessment process, auditors frequently have to summarise meeting minutes, internal audit reports, customer complaints, legal issues, and more. AI can assess and summarise all of them more quickly, saving the auditor's time (CPA, 2020). With AI, trend analysis over several periods can be completed more quickly to find outliers while accounting for variables like industry trends (CPA, 2020). To help identify high-risk areas, the audit team may make use of the AI exceptions and reports in addition to their knowledge of the auditee, past audit findings and misstatements, and internal audit reports (CPA, 2020).

Unsupervised learning can also be used in the risk assessment phase to predict future outcomes based on patterns identified through data analysis, even if historical data does not exist (Dickey et al., 2019). This means that there are no labels on the output variables. In other words, the system is not fed with a predetermined answer. Instead, it relies on the input data

to identify patterns and independently produce the outcome based on the data (Dickey et al., 2019). Auditors can therefore make use of unsupervised learning to produce independent outcomes and expectations from management, which can be used to corroborate management information.

R4: Autonomous learning produces independent outcomes as it does not rely on historical data.

Unsupervised learning does not rely on a pre-determined outcome and can differentiate and operate under various scenarios (Munoko et al., 2020; Rao & Verweij, 2017). Auditors can harness their abilities by using unsupervised learning to identify risks that were previously overlooked in the risk assessment phase (Dickey et al., 2019). This is because of its independent pattern analysis abilities, which can be used to identify patterns indicative of risk factors based on the input data (Munoko et al., 2020; Rao & Verweij, 2017), which may have been too subtle for the auditors to notice.

R5: Autonomous learning uses patterns and can be used as part of the risk assessment process to discover previously unforeseen risks.

Gathering and evaluating audit evidence

Auditors usually work through huge quantities of unorganised data when performing an audit (Bowling & Meyer, 2019). Cognitive technologies can assist in how the data is understood and put to greater use by the auditor (Lee, 2016). AI technologies can, therefore, be used to work through high volumes of data in a shorter time frame compared to an auditor (Lee, 2016).

AI enables the ease of data collection from multiple sources to obtain information and the information can be traced back to the sources, whether internal or external parties are involved (Al-Sayyed et al., 2021). Consequently, auditors can use AI to make sense of complex patterns and behaviours obtained from various sources of structured and unstructured data (Justice, 2020).

R6: Assists auditors in understanding unstructured data and revealing complex interactions and behaviours obtained from various sources of structured and unstructured data.

In traditional auditing techniques, auditors have had to rely on various sampling techniques due to capacity constraints and costs associated with testing 100% of the population (Meleshenko & Usanova, 2014). The traditional auditing methods require auditors to select samples of transactions to test as they cannot test all transactions, this introduces the risk that the transactions which contain misstatements are not selected as samples and therefore misstatements are not detected (Meleshenko & Usanova, 2014). Furthermore, auditors sometimes fail to extrapolate the errors identified in the sample over the entire population due to bias when evaluating the impact of the error (Elder et al., 2013).

AI's ability to scrutinise data, uncovering patterns and trends, will improve the reliability of audit opinions as it aids in obtaining sufficient audit evidence (Gopal, 2023). Concurrently, audit firms can use machine learning to test the entire data set instead of merely relying on sampling techniques to test data (Dickey et al., 2019; Noordin et al., 2022). A complete set of data can be fed into the machine learning tools to identify anomalies and exceptions in transactions that do not match the normal expected patterns (Shimamoto, 2018).

Auditors' ability to work with the entire population of data enables them to perform better focused and intentional audit procedures (Dickey et al., 2019), which minimises the risk that they do not detect a material misstatement in the financial statements (Gopal, 2023). It also allows auditors to make decisions and judgements based on the full scope of transactions, which results in more reliable audit conclusions (Dalwai et al., 2022). Fedyk et al.(2022) found that audit firms that use AI tools experienced significantly lower restatements in financial misstatements because of improvements in audit quality by being able to analyse audit evidence and pick up areas of misstatements in the financial statements.

R7: Makes full data testing possible.

Tasks that require problem identification and solving can be performed using AI systems (Chan et al., 2018). Unlike statistical analyses, which make use of probability theory, machine learning finds the combination of mathematical equations that best predicts an outcome (Dickey et al., 2019). This places machine learning in a unique position to solve various problems that involve classification, linear regression and cluster analysis[2] (Dickey et al.,

[2] Classification: Data is categorised under different labels based on specific parameters.
Linear regression: Used to predict numerical data instead of labels for example a person's income from their age.
Clustering: The grouping of unlabelled data.

2019). The ability to classify data can enhance the auditor's ability to stratify data sets based on similar traits to perform audit procedures.

Machine learning can process vast amounts of data to distinguish irrelevant data from relevant data and apply the learning to foresee outcomes in similar data points (Shimamoto, 2018). For example, various entertainment channels make use of machine learning to suggest shows to watch based on their previously watched shows by making use of factors like genre, actors, etc. to foresee which shows the viewer is most likely to enjoy watching (Shimamoto, 2018; Sung et al., 2021; Suresh et al., 2020).

Similarly, auditors can make use of machine models' ability to predict outcomes to assist in detecting indicators of fraud and other misstatements (EY, 2018). Machine learning models can learn from the conclusions reached by the auditors on transactions or exceptions with specific characteristics and apply the same principles and outcomes to other items that possess identical characteristics (Dickey et al., 2019).

R8: Machine learning is well suited for a broad range of problems that involve the classification of data into categories, predicting outcomes and stratifying datasets

Furthermore, natural language processing and machine learning techniques can be used to analyse audit evidence such as lease contracts (Tysiac, 2017). AI can work through vast amounts of audit evidence faster as part of the execution phase of the audit to identify exceptions such as duplicate payments and transactions indicative of fraud (Gopal, 2023). The big four audit firms already use AI systems to pick up abnormal transactions and potentially problematic areas, which results in a more efficient audit (Gopal, 2023; Reuters, 2023).

PricewaterhouseCoopers (PwC) uses AI to analyse multiple pages of a contract in seconds (Chan et al., 2018). Auditors require at least 4 hours to perform the same task without the use of AI (Chan et al., 2018). This effectively means that the time spent obtaining and evaluating audit evidence is reduced through the use of AI systems (Raphael, 2017). Standard tasks like contract reviews and inventory counts can be performed by AI systems (EY, 2018; Ting & Vasarhelyi, 2017).

AI computer vision can be used to perform inventory stock counts in various locations, **i**ncreasing coverage (CPA, 2020). AI systems can also be applied in control testing, for

example, using the frequency of reviews and the typical time it takes to review and authorise a transaction, AI can detect anomalies where a review took significantly less time or was significantly less than indicative of potential (CPA, 2020).

NLP gives AI systems the ability to understand human language. AI systems can extract information from documents, such as invoices, improving the process of data entry and matching audit evidence to what is being tested by the auditor (Gopal, 2023). For example, audit firms are making use of Data Snipper, which is a tool within Excel used to extract data from PDFs and other formats. Instead of manually typing the data, the tool can also extract specific data, matching data such as invoice amount, supplier name, etc. into Excel working papers (Arnold & Kong, 2022; Michael Abresch, 2023). A survey conducted by KPMG revealed that financial executives expect auditors to utilise AI systems to better understand their operations, scrutinise transactions and perform real-time auditing (KPMG, 2023).

R9: Automate certain audit procedures.

Decision-making and judgement

By automating certain audit procedures and tasks, such as the evaluation of audit evidence, AI effectively grants auditors more time to apply the more critical skills required in an audit, which are professional judgment and professional scepticism as they perform fewer of the standard tasks (Raphael, 2017).

R10: Free up time to exercise professional judgement and scepticism.

Deep learning can be used to identify relationships between financial statements/records and other information, such as news, interviews, Twitter feeds and the sentiments of this information to support auditors' judgements (Raphael, 2015). It relies mainly on the sentiments of the information being evaluated and requires minimal human effort (Ting & Vasarhelyi, 2017). Consequently, deep learning can be used without the need for text processing to predict financial misstatements by relying on the sentiments of management's discussions and analysis (Sun & Vasarhelyi, 2017). In essence, auditors can use deep learning techniques to make better-informed judgements (Dickey et al., 2019; Raphael, 2015). This is corroborated by Raschke et al. (2018), who discovered that by automating data gathering and analysis, AI systems greatly improve the effectiveness of audit enquiries and free up auditors to concentrate on more complex tasks that require judgement.

R11: Deep learning and machine learning can be used to support auditor's judgements and evaluate management estimates by predicting outcomes.

Concurrently, supervised learning can be used to make future predictions using historical data (Sun & Vasarhelyi, 2017; Topol, 2019). For example, supervised machine learning can predict which customer is likely to not meet their payment obligations using the historical data of that customer (Dickey et al., 2019). In essence, deep learning and machine learning techniques can be applied to effectively identify and understand complex relationships using machine learning abilities and neural networks (Dickey et al., 2019).

Machine learning can recognise patterns in data (Shimamoto, 2018), this functionality can assist auditors in making decisions by providing better insights and understanding of complex issues, which ultimately results in more accurate and reliable audit reports (Hassan, 2022; Qi & Yuan, 2023). One of the key and challenging areas of an audit is the evaluation of management estimates, as judgements and assumptions are used as the basis for management estimates and are susceptible to management bias and manipulation. By utilising machine learning, the audit team can create independent outcomes and predictions, for example, regarding provisions for bad debts based on historical instances (CPA, 2020).

AI systems also pull through various sources of data, such as industry data, press and market data, which can be utilised to evaluate management estimates (CPA, 2020). Further insights would give auditors the ability to ask more relevant and focused questions to management and add value to the clients they service (EY, 2018).

Auditors can utilise AI models to predict outcomes in various scenarios, which can be used to assess the reasonableness of management estimates and identify management bias in their accounting estimates (Gopal, 2023). The use of both structured and unstructured data by AI models will enable auditors to perform a more robust analysis and evaluation of the reliability of management's assumptions and identify areas that require further analysis and evaluation (Gopal, 2023). In essence, AI gives auditors the ability to utilise various sources of data, both structured and unstructured, which will allow the auditors to identify inconsistencies in audit evidence and consequently increase the scope and type of data that auditors can collect to support their judgements and assess management estimates. Raschke et al. (2018) found that AI can help auditors make decisions by offering pertinent data and predictive analytics, which will ultimately raise the calibre of audit findings.

R12: AI allows for triangulation by increasing the scope of data and the type of data that can be collected.

This section explores the conflicting viewpoints in the literature regarding the potential drawbacks of AI in auditing.

2.3 Potential drawbacks of AI in auditing

The use of AI in auditing has sparked significant academic and professional interest. While many scholars and practitioners highlight AI's numerous benefits, including enhanced efficiency, accuracy, and the ability to analyse large datasets, there are contrasting viewpoints on the flaws and risks associated with AI in auditing. Concerns include ethics, dependability, loss of professional judgement, data privacy, and the likelihood of reduced job opportunities for junior auditors.

Proponents of AI adoption argue that AI's ability to analyse huge amounts of data faster and more accurately than humans can increase audit quality and reduce human errors (Zhou and Lee, 2021). AI can help auditors make data-driven decisions, thus boosting audit objectivity (Zhou & Lee, 2021). Detractors stress that depending on AI techniques may leave auditors unable to explain how a certain result was obtained (Zhou & Lee, 2021). For example, if an AI system identifies a discrepancy in financial statements, auditors may lack the technical knowledge to fully appreciate and explain the underlying process.

Lack of transparency may cause issues if audit findings are contested by stakeholders or regulators (Zhou & Lee, 2021). There are concerns regarding AI's opacity, which may impact auditor accountability and their reliance on machine-generated outcomes without proper oversight (Zhou & Lee, 2021).

The quality and completeness of the data used to train AI for auditing are key to its success. Poor or biased data may result in incorrect or misleading results, weakening the audit's credibility (Cao & Lin, 2022). AI systems that are not well calibrated or use incomplete datasets may generate inaccurate or incomplete results, jeopardising the audit's credibility (Cao & Lin, 2022). Proponents argue that AI's ability to analyse large datasets and find trends and anomalies that humans may miss can increase audit accuracy and thoroughness (Cao & Lin, 2022). They believe that by evaluating data on a large scale and at high speed, AI approaches can improve fraud detection, risk assessment, and data consistency.

Sceptics argue that AI algorithms are only as good as the data on which they are trained (Cao & Lin, 2022). If an AI model is trained on biased, incomplete, or poor-quality data, the results will be similarly flawed (Cao & Lin, 2022). This can lead to incorrect conclusions, such as failing to detect fraud or overlooking critical audit weaknesses (Cao & Lin, 2022). For example, if the training data is insufficient, AI systems used for fraud detection may misidentify normal transactions as suspicious or ignore fraudulent behaviour (Cao & Lin, 2022).

While AI can improve the auditing process, its usefulness is directly proportional to the quality of the data it handles (Cao & Lin, 2022). This makes AI programs prone to errors when dealing with inadequate or inaccurate data (Cao & Lin, 2022). The primary issue is that AI, with its automated processes and decision-making abilities, may diminish the value of auditors' professional judgement (Glover et al., 2017).

Historically, auditors have used their talent, experience, and intuition to make subjective choices, especially when objective measures are insufficient or unavailable (Glover et al., 2017). The issue is that when AI technologies take over more routine and analytical tasks, auditors may lose their capacity to apply judgement, affecting audit quality (Glover et al., 2017).

Supporters argue that AI should not replace auditors but rather improve human capacities (Glover et al. 2017). AI can automate tedious duties, freeing auditors to focus on areas where human judgement and critical thinking are most needed, such as complex risk assessments, client communication, and ambiguous decision-making (Glover et al., 2017).

Critics, however, are concerned that auditors may become overly reliant on AI-generated outputs, resulting in a loss of critical thinking and judgement, both of which are required for auditing (Glover et al., 2017). Overreliance on AI may cause auditors to accept AI model results without adequate scrutiny or comprehension, reducing audit quality and increasing the likelihood of errors or fraud being overlooked (Glover et al., 2017).

The use of AI in auditing has prompted concerns about job losses, especially among junior auditors who perform routine and manual tasks that could be automated. While AI promotes efficiency and productivity, it raises the question of whether this technological shift will result in job losses. This issue has been addressed in a number of scholarly publications, each with a unique perspective on the long-term employment consequences of AI in auditing.

Vasarhelyi and Kogan (2001) discuss the economic implications of audit automation, with a focus on job loss, particularly among junior auditors. They point out that automating routine processes may reduce the demand for lower-level employees, perhaps leading to job losses or changes in auditing work (Vasarhelyi and Kogan, 2001).

While AI may replace some jobs, some studies imply that it may lead to a shift in auditors' roles rather than employment losses (Brown & Vasarhelyi, 2015). As AI replaces more monotonous and mechanical roles, auditors may be compelled to focus on higher-value activities such as comprehending AI results, making strategic decisions, and doing complicated analysis (Brown & Vasarhelyi, 2015). This could result in a shift in the sorts of skills required in the auditing sector, with a greater demand for auditors with specific skills in data analytics and AI management (Brown & Vasarhelyi, 2015).

As a result, concern over job losses may be focused on work transformation and reskilling rather than total displacement (Brown & Vasarhelyi, 2015). Brown and Vasarhelyi (2015) argue that, while AI may reduce the need for certain manual tasks, it will also generate new roles that require specialised skills, such as data analytics and AI management. These authors argue that auditors will have to adjust and focus on increasingly complex and judgement-based tasks that AI cannot easily replicate. The study examines concerns that as AI handles more audit activities, auditors' role in making subjective judgements may decline, potentially reducing the value they offer to the audit process.

The regulatory landscape for AI in auditing is also constantly changing. Many regulatory bodies, like the Public Company Accounting Oversight Board (PCAOB) and the International Auditing and Assurance Standards Board (IAASB), are grappling with how to incorporate AI approaches into existing auditing frameworks (Kogan & Vasarhelyi, 2014). A lack of specified criteria may result in disparities in AI adoption and utilisation, as well as issues in ensuring auditing compliance (Kogan & Vasarhelyi, 2014).

Supporters of AI integration argue that the regulatory structure will grow to incorporate AI, guaranteeing that its use meets established auditing standards (Kogan & Vasarhelyi, 2014). They claim that AI can improve regulatory compliance by boosting audit accuracy and consistency (Kogan & Vasarhelyi, 2014).

Critics believe that using AI in auditing may go beyond regulatory development, raising ethical and legal difficulties (Kogan & Vasarhelyi, 2014). There is concern that AI will be used in ways that do not entirely conform with existing standards or that AI-based audits could be

misconstrued or manipulated if not properly managed (Kogan and Vasarhelyi, 2014). The study highlights the regulatory issues raised by AI in auditing, such as the challenge of adapting existing standards to the complexities of AI-driven audit systems.

Table A: Concept Matrix for the impact of the use of AI on audit quality

Article	Automation of tasks	Risk assessment and response	Gathering and evaluating audit evidence	Decision-making and judgement	Available time
Al-Sayyed et al. (2021)		X	X		
Arnold & Kong (2022)			X		
ASA (2023)	X		X		
Blake (2023)	X				X
Bowling & Meyer (2019)		X	X		
Chan et al. (2018)		X			
CPA (2020)	X	X	X	X	
Dalwai et al. (2022)	X		X		
Dickey et al. (2019)		X	X	X	
Elder et al. (2013)			X		
Elliot et al. (2020)		X			
EY (2018)	X		X	X	
Fedyk et al. (2022)			X		
Gopal (2023)	X	X	X	X	
Hassan (2022)				X	
IABAC (2023)	X	X			
Justice (2020)			X		

Article	Automation of tasks	Risk assessment and response	Gathering and evaluating audit evidence	Decision-making and judgement	Available time
KPMG (2023)			X		
Law (2020)		X			
Lee (2016)			X		
Meleshenko & Usanova (2014)			X		
Michael Abresch (2023)			X		
Munoko et al. (2020)	X	X			X
Noordin et al. (2022)	X	X	X		
Rao & Verweij (2017)	X	X			X
Raphael (2017)				X	
Reuters (2023)			X		
Shimamoto (2018)			X	X	
Sun & Vasarhelyi (2017)				X	
Sung et al. (2021)			X		
Suresh et al. (2020)			X		
Ting & Vasarhelyi (2017)			X	X	
Tysiac (2017)			X		
Yuan (2023)				X	

The characteristics of audit quality and functional abilities of artificial intelligence as explored above are summarised in Table I in Appendix A. Having explored the literature in detail above, the methodology and method employed in this research are detailed in the following section.

3. Data and method

This section covers the data and chosen research approach. Section 3.1 discusses the methodological paradigm that was applied in this study. More information on the content analysis used to identify the row and column headings for a correspondence analysis may be found in Section 3.2. The correspondence analysis is discussed in Section 3.3. The sample approach used in this research is described in Section 3.4. Information about the processes for collecting and organising data can be found in Section 3.5. Section 3.6 provides details about data analysis. An explanation of the validity and dependability of the data is given in Section 3.8, and an examination of the study's assumptions is given in Section 3.9.

3.1: Methodological paradigm

This study presents an acceptable body of knowledge that may be employed to develop answers to issues, in line with pragmatism, by focusing on what is observable and subjective (Creswell, 2014; Saunders, 2011). In contrast to the perspectives of pragmatists (Moon & Blackman, 2014), a mixed-method approach is employed to address the research topic (Creswell, 2014). This research is grounded in an interpretive pragmatist epistemology, in line with the theories of (Carruthers, 1995; Hopwood, 1987; Ravenscroft & Williams, 2009). Unlike positivists, the goal of this research is not to draw a broadly applicable conclusion (Creswell, 2014; Moon & Blackman, 2014).

3.2 Content analysis: developing rows and columns for the correspondence analysis

To determine whether using artificial intelligence to conduct an audit affects the audit's quality, a review of previous research is conducted (Guest et al., 2013). The literature on audit quality is chosen and examined to find major themes that are recurring when discussing the variables that influence an audit's quality (Section 2.1) (Leedy & Ormrod, 2014). Section 2.2 summarises the themes related to artificial intelligence. These are examined with reference to their potential relationships to the variables influencing audit quality (Leedy &

Ormrod, 2014). The goal of the analysis is not to establish a statistical association between the artificial intelligence and audit quality themes (Ram et al., 2016). The only reason it was done was to establish preliminary connections and correlations between the themes (Ram et al., 2016).

3.3 Correspondence analysis

Correspondence analysis is conducted with auditing professionals (Ram, 2018) after the content analysis (Beh & Lombardo, 2014; Kudlats et al., 2014). To shed light on how artificial intelligence affects audit quality, the correspondence analysis builds on content analysis and examines the relationship between the themes related to audit quality and artificial intelligence. Studies in a variety of fields, including architecture (Habib et al., 2012), auditing (Maroun, 2014), taxation (Ram, 2018), Bitcoin accounting (Ram et al., 2016), and management accounting (Chatzipetrou & Moschidis, 2016), have employed correspondence analysis. This study is consistent with previous research that placed a strong emphasis on investigating pertinent topics.

One of the primary limitations of correspondence analysis is the difficulty in interpreting the results. Correspondence analysis generates biplots, which are graphical representations of data that show the relationship between categories (Greenacre, 2007). While these charts may provide important insights, analysing them can be subjective, particularly when there are several categories or the categories have complex correlations (Greenacre, 2007). The proximity of categories in the biplot suggests their correlation, albeit the strength of this relationship is not always clear from the plot alone (Greenacre, 2007). To mitigate this limitation, the researcher has combined the correspondence analysis graphical output with quantitative measurements like inertia and chi-squared statistics to gain a more comprehensive picture of the correlations (Greenacre, 2007).

Correspondence analysis can be difficult with high-dimensional data, particularly when the dataset comprises a significant number of categories or variables. As the number of categories increases, the biplots may get congested, making it difficult to identify major patterns. Interpreting these intricate relationships becomes extremely challenging (Lebart et al. 2006). Correspondence analysis can be difficult with high-dimensional data, particularly when the dataset comprises a significant number of categories or variables. As the number of categories increases, the biplots may get congested, making it difficult to identify major patterns. Interpreting these intricate relationships becomes extremely challenging (Lebart et al. 2006). Dimensions that account for very little of the variance are usually discarded.

The researcher developed a correspondence map using a principal component analysis (Kudlats et al., 2014) to plot the points (Doey & Kurta, 2011; Maroun, 2014). The correspondence plot depicted in Figure 2 was used to inform further analysis. The study makes use of three dimensions, which account for 81.06% of the total inertia (Section 4).

The correspondence table is used as a contingency table for statistical analysis. The finalised correspondence table is presented in Appendix 2. It cross-tabulates the audit quality indicators (C1 to C12) and the characteristics/functional abilities of artificial intelligence technologies (R1 to R12). The final correspondence table, therefore, consists of 12 columns and 12 rows. The data in the table is not organised in any particular order. The symbols C and R have no specific meaning (Ram et al., 2016a).

3.4: Sample

Purposive sampling is used to choose the auditing specialists to guarantee that research participants possess the necessary auditing knowledge (Leedy & Ormrod, 2014). Forty is the chosen sample size for the correspondence analysis. Given that the goal of this work is not to provide results that can be applied to a large population, this small sample is appropriate and aligned with the principles of positivism. The choice of a small sample is also supported by earlier exploratory research (Kudlats et al., 2014; Maroun, 2014).

Correspondence analysis is a method for studying categorical data and investigating the relationships between variables that is often represented using contingency tables (Greenacre, 2007). A sample size of 40 experts is generally considered adequate to ensure that the analysis catches key patterns and correlations without introducing excessive noise (Greenacre, 2007). When conducting expert opinion research, the sample size is usually less than when examining a larger population (Patterson, 2002).

The goal of expert-based research is to capture in depth, specialised knowledge, and a sample of 40 experts provides a varied range of opinions while retaining the quality of findings (Patton, 2002). A sample of 40 experts discovers a balance between having enough diversity of opinion to capture the full range of expert opinions and keeping the sample manageable while giving high-quality, nuanced data (Patterson, 2002).

Correspondence analysis can be computationally demanding, particularly when dealing with large datasets (Benzécri, 1992). A sample of 40 specialists finds a balance between having

enough participants to uncover meaningful trends in categorical data and without overwhelming the study process or introducing technical challenges (Benzécri, 1992). A sample size of 40 experts is large enough to provide variability in replies, which is essential for correspondence analysis to uncover important links, but small enough to ensure analytical viability (Benzécri, 1992). Large datasets may result in overfitting or overly complex models, particularly when using exploratory approaches such as correspondence analysis, which might hamper the interpretability of the results (Benzécri, 1992).

3.5: Data collection and management

Direct communication between the researcher and the experts who will fill out the correspondence table will be used to explain the purpose and nature of the study (Ram, 2018). The responders are briefed on the purpose and methodology of correspondence analysis as well as the correspondence table (Ram, 2018). To ensure that there is no confusion, there are explicit instructions provided on how to complete the correspondence table (Maroun, 2014). (Ram, 2018). (Ram, 2018). Excel is used to manage the data and replicate the table.

The experts are required to mark with a ‘’1’’ cell where they believe that the abilities of artificial intelligence technologies (rows) correspond positively with the factors that affect audit quality (columns) (Maroun et al., 2011b). Respondents are informed that cells can be left blank or marked with a ‘0’ and that there are no limitations to the number of ‘’1’’s’, they can fill in as they deem appropriate (Ram et al., 2016a). A contingency table is created using the aggregated results of the respondents (Ram et al., 2016a).

3.6: Data analysis

A data map is created (Kudlats et al., 2014). The determination of the masses of the rows and columns is done as part of the first phase (Habib et al., 2012). The inertia of each point in the table is determined in the second phase using the masses determined in the first phase (Maroun et al., 2011b). The relationship between the variables which are under analysis is ascertained by a correspondence analysis through a concept referred to as inertia (Kudlats et al., 2014). Every point of data in the analysis has specific coordinates and the location in the visual map is ascertained using these coordinates (Kudlats et al., 2014). The points are,

thereafter, positioned a certain distance away from the average of all the data points (Kudlats et al., 2014). The degrees of freedom are determined to be 11[3] (Kudlats et al., 2014).

A correspondence map is developed using a principal component analysis (Kudlats et al., 2014) to plot the points (Doey & Kurta, 2011; Maroun, 2014). The summary of statistics and the correspondence plot are developed using STATA (Doey & Kurta, 2011; Habib et al., 2012; Kudlats et al., 2014). The researcher, thereafter, interprets the results from the STATA. The interpretation is done through a visual inspection to determine the relationship between the row and column points (Kudlats et al., 2014).

The final plot is created using points that have an above-average inertia contribution or slightly below-average inertia contribution (Ram et al., 2016a). The column headings on the x- and y-axes in the final correspondence plot are labelled using the correlation coefficients and sign of the points based on inertial contributions[4] (Kudlats et al., 2014). A similar method is used to calculate the row points in the varied dimensions graphic (Kudlats et al., 2014). Finally, the researchers assess the relationship between the dimensions (row headings) and the capabilities of artificial intelligence technologies (column headings) (Kudlats et al., 2014; Maroun et al., 2011)

3.7: Validity and Reliability

In the context of this study, validity and reliability relate more to the clear and succinct portrayal of views than to the extent and statistical accuracy of the findings (Brink, 1993; Maroun et al., 2011). The consistency and suitability of the instruments, procedures, and data used in this research are also considered aspects of validity and reliability (Brink, 1993; Leung, 2015). Since the goal of most qualitative research is not to provide results that can be applied to other contexts, validity only refers to internal validity and does not include external validity (Leung, 2015). The study's validity and reliability are ensured through the following measures;

- Given that this is an exploratory study, the correspondence analysis used is appropriate since it illustrates various viewpoints from comparatively small sample numbers (M. Bendixen, 1996), and the information is compiled and displayed in an easy-to-understand manner (Maroun et al., 2011).

[3] The lesser of the number of columns (12 audit quality themes) and rows (12 artificial intelligence themes) less 1 was determined as the maximum number of dimensions, also referred to as the degrees of freedom.
[4] If 3 dimensions are used, this will be x, y and z.

- To guarantee the validity and trustworthiness of the study, literature from reliable sources including JSTOR, Science Direct, Social Science Research Network (SSRN), and Wiley is used (Ram et al., 2016).

- To ensure that only informed participants are included, the deliberate selection of responders through small sample sizes improves the calibre of the research findings (Blaxter et al., 2003; Brennan & Kelly, 2007).

- Report supervisors evaluated the study to make sure the research report was understandable to individuals besides the researcher, and peer debriefing was implemented (Creswell, 2014).
- Pearson's chi-squared statistic is utilised to evaluate the degree of correlations between rows and columns to ensure statistical internal consistency (Kudlats et al., 2014; Maroun et al., 2011).

- The number of dimensions used is determined according to the inertial contribution (Ram et al., 2016). To ensure that this study is carried out in a responsible and morally accountable manner, an ethical clearance form is obtained. The research instrument will be improved by incorporating the comments and recommendations received from the pilot study, which is being conducted to establish the viability of the project.

3.8: Assumptions

The assumptions applicable to a study are driven by the worldview or research paradigm adopted in that study (Creswell, 2014). Interpretivists employ qualitative research techniques to the subject matter to observe multiple realities, contrary to positivists who use qualitative research techniques to establish a singular and universal objective reality (Guest et al., 2013).

This study is based on an interpretive approach. This paper takes the view that audit quality is socially constructed. As a result, the impact of the use of artificial intelligence in auditing on audit quality is studied by exploring prior literature and entreating the views of experts (Lehman, 2010; Parker, 2008).

In addition, despite the precautions covered in Section 3.6, it is assumed that the respondents fill out the correspondence table honestly and completely. The following presumptions guide

the execution of a correspondence analysis: discrete data is being analysed; there are multiple categories; all values in the correspondence table are non-negative; and the data in rows and columns tends to be statistically comparable (Doey & Kurta, 2011).

The significance of row-column correlations is assessed using Pearson's chi-square, and the final data is examined for each of the aforementioned presumptions (Kudlats et al., 2014; Maroun et al., 2011).

4. Results

This section explores the results of the aggregated frequency table from the respondents. The descriptive statistics have been interpreted by the researcher and presented in Table II. Table III presents statistically significant audit quality themes and Table IV presents the significant AI traits with the corresponding dimensions and axes. The final correspondence plot is presented in Figure 2 and is analysed in Section 5.

Although CA is largely a descriptive approach, it is frequently useful when used with statistical significance tests for example the Chi-squared test to examine the strength of the connections between categories (Heijden & Ark 2019). A Chi-squared test of association was used to determine whether the proximity of categories in the CA biplot suggests a statistically significant link (Heijden & Ark, 2019).

The Chi-square statistic ($X^2_{df=21}$ = 190) is more than the critical value at a 99.9% confidence level (adapted from (Dikuua et al., 2023; Ram et al., 2016)). The statistically significant finding of the study indicates that the correlation between categories is not random, which adds rigour to the relationship's interpretation (Heijden & Ark 2019). This indicates that the relationships between the audit quality characteristics and the functional abilities of AI in the correspondence table are statistically significant (Dikuua et al., 2023; Ram, 2018). The significant link, lends weight to the assumption that the closeness between categories indicates a meaningful connection (Heijden & Ark 2019). It provides confidence that the associations revealed in the biplot are not false (Heijden & Ark 2019).

To interpret the strength of relationships in the correspondence analysis, the proximity or distance between row and column categories in the resulting biplot was considered. ccategories that are plotted close together are thought to have a stronger correlation, whereas those farther apart are less related. The inertia was used to measure the strength of

correlations as it measures the overall variance explained by the biplot's axes (Greenacre, 2007).

The number of dimensions that account for the total inertia is 11. Three dimensions account for 81.06% of the total inertia (see Table II). The 3 dimensions are split into axes in the visual map. The x-axis represents Dimension 1, Dimension 2 is represented by the y-axis and Dimension 3 is reflected as the z-axis (Ram, 2018).

Table II: Descriptive statistics

Statistic	Value
Active rows	12
Active columns	12
Number of observations	2 537
Pearson’s x 2 (121)	190.43
Prob > x 2	0.0001
Total inertia	0.0751
Number of dimensions	3
Explained inertia (three dimensions)	81.06%

The higher inertia suggests that the first few dimensions account for a considerable share of the variance in the data, which can help discover the most relevant associations. A high inertia in the first dimensions indicates that there is a significant association between categories in those dimensions. Typically, a visual map with 2 dimensions is acceptable as appropriate because of the challenges that arise with analysing visual maps consisting of more than 2 dimensions (Agresti & Wiley, 2002; Hair et al., 2010; Ram, 2018). Three or more dimensions can still be used where the total inertia is not appropriately accounted for by 2 dimensions (Agresti & Wiley, 2002; Hair et al., 2010; Ram, 2018). In this research, two dimensions only accounted for 69.47% of the inertia resulting in the need for the use of a third dimension (Ram, 2018).

Audit quality characteristics (C’s) and AI functional abilities with inertia which exceeds the average are considered statistically significant points and included in the correspondence plot (Dikuua et al., 2023; Ram et al., 2016). The average inertial contribution was determined to be 8.33%. This was calculated by dividing the 100 inertia per cent by 12 rows and 12 columns (see Appendix A), respectively (adapted from (Ram, 2018). Appendix E and F depict the points which were determined to be statistically significant points warranting inclusion in the correspondence plot (Ram et al., 2016).

Below is a summary of significant audit themes and AI traits.

Table III: Significant audit quality themes

Column heading	Audit quality themes
C1	Acknowledging the importance of resources and competency of the engagement team as well as the need for full compliance with ISA.
C3	The rigorousness of the risk assessment process.
C4	The auditor's ability to understand the client and the key risks of the client's operation.
C6	The use of detailed analytics rather than a high-level trend analysis.
C7	The amount of time available to perform audit evidence gathering and evaluation tasks.
C8	The persuasiveness of the models used to obtain and evaluate audit evidence.
C9	The extent of testing.
C10	Informed judgements are made after consultation, supervision and review to form audit opinion.
C11	Audit work being performed in compliance with professional standards, and legal and regulatory requirements.

Table IV: Significant Artificial Intelligence Traits

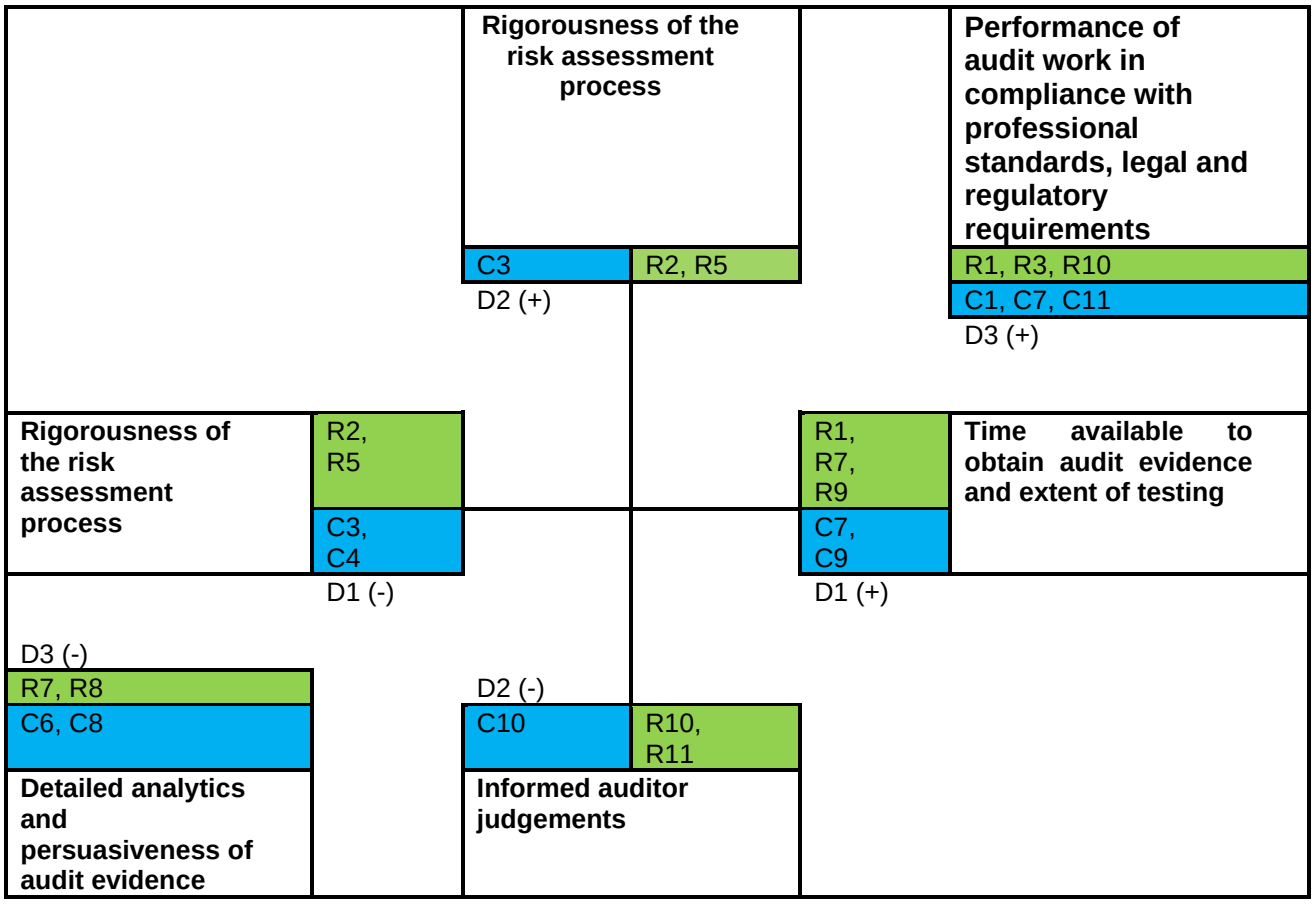
Row heading	Artificial Intelligence traits
R1	Performs time-consuming repetitive tasks which previously required the auditor's effort.
R2	Identifies the level of risk of a given transaction as part of the risk assessment process.
R3	Enables auditors to devote their time to identifying and developing an audit approach for high-risk areas.

R5	Autonomous learning uses patterns and can be used as part of the risk assessment process to discover previously unforeseen risks.
R7	Makes 100% data testing possible.
R8	Machine learning is well suited for a broad range of problems that involve classification of data into categories, predicting outcomes and stratifying datasets.
R9	Certain audit procedures can be automated.
R10	Frees up time to exercise professional judgement and scepticism.
R11	Deep learning and machine learning can be used to support auditor's judgements and evaluate management estimates by predicting outcomes.

The correspondence plot is drawn using the significant audit quality themes and AI traits and establishing their position on the axis (Bendixen, 1996; Maroun et al., 2011). The x, y and z-axis are labelled using the sign of the coordinates and dimensions of the audit quality theme (C's).

The coordinate sign could either be negative or positive in each dimension, however, the sign is only indicative of the position of the coordinate on the axes and does not provide evidence of the strength of any relationship (Dikuua et al., 2023; Ram et al., 2016b; Ram, 2018).

FIGURE 2: Correspondence plot.



The axes with an inertial contribution that exceeds the average of 8.33% were interpreted and labelled by the researcher. Labels are included in Table V (Ram, 2018). AI traits (R's) are presented in Table VI (Ram, 2018).

The correspondence plot depicted in Figure 2 is used to inform further analysis and is developed using the labelled axes referred to above (Ram, 2018). The results of the above inertial contribution points were split into the respective dimensions taking into account the sign of the coordinates (Ram, 2018). For instance, the inertial contribution relating to R5 exceeded the average of 8.33% in Dimensions 1 and 2 (contributions of 27.70% and 11%, respectively). The R5 coordinate was negative in dimension 1 and positive in dimension 2, indicating that R5 lies on the negative dimension 1 (x-axis) and positive dimension 2 (y-axis) (Ram, 2018). Figure 3 also includes the names of the axes as interpretively determined by the researcher (Ram, 2018).

Table V: Names of the X-axis

Axis	Significant Audit quality themes	Axis name
Positive x-axis (Dimension 1 in Figure 2	C7: The amount of time available to perform the audit evidence gathering and evaluation tasks. C9: The extent of testing.	Time available to obtain audit evidence and extent of testing
Negative x-axis (Dimension 1 in Figure 2)	C3: Rigorousness of the risk assessment process. C4: The auditor's ability to understand the client and the key risks of the client's operation.	Rigorousness of the risk assessment process
Positive y-axis (Dimension 2 in Figure 2)	C3: Rigorousness of the risk assessment process.	Rigorousness of the risk assessment process
Negative y-axis (Dimension 2 in Figure 2)	C10: Informed judgements being made after consultation, supervision and review to form audit opinion.	Informed auditor judgements
Positive z-axis (Dimension 3 in Figure 2)	C1: Acknowledging the importance of resources and competency of the engagement team as well as the need for full compliance with ISA. C7: The amount of time available to perform audit evidence-gathering and evaluation tasks. C11: Audit work being performed in compliance with professional standards, and legal and regulatory requirements.	Performance of audit work in compliance with professional standards, legal and regulatory requirements
Negative z-axis (Dimension 3 in Figure 2)	C6: The use of detailed analytics rather than a high-level trend analysis. C8: The persuasiveness of the models used to obtain and evaluate audit evidence.	Detailed analytics and persuasiveness of audit evidence

Table VI: Relationship between axes and audit quality themes

Axis	Significant Artificial Intelligence Traits
The positive x-axis (Dimension 1 in Figure 2) Time available to obtain audit evidence and extent of testing	R1: Performs time-consuming repetitive tasks which previously required the auditor's effort. R7: Makes 100% data testing possible. R9: Certain audit procedures can be automated.
Negative x-axis (Dimension 1 in Figure 2) Rigorousness of the risk assessment process	R2: Identifies the level of risk of a given transaction as part of the risk assessment process. R5: Autonomous learning uses patterns and can be used as part of the risk assessment process to discover previously unforeseen risks.
The positive y-axis (Dimension 2 in Figure 2) Rigorousness of the risk assessment process	R2: Identifies the level of risk of a given transaction as part of the risk assessment process. R5: Autonomous learning uses patterns and can be used as part of the risk assessment process to discover previously unforeseen risks.
The negative y-axis (Dimension 2 in Figure 2) Informed auditor judgements	R10: Frees up time to exercise professional judgment and scepticism. R11: Deep learning and machine learning can be used to support auditor's judgements and evaluate management's estimates by predicting outcomes.
Positive z-axis (Dimension 3 in Figure 2) Performance of audit work in compliance with professional standards, legal and regulatory requirements	R1: Performs time-consuming repetitive tasks which previously required the auditor's effort. R3: Enables auditors to devote their time to identifying and developing an audit approach for high-risk areas. R10: Frees up time to exercise professional judgment and scepticism.
Negative z-axis (Dimension 3 in Figure 2) Detailed analytics and persuasiveness of audit evidence	R7: Makes 100% data testing possible. R8: Machine learning is well suited for a broad range of problems that involve classification of data into categories, predicting outcomes and stratifying datasets.

5. Discussion

This section analyses the final correspondence plot as presented in Figure 2. The significant relationships are analysed by the researcher and the analysis has been summarised according to the axis names per the plot for ease of reference (Dikuua et al., 2023).

5.1.1 Rigorousness of the risk assessment process (C3 and C4)

Respondents perceive there to be a strong correlation between AI's ability to identify risks (R2 and R5), the auditor's ability to understand the client and key risks of their operations (C4) and the rigorousness of the risk assessment process (C3). This is evidenced by AI's ability to identify a level of risk for a given transaction (R2) and the use of patterns to discover previously unforeseen risks (R5) which are significant traits in both the x and y-axis.

AI enables auditors to obtain and analyse data from various sources that can be used as part of the risk assessment phase (Al-Sayyed et al., 2021; Lee, 2016), therefore, aiding in a more comprehensive risk assessment process. Using AI, auditors can incorporate data from various sources, such as newsfeeds, which increases their understanding of the auditee and key risks arising from their operations (CPA, 2020). This is a crucial element for the identification of risks, as a broad understanding of the client is required for a more accurate risk assessment (Gartland, 2017). Furthermore, AI can analyse the tone and sentiment in the data and, using algorithms, automatically categorise the data, which can be used to identify risks (CPA, 2020). (Adeoye et al., 2023) also found that AI systems' ability to identify risk areas will result in enhanced audit quality.

In essence, AI can analyse 100% of available data, which means that the auditor makes judgements relating to risk factors on all available information, resulting in more accurate judgements and decisions regarding the risk factors of the auditee. An earlier study by (Noordin et al., 2022) shared the same sentiment that the capability of AI to analyse 100% of vast amounts of data is significantly correlated to a more robust risk assessment.

The above functionalities of AI aid in increased audit efforts through the incorporation of various data sources and pattern analysis. The results are, therefore, consistent with the observations from the study conducted by (Xiao et al., 2020) which revealed that increased audit effort results in a robust understanding of the auditee, leading to a more comprehensive analysis of the risk of material misstatements. Furthermore, the pattern analysis abilities of AI

can highlight high-risk transactions, which inform the risks either due to fraud or error (Bowling & Meyer, 2019; Gopal, 2023).

Unsupervised learning can identify patterns and predict outcomes based on given data sets without relying on historical data, therefore alerting auditors to previously unforeseen risks (Dickey et al., 2019). It can be used to create independent expectations based on the predictive analysis and identify inconsistencies with management results and outcomes, which can be incorporated into the risk assessment (Munoko et al., 2020; Rao & Verweij, 2017).

This was also supported by Puthukulam et al. (2021), who revealed that AI's predictive analysis functions assist in detecting errors and areas of fraud in an audit. Similarly, (Noordin et al., 2022) identified a significant correlation between the use of AI tools and the identification of transactions indicative of fraud. The use of automated tools therefore increases the auditor's ability to identify risks; the same sentiment is shared by ISA 315, as automated tools enable auditors to perform risk assessment procedures using extensive volumes of data (IAASB, 2019).

Thorough risk assessment in the engagement the firms undertake will better inform the firm's risk identification process in terms of ISQM1 and be in a position to develop appropriate plans to respond to the risks as required by ISQM1. If the auditor fails to identify risks in an engagement, they consequently fail to design adequate procedures that collaborate with the conclusions reached (Munter, 2023). This exposes the firms to various risks, such as reputational risks for issuing incorrect audit opinions and consequently raises questions about the firm's competence. Ultimately, the thorough identification of high-risk areas is important as it enables firms to devote more time to areas of high risk, improving the quality of an audit as these areas are more susceptible to material misstatements (Wooten, 2003).

5.1.2 Time available to obtain audit evidence (C7)

The negative z-axis highlights AI's ability to perform time-consuming tasks that previously required an auditor's effort (R1) and automate certain audit procedures (R9) increasing the time available to perform audit evidence gathering and evaluation tasks (C7) and the extent of testing (C9).

Auditors often have to evaluate audit samples, which may involve activities such as the inspection of multiple documents such as invoices, delivery notes and contracts to vouch for

selected transactions. AI automates the process of data capture and extraction from audit evidence into audit documentation that is re-performable (ASA, 2023; EY, 2018).

The results are consistent with prior literature, where the usefulness of AI in evaluating huge quantities of audit evidence was observed (Noordin et al., 2022). AI can perform invoice matching to the selected transactions and identify exceptions, therefore, the auditor would only need to follow up on the exceptions instead of the actual batch and ticking of audit evidence (Gopal, 2023).

Making use of AI means auditors will no longer have to perform repetitive time-consuming tasks such as the ticking in of audit evidence. AI's ability to perform repetitive tasks (R1) through the automation of audit procedures increases the amount of time that auditors have to perform audit gathering and evaluation tasks, which require human judgement and intervention.

Similarly, the time freed up through the automation of certain audit procedures increases the capacity of the audit team. AI is an audit resource that can perform audit procedures which means fewer human resources/human audit hours will need to be allocated to those audit sections as they would only need to evaluate the reasonability and reliability of the AI documentation and follow up on identified issues. Therefore, auditors will have more time to perform audit evidence and evaluation tasks as AI performs some of the tasks.

Increased capacity and more available time may result in auditors being able to meet their reporting deadlines. A study conducted by (Gentner et al., 2018) also revealed a positive association between the use of AI, audit quality and timely financial reporting, while (Adeoye et al., 2023) revealed that AI improves audit quality as it results in accurate, reliable and timely financial reporting.

The auditors can then use the available time to focus on more critical and high-risk areas that require judgment. This enables the auditor to devote their time to identifying and developing approaches to high-risk areas. This analysis is further supported by the results of the study as per the positive z-axis, the time available to gather and evaluate audit evidence (C7) is significantly correlated to the auditor's ability to devote their time to high-risk areas of the audit (R3).

In terms of ISQM 1, the engagement team members should be given sufficient time and capabilities to enable them to consistently perform quality engagements (IAASB, 2022). Therefore, the elimination of repetitive tasks through automation will enable teams to have more time to focus on more crucial parts of the audit towards quality engagements. Resources in terms of ISQM 1 include technical resources, therefore, ISQM 1 also encourages the use of appropriate technical resources to perform audits (IAASB, 2022). Technological resources increase the capacity of the engagement team by automating certain tasks.

The extent of testing (C9)

Figure 2 reveals that AI's ability to make 100% data testing possible (R7) is positively correlated with the extent of testing (C9). The full population of data can be audited using machine learning as it can identify anomalies and exceptions through pattern analysis (Dickey et al., 2019; Noordin et al., 2022; Shimamoto, 2018). Testing the full population is possible, which eliminates sampling risk (Gopal, 2023). In addition, a study performed by (Noordin et al., 2022) also found that AI can easily detect high-risk transactions, contrary to traditional auditing methods, through 100% testing of transactions and it eliminates the sampling risk.

The reliability of the audit report is also improved as the auditors evaluate the full transactions and therefore make judgements and decisions on the full scope of transactions contrary to merely a sample and reliance on extrapolation of misstatements within the sample (Dalwai et al., 2022; Fedyk et al., 2022). Another study also found that AI's ability to automate certain audit procedures and perform testing on the full set of data instead of sampling improves audit quality (Raji & Buolamwini, 2019). AI will enhance professional judgement as audit teams will make more reliable decisions after evaluating the full scope of transactions, which will lead to more reliable decisions being made.

The result is that AI will aid in the sufficiency of audit evidence as required by ISA 500 as it increases the number of transactions that can be evaluated by audit teams and the evidence that can be evaluated. Xiao et al. (2020) found that greater audit effort results in improved audit quality. (Fedyk et al., 2022) found that audit firms that use AI tools experienced significantly lower restatements in financial misstatements because of improvements in audit quality by being able to analyse audit evidence and identify areas of misstatements in the financial statements.

The persuasiveness of the models used to obtain and evaluate audit evidence (C8)

The results reveal a significant correlation between AI's ability to make 100% data testing possible (R7) and the persuasiveness of audit evidence (C8). According to ISA 500, the amount of audit evidence gathered determines whether the audit evidence is sufficient, which is related to the audit evidence's persuasiveness (IAASB, 2009a). When assessing the persuasiveness of audit evidence, the appropriateness and adequacy of the evidence are crucial considerations (IAASB, 2019a). Evidence is persuasive if an experienced auditor is persuaded to reach the same conclusions based on the evidence (IAASB, 2019a). Consequently, 100% data testing improves the audit evidence's sufficiency and contributes to its persuasiveness. According to ISQM 1, to substantiate the findings that form the foundation of the audit opinion, sufficient and relevant audit evidence must be acquired. (IAASB, 2022).

Machine learning models' ability to classify data sets, predict outcomes and stratify data sets was also considered to have a significant correlation with the persuasiveness of audit evidence. This is because machine learning models can forecast outcomes, and those predictions can be used to assess accounting estimates and find discrepancies in audit evidence that was collected from management (Dickey et al., 2019). This aids in a more robust and therefore sufficient evaluation of audit evidence. (Puthukulam et al., 2021) found that AI improves the auditor's ability to detect errors in financial misstatements as it results in a more persuasive evaluation of the audit evidence. ISA 530 recommends the stratification of populations by dividing the populations into sub-populations that have similar characteristics as they will be audited using similar audit evidence (IAASB, 2009e). Stratification limits the variability of the type of audit evidence required in each stratum as transactions are grouped based on their similar nature (IAASB, 2009e).

When performing substantive tests of details, the population is typically divided into value-based groups (IAASB, 2009e). This makes it possible to devote more audit attention to the higher-value items since they have the highest potential for misstatements (IAASB, 2009e). The results are aligned with the findings of a study carried out by Adeoye et al. (2023), which found that AI, particularly natural language processing, results in quicker stratification of data during the audit, which was valued by respondents as aiding in audit quality. The greater audit effort applied to large value items therefore aids in the persuasiveness of audit evidence obtained for items that have high risks of material misstatements. In addition, Xiao (2020) claims that increasing the audit effort increases the likelihood of finding misstatements since it allows the auditor to implement thorough audit methods and gather compelling audit evidence.

The use of detailed analytics rather than a high-level trend analysis (C6)

Similarly, the pattern analysis and the ability to group data into categories allow for more detailed analytics to be performed on the data than a high-level analysis. To identify a misstatement in terms of the ISAs, analytical methods must be carried out with a precise expectation. With the help of machine learning capabilities, data will become better categorised, making it possible to apply exact expectations to spot irregularities and misstatements. Consequently, it follows that the use of AI will enable the performance of more detailed analytical procedures that can be used to identify trends or relationships in data that are not consistent with other information obtained by the audit team and identify misstatements.

Informed auditors' judgement

The negative y-axis reflects that respondents believe the use of AI will result in informed audit judgements (C10) as a result of AI's ability to free up time to exercise professional judgement and scepticism (R10) and to evaluate management's estimates by predicting outcomes (R11).

AI's ability to automate certain audit procedures and tasks, such as data entry and evaluation of audit evidence, grants auditors more time to apply the more critical skills required in an audit which are professional judgement and professional scepticism as they perform fewer of the standard tasks (Raphael, 2017). In terms of ISQM 1, engagement teams should exercise appropriate professional and professional scepticism during engagement performance (IAASB, 2022). The additional time granted by AI enables auditors to have sufficient time to reflect on the audit evidence with a questioning mind and due care, identify areas of inconsistency and make informed professional judgements. This is crucial, as ISQM 1 requires engagement teams to exercise appropriate professional and professional scepticism during engagement performance (IAASB, 2022).

Deep learning can be used to either collaborate or disprove financial data as it can incorporate non-financial data through analyses of sentiments in non-financial data, which can be used to support and assess the reasonability of management estimates (Raphael, 2015). A study performed by (Danielle Lombardi, 2023) demonstrated that using an AI system featuring structured and interactive information processing capabilities is useful for decision-making and improving auditor judgment when performing complex tasks. Data such as news feeds and management minutes of meetings can be analysed without the need for text processing and used to make predictions to assess the reliability of management estimates (Ting &

Vasarhelyi, 2017). Therefore, this can enable auditors to make better-informed decisions (Dickey et al., 2019). The findings are aligned with the research conducted by Noordin et al. (2022), which discovered that AI assists with professional scepticism and judgement by using predictive analysis methods.

The study conducted by Puthukulam et al. (2021) provides support for the findings. It discovered a strong positive correlation between the use of AI systems and professional scepticism and judgement. This is because AI can transform large amounts of unstructured data into valuable, dependable, and qualitative information that auditors can use to apply professional scepticism and judgment. Audit quality is impacted by the determination of whether management estimates are conservative or aggressive, depending on the auditor's opinion (AUASB, 2022).

Audit work being performed in compliance with professional standards, and legal and regulatory requirements.

To make sure they can fulfil their obligations in compliance with professional standards, businesses should put in place a quality management system (IAASB, 2022). Firms must assess whether they can fulfil an engagement in compliance with legal, regulatory, and professional standards before accepting or continuing with it (IAASB, 2022). The availability of the necessary resources to complete an engagement has an impact on a firm's capacity to carry out tasks in compliance with professional standards (IAASB, 2022).

Respondents found a positive correlation between AI's ability to perform repetitive tasks (R1) and the capacity of the engagement team to carry out tasks per professional standards and acknowledgement of resources (C1 and C11). AI can perform the time-consuming repetitive tasks that previously required auditors' effort and therefore form part of the firm's resources which can be utilised to perform engagements. This is consistent with the study by (Aduloju, 2014), which revealed that the application of AI as a resource saves time and therefore results in the earlier completion of the audit work and meeting audit deadlines without compromising the audit being completed accurately and thoroughly applying professional standards.

As a result, AI strengthens the engagement team's capabilities and aids in determining the resources needed to complete engagements in accordance with professional standards. ISQM 1 reviews technological resources crucial in enabling audit firms to perform quality engagements, as it is of the view that firms should implement appropriate technical resources (IAASB, 2022).

Consequently, auditors have more time to focus on high-risk areas of the audit as a result of AI being adopted as a resource, which means human resources will spend less on tasks that can be automated and handled by AI. The audit team's capacity is increased by the extra time. Thus, respondents discovered a favourable association between their capacity to focus on high-risk audit areas (R3) and their ability to complete engagements in accordance with professional standards (C1 and C11) when using AI. High-risk areas are more susceptible to misstatements and as a result, focusing on these will enable auditors to identify misstatements and gather the necessary audit evidence to support the audit opinion as mandated by both ISAs and ISQM 1.

The ability to free up time by automating certain tasks and enabling auditors to focus on high-risk areas allows the auditors to have sufficient time to consider areas that are susceptible to judgment. Auditors therefore have more time to evaluate audit evidence and findings with due care and apply professional judgement and scepticism to support and enhance the standard of their judgement. This was corroborated by AI's ability to exercise professional judgement having a strong correlation with the ability of the auditor to carry out tasks in accordance with professional standards. This is consistent with the study by (Aduloju, 2014), which revealed that the application of AI as a resource saves time and therefore results in the earlier completion of the audit work and meeting audit deadlines without compromising the audit being completed accurately and thoroughly in line with professional standards.

5.1.5 Appropriateness of the audit report

Even though respondents found that AI will result in the ability to make informed judgements to form the audit opinion (C10), they did not particularly believe that it will affect the appropriateness of the audit report.

According to the ISA, the appropriateness of an audit report is determined not only by the audit opinion but also by the report's structure and contents (IAASB, 2016). In addition to the audit evidence obtained, the auditor should consider the adequacy of disclosures in the financial statements, such as disclosures of significant accounting policies, an assessment of the relevance, reliability, comparability, and understandability of the information presented, and terminology used, such as the title of each financial statement (IAASB, 2016). Therefore, it is evident that even though AI assists in evaluating audit evidence and identifying misstatements to form the audit opinion various other factors form part of forming an appropriate audit report in addition to the appropriateness of the audit opinion.

5.1.6 Concerns relating to the use of AI in auditing

Auditors must prepare documentation that can be re-performed by an experienced auditor to understand how conclusions were reached without prior knowledge of the audit (IAASB, 2009a). Prior literature has raised concerns relating to the explainability and transparency of the decisions made, and conclusions reached by AI (Buhmann et al., 2020; Martin, 2019; Stockle, 2023). AI operates using complex algorithms, which makes it difficult for auditors to understand and explain the conclusions reached by AI (Bijay, 2023). This is relevant as current forms of AI cannot explain why certain items and patterns have been flagged for risk (Stockle, 2023).

Many AI systems, particularly deep learning models, are considered "black boxes" due to their lack of transparency (Kroll et al., 2020). This lack of explainability could be problematic in auditing since auditors may not completely understand how AI arrived at its conclusions (Kroll et al., 2020). Auditors may struggle to justify AI-driven conclusions to auditees, stakeholders, or authorities (Kroll et al., 2020). If AI's decision-making process is opaque, auditors may struggle to defend or explain AI-generated results, which may result in eroding trust in the audit process (Kroll et al., 2020; Zhang et al., 2021). Auditees may challenge the accuracy of audit opinions if they do not understand how AI algorithms produced specific outcomes (Kroll et al., 2020; Zhang et al., 2021). Furthermore, a lack of transparency can make it more difficult to identify any system weaknesses or problems (Kroll et al., 2020; Zhang et al., 2021).

To address the issue of explainability, auditing firms should promote explainable AI solutions that allow auditors to understand and examine the reasoning behind AI decisions (Kroll et al., 2020). AI models should establish clear audit trails and produce interpretable results that auditors can evaluate and explain (Kroll et al., 2020).

The use of AI, therefore, poses the risk of a lack of audit trail in its algorithms and consequently inadequate documentation (Sutaria, 2020). The complex underlying AI algorithms are also perceived to be the basis for the majority of the ethical challenges that arise from AI-based decision-making (Lehner et al., 2022). This is because AI operates based on input data that is supplied and selected by humans, therefore imparting an element of potential bias (Lehner et al., 2022). AI systems, particularly machine learning algorithms, can inherit and perpetuate biases present in training data (O'Neil, 2016). If the data used to train AI models incorporates historical biases (e.g., gender, racial, or socioeconomic biases), the resulting algorithms may reinforce existing biases, resulting in biased auditing results (O'Neil, 2016). This is especially

concerning when AI is used for fraud detection or risk assessment, as biased algorithms may unfairly target specific individuals or firms (O'Neil, 2016).

For example, an AI model trained on historical data could incorrectly classify specific types of transactions as fraudulent due to bias in past patterns, resulting in false positives or unwarranted audit judgements (Barocas et al., 2019). This could undermine the audit process' integrity, as well as that of clients or stakeholders (Barocas et al., 2019). Continuous monitoring and auditing of AI systems is essential to uncover and fix algorithmic biases (O'Neil, 2016). Auditors should be involved in the development and testing of AI models to ensure that ethical standards are followed, and biases are reduced (O'Neil, 2016). Furthermore, employing multiple datasets and doing bias audits may help ensure fairness in AI models (O'Neil, 2016).This makes AI susceptible to manipulation to obtain favourable results (Lehner et al., 2022).

IRBA also issued a communication that, notwithstanding the benefits of the use of AI, such as understanding texts and generating documents, the regulator has emphasised the risks prevalent to the use of AI as it can be used to produce non-existent audit evidence and fabricated working papers which can all result in inaccurate conclusions (IRBA 2023). The lack of transparency regarding how conclusions are reached has the potential to present challenges in recognising elements of bias or inaccuracies (Bijay, 2023). Auditors should verify the authenticity and trustworthiness of audit evidence and working papers (IRBA 2023).

AI systems are designed to follow algorithms and patterns, which can result in the loss of human judgement and professional scepticism (Knechel et al., 2015). Professional scepticism is the critical mindset that auditors must adopt when questioning the legitimacy of financial accounts, detecting fraud, or assessing risk (Knechel et al., 2015). However, AI systems lack the human ability to exercise judgement in ambiguous or complex situations (Knechel et al., 2015). AI may lead auditors to become unduly reliant on the system's output without properly assessing the outcomes (Zhang et al., 2021). This over-reliance may jeopardise the overall quality of audits, especially when AI encounters scenarios that deviate from the norm or need ethical judgement (Zhang et al., 2021). Due to a lack of human control, AI-generated conclusions may be accepted without inquiry, resulting in inaccuracies or overlooking potential fraud or anomalies (Zhang et al., 2021).

A balanced approach is necessary, in which human auditors use AI to boost analysis while keeping ultimate judgement and scepticism (Knechel et al., 2015). It is vital to train auditors to use AI successfully, utilising professional judgement to evaluate AI-driven insights (Knechel et al., 2015).

One of the most common concerns about AI adoption in auditing is job displacement (Bessen, 2019). AI systems can automate duties that were previously performed by human auditors, like data entry, transaction testing, anomaly detection, and risk assessments (Bessen 2019). As a result, lower-level and routine duties done by junior auditors or clerks may be automated, potentially replacing human workers in the auditing business (Bessen, 2019).

Job displacement may occur, particularly in positions that involve repetitive or manual tasks that are currently being automated (Brynjolfsson & McAfee, 2014). This trend may lessen demand for human auditors in certain areas of the profession (Brynjolfsson & McAfee, 2014). Furthermore, greater reliance on AI may result in a skills gap, since current auditors may lack the necessary ability to interact with AI systems or assess AI-generated results (Brynjolfsson & McAfee, 2014).

While AI may displace some jobs, it may also create new, higher-value ones, such as AI system management, oversight, and interpretation (Brynjolfsson & McAfee, 2014). Furthermore, AI can improve human duties by offloading routine labour, allowing auditors to focus on more strategic aspects of auditing, such as fraud identification and risk analysis (Brynjolfsson & McAfee, 2014).

Puthukulam et al. (2021) also found that, as AI cannot consider the ethical implications and validity of data, human intervention will be required to fulfil this role. Auditors will be required to apply reasoning to ensure that the results are credible and valid. It is important to note that the complexity of the algorithms, however, does not preclude the firm or auditors from accountability and the proper use of data (Buhmann et al., 2020).

The application of AI in auditing frequently involves the processing of large amounts of sensitive financial and personal data (McKinney & Koller, 2019). AI systems need access to this data to identify patterns, detect fraud, and assess risks (McKinney & Koller, 2019). However, adopting AI increases the risk of data breaches, hacking, or unauthorised access to sensitive client information (McKinney & Koller, 2019). If AI technologies are exploited or misused, auditors may unwittingly expose their customers to security risks, resulting in data theft or financial losses (Kshetri, 2021). Furthermore, there are regulatory and compliance

concerns about sensitive data protection, particularly under European Union rules such as the General Data Protection Regulation (GDPR) and South Africa's Protection of Personal Information Act (POPIA) (Kshetri, 2021).

Auditing companies must implement strong data security procedures and ensure that AI systems follow data privacy guidelines (Kshetri, 2021). Regular cybersecurity audits, as well as the use of encryption or anonymisation techniques, can help to safeguard sensitive client information. Furthermore, AI technology should have privacy safeguards to limit the risk of data breaches (Kshetri, 2021).

In terms of ISQM 1, the audit firm should use appropriate technological resources in the performance of engagements (IAASB, 2022). AI is a relevant technical resource in terms of ISQM 1, as engagement teams can utilise it to perform engagements. It can be used directly by engagement teams in their performance of engagements (IAASB, 2022). Auditors remain responsible for the work performed by AI, as leadership is responsible and accountable for quality in terms of ISQM 1 (IAASB, 2022). Firms should ensure that the outputs from IT resources achieve the purposes for which they will be used and that the data inputs are complete and accurate (IAASB, 2022).

The concerns and risks relating to AI are supported by this study, as even though respondents indicated that AI would result in a more extensive risk assessment process and sufficient audit evidence, the respondents did not particularly believe that the adoption of AI would have an impact on the credibility of the auditing profession (C2). The above demonstrates that issues of explainability, ethical challenges, and data veracity must be addressed before AI may contribute to the legitimacy of the auditing profession.

Auditors need to be able to explain why AI has selected transactions as exceptions or containing misstatements. If the auditor is unable to explain AI’s reasoning, it will be difficult to determine that sufficient and adequate audit evidence has been acquired to support the audit opinion (CPA, 2020).

Respondents also found no significant relationship between AI’s ability to produce independent outcomes (R4) and its ability to understand and reveal complex interactions from both structured and unstructured data sources (R6). Furthermore, respondents did not perceive a material relationship between audit quality and AI’s ability to increase the scope and type of data to be collected (R12).

The findings are in line with earlier research that suggested that while AI can generate autonomous results and broaden the scope of data, human intervention is still necessary for the analysis of the data's validity and relevance. Moreover, auditing must be conducted using AI in conjunction with human intervention to increase auditing efficiency (Puthukulam et al., 2021).

Furthermore, the results are aligned with the research conducted by Noordin et al. (2022), which revealed no correlation between audit quality and AI's capacity to facilitate autonomous re-execution of intricate computations and modelling. Additionally, AI can detect anomalous trends and deviations that may not be achievable through conventional audit methods.

The use of artificial intelligence (AI) in auditing has raised fundamental questions about the effectiveness of present regulatory systems. While artificial intelligence has the potential to dramatically improve audit effectiveness and efficiency, it also introduces new challenges to accountability, transparency, fairness, and security. Current regulatory frameworks, particularly those governing financial audits, may not be fully prepared to address these challenges.

One of the most pressing challenges in the current legal landscape is the absence of AI-specific auditing regulations (Vasarhelyi and Kogan, 2015). The auditing profession's laws, such as the International Standards on Auditing (ISA) or national regulations, such as the Public Company Accounting Oversight Board (PCAOB) standards in the United States, are primarily concerned with human judgement, professional scepticism, and traditional auditing methodologies (Vasarhelyi and Kogan, 2015). These frameworks have yet to give clear rules for applying AI to decision-making, risk assessment, fraud detection, and the automation of regular audit activities (Vasarhelyi and Kogan, 2015).

Without specific legislative guidance, auditors may rely too much on AI systems, failing to fully understand their limitations, biases, and ethical implications (Knechel et al., 2015). This could result in errors, inaccuracies, or overreliance on technology, jeopardising audit quality and dependability (Knechel et al., 2015).

The current regulatory frameworks do not provide specific rules for reducing bias in AI-driven audit processes (Barocas et al., 2019). Without regulatory oversight to address bias and

fairness, AI technologies may have unintended consequences, such as biased audits or misidentifications of financial irregularities that could affect businesses or individuals (Barocas et al., 2019).

Current regulatory frameworks are intended to guarantee that auditors provide clear, auditable records of their decision-making processes (Kroll et al., 2020). However, AI systems may not readily provide explanations for their behaviours, therefore jeopardising accountability and audit quality (Kroll et al., 2020). Without laws mandating explainable AI models in auditing, audits may be difficult to explain or defend to clients, regulators, or the general public (Kroll et al., 2020). If AI-generated outcomes are difficult to explain or justify, trust in the audit process may suffer, as would the ability to hold auditors accountable for their use of AI (Kroll et al., 2020).

AI systems are usually seen as tools that assist auditors in reaching judgements. However, if an AI system makes an error or produces an incorrect audit finding, it is unclear who is ultimately responsible or liable for the outcomes (Vasarhelyi and Kogan, 2015). Current auditing standards highlight human accountability, asking auditors to justify their findings and accept responsibility for their decisions (Vasarhelyi & Kogan, 2015). AI complicates decision-making by making ownership questionable (Vasarhelyi and Kogan, 2015).

Without clear regulatory guidelines regarding data privacy and security when utilising AI, auditors may mistakenly expose sensitive client data to security risks or violate privacy standards when using AI techniques (McKinney & Koller, 2019). This can result in legal and reputational concerns for auditing companies, as well as financial losses for clients (McKinney & Koller, 2019).

AI technology is rapidly developing, whereas regulatory frameworks evolve slowly (Krause et al., 2020). As a result, regulatory delays are a significant concern. Regulatory authorities may struggle to keep up with the rapid integration of AI into audits, and their ability to create or alter criteria for new technological advancements is frequently delayed (Krause et al., 2020).

While the use of AI in auditing has notable advantages, such as increased efficiency and detection abilities, current legal frameworks are frequently insufficient to address the full range of challenges posed by AI integration. These challenges include ethical concerns, accountability, transparency, data protection, and regulatory delays.

As a result, authorities must develop more precise, forward-thinking frameworks that lay out explicit criteria for the ethical use of AI in audits, protect against biases, ensure data protection, and clarify accountability mechanisms. To properly monitor AI-enhanced auditing processes, regulatory agencies must prioritise explainable AI and openness, as well as keep up with technical advances.

6. Conclusion

This section summarises and tabulates the key findings of the research study, the implications of the results and recommendations are then discussed. Finally, areas of future research are identified.

Table VII: Key findings of the research study

Key audit quality trait	**Impact of AI on Key Audit Quality Trait**
Rigorousness of the risk assessment process	Auditors can use AI to perform comprehensive risk assessments through the analysis of 100% data.
Time available to obtain audit evidence	AI automates repetitive tasks, which increases the capacity of the audit team to focus on more critical and high-risk areas which require judgment.
The extent of testing	The reliability of the audit report is enhanced as audit judgements and conclusions are based on the entire set of data, not just a sample.
The persuasiveness of the auditing models	The persuasiveness of audit evidence is enhanced through the testing of the full population and predictive analyses.
The use of detailed analytics	AI's pattern analysis and ability to categorise data into categories enables the auditor to perform analytics on more refined categories of data and apply precise expectations to identify misstatements.
Informed Auditors' judgement	AI's predictive analyses can be used to evaluate management's estimates resulting in informed judgements. The free-up time through the automation of tasks allows more time for auditors to exercise professional judgment

Audit work should be performed in compliance with professional standards, and legal and regulatory requirements	AI can perform mundane tasks increasing the capacity and resources of the audit team to perform engagements. Automation of tasks also increases the time available to evaluate audit evidence.
The ability of the auditor to explain work completed by AI and ethical issues are some of the challenges of auditing using AI.	For auditors to prove that relevant and sufficient audit evidence has been acquired, they must be able to explain the work done by AI. Auditors need to put in work to confirm the validity and dependability of audit evidence assessed by AI.

Implications and recommendations

At an overall level, the use of AI will result in an improvement in the quality of audit engagements, as the functional abilities of AI are positively correlated with key audit quality traits. The functional abilities of AI will enable firms to realise quality benefits by accomplishing the key objectives of a quality management system in terms of ISQM 1. AI is positively associated with the firm's ability to perform engagements in line with professional standards, and legal and regulatory requirements. This is one of the key objectives of a firm's quality management system and firms are required to determine if they will be able to conduct the engagement in line with such standards before even accepting or continuing with the engagement. Therefore, firms are recommended to utilise AI to achieve the objectives of a quality management system.

Having the right resources and time to complete the engagement is essential to the firm's ability to carry out the engagement in accordance with legal, professional, and other obligations (IAASB, 2022). AI can be used to automate audit evidence-capturing and evaluation processes (ASA, 2023; EY, 2018). To increase the ability of the engagement team to concentrate on other, more important tasks within the engagement or the firm's capacity to take on more firms should incorporate AI into their resource mix because they will have the necessary resources and time to perform more engagements. Due to the enhanced capacity and time saved when AI handles some of the activities, audit companies would also be better able to meet reporting deadlines.

One of the things that respondents regarded as essential to the quality of an audit was the thorough risk assessment procedures that AI produces. This is an important component since it serves as the foundation for the entire audit, and without accurately identifying risks, auditors would not be able to develop responses for risks that they are unable to detect (Munter, 2023).

The final effect is that the auditor would not discharge their duty to the highest standard given that the audit opinion would be unsuitable as there is insufficient and inappropriate audit evidence to support it (AFRC, 2023). This exposes the firms to various risks, such as reputational risks for issuing incorrect audit opinions and consequently raises questions about the firm's competence and legitimacy. Consequently, it is recommended that firms adopt AI to enhance the rigorousness and accuracy of their risk assessment process.

AI's capacity to automate tasks creates more time for engagement teams to concentrate on more critical and high-level duties, improving the accuracy and dependability of the decisions taken and, as a result, audit quality. This is crucial for engagement teams, as ISA's and quality standards emphasise that engagement team members should be given sufficient time and capabilities in order to enable them to consistently perform quality engagements (IAASB, 2022).

The reliability of the audit report is also improved by AI's ability to evaluate 100% of the population as the auditors evaluate the full transactions and therefore make informed judgements and decisions on the full scope of transactions (Dalwai et al., 2022; Fedyk et al., 2022). In light of AI's predictive analysis capabilities, audit evidence may be more persuasively evaluated, which enhances auditors' capacity to detect misstatements and reach well-informed conclusions.

Firms can utilise AI to improve the quality of judgements and decisions. This is expected to result in high detection of material misstatements. This expectation is further supported by a previous study by Fedyk et al. (2022), which discovered that audit firms using AI tools saw a significant decrease in restatements in financial misstatements as a result of an improvement in audit quality brought about by the ability to analyse audit evidence and identify financial statement misstatements.

Financial statements will, therefore, be exposed to lower chances of restatement, improving the legitimacy and reliability of the profession. This is crucial given that the overall role of auditors is to identify misstatements, propose adjustments and report on remaining material misstatements to deliver an audit opinion that can be relied upon (Xiao et al., 2020). Detection of material misstatements and lower restatements will enhance the legitimacy of the specific audit firms as their reputation is enhanced through the reliability of their work, giving them a competitive advantage. As a result of this, auditors can use AI to gather adequate audit proof to comply with ISQM 1 and support the audit report.

In addition to informed judgements and identification of misstatements, auditors can utilise AI to enhance their abilities to ask the right questions and challenge management's estimates (KPMG, 2023b). The auditor will be able to provide value to their clients by offering pertinent suggestions for business changes through the use of data analysis, which will allow them to gain greater insights (Ken, 2022).

While there is a favourable correlation between the usage of AI and audit quality, there are some risks and concerns that companies must address before using AI to execute engagements. For auditors to prove that relevant and sufficient audit evidence has been acquired, they must be able to explain the work performed through AI. AI is incapable of taking the veracity of data and ethical considerations into account. Auditors must perform work to verify the authenticity and reliability of audit evidence and working papers.

The application of artificial intelligence (AI) to auditing and financial reporting has the potential to radically transform the profession and the greater financial ecosystem. While AI promises many advantages, including increased efficiency, fewer errors, and better fraud detection, it also poses new challenges and changes to auditor responsibilities, reliance on technology, regulatory supervision, and trust in financial reporting systems.

AI usage in auditing is likely to significantly alter auditing procedures. Traditionally, audits consisted of laborious data collecting, sampling, and substantive testing to evaluate financial accounts (Vasarhelyi & Kogan, 2015). Many of these operations can be automated using AI, boosting audit coverage and accuracy. AI allows auditors to analyse huge datasets in real time, uncover patterns, and detect abnormalities that would otherwise go unnoticed in traditional audits (Vasarhelyi & Kogan, 2015).

Artificial intelligence enables auditors to undertake more complete data analysis with less resources (Kokina & Davenport, 2017). For example, AI can analyse all transactions rather than depending on samples, which improves the quality and reliability of the audit (Kokina & Davenport, 2017). Artificial intelligence systems, particularly those based on machine learning, can continually analyse financial transactions, allowing for real-time audits.

This is especially useful in situations where financial data and market conditions are constantly changing, allowing auditors to deliver more timely insights. AI technologies can reduce human error and subjective biases, which have traditionally influenced audits. Algorithms can process

data using objective criteria rather than individual judgement, resulting in more consistent outcomes.

AI integration in financial reporting has the potential to increase financial statement accuracy and timeliness. AI systems can automate complicated financial statement preparation operations such as data reconciliation, transaction classification, and report production. These advancements have the potential to improve the quality of financial reporting and help businesses comply with accounting requirements more effectively.

AI can also automate data entry and processing, lowering the possibility of errors and discrepancies in financial accounts (AICPA, 2019). Increased automation can also accelerate the reporting process, allowing businesses to publish more timely financial statements (AICPA, 2019).

AI adoption is anticipated to result in a restructuring of the auditor's role. While conventional audits depended mainly on auditors to complete manual inspections and make judgements, AI will automate many of these processes. The auditor's responsibilities will change from basic chores to higher-level decision-making, interpreting AI findings, expressing professional scepticism, and overseeing the ethical and responsible use of AI.

With AI automating mundane procedures such as data processing and transaction testing, auditors will be able to focus on high-value activities like risk assessment, fraud detection, and providing strategic insights to customers (Knechel et al., 2020).

Despite AI's ability to review large datasets and identify anomalies, human auditors will still need to apply professional scepticism and judgement, particularly in complex or ambiguous scenarios (Zhang et al., 2021). Auditors' tasks will expand to include overseeing AI systems, ensuring their ethical and successful use (Zhang et al., 2021). Auditors will need to learn new skills, including data science, machine learning, and AI ethics, as part of the AI integration process. Auditors must be capable of assessing AI-generated insights and ensuring that these tools are used in accordance with ethical standards.

The extensive use of AI in auditing also raises important regulatory and ethical concerns. There are also concerns regarding AI-related issues such as algorithmic bias, accountability, and data privacy (Kshetri, 2021). AI adoption raises the question of who is held accountable in the event that an AI system fails or makes a wrong choice during an audit. This shift in

accountability may necessitate new legislation and guidelines defining the roles and obligations of auditors, AI developers, and firms in the event of an audit failure.

AI usage in auditing and financial reporting is expected to result in both transformative benefits and major obstacles. On one hand, AI offers more efficiency, precision, and the possibility of real-time auditing, hence improving the dependability and transparency of financial reporting. On the other hand, the profession must address ethical concerns, regulatory loopholes, and new duties associated with the use of AI in auditing. To fully realise AI's potential while limiting its risks, regulators, auditors, and organisations must work together to provide clear rules and safeguard mechanisms for the ethical and effective use of AI in the auditing profession.

As AI integration into auditing accelerates, audit companies must be proactive in planning for the shift. The use of AI can improve auditing processes, increase efficiency, and increase the ability to detect fraud and anomalies, but it also creates new issues that must be properly managed. Audit firms can take a number of particular steps to ensure they are well prepared for the rising incorporation of AI into their businesses. These recommendations cover topics such as talent development, technology adoption, regulatory compliance, and ethics management.

To fully realise the potential of AI, auditors must learn a combination of traditional auditing abilities and data science competencies. Training auditors in AI-related technologies like machine learning, data analysis, and artificial intelligence ethics is critical. This will allow people to analyse AI-driven insights, comprehend the underlying algorithms, and make high-quality decisions based on AI-generated results.

Audit firms should engage in on-going development programs to provide auditors with the skills required to effectively manage AI tools. These programs should cover not only technical AI skills but also critical thinking, data interpretation, and incorporating AI insights into the audit process.

Firms can form partnerships or collaborations with data scientists and AI experts to construct training programs and guarantee auditors are up to date with the most recent breakthroughs in AI technology (AICPA, 2019). While AI can automate many jobs, auditors must still use professional scepticism and judgement (Knechel et al., 2020). Training programs should focus on how auditors may mix AI results with human knowledge to improve decision-making (Knechel et al., 2020).

Rather than depending entirely on off-the-shelf solutions, audit firms should consider investing in customising AI tools to match their individual needs, ensuring that the AI systems align with the firm's audit objectives and client expectations (Kokina & Davenport, 2017). Audit businesses could use AI-enabled solutions that are expressly developed for auditing duties, such as automated transaction testing, fraud detection algorithms, and continuous auditing systems (Knechel et al., 2020).

With an increasing reliance on data and AI, it is critical to ensure AI system security and data privacy. To prevent breaches or exploitation of sensitive client data, businesses must invest in cybersecurity infrastructure (Knechel et al., 2020). AI systems in auditing can raise ethical concerns, such as algorithmic bias and a lack of transparency in decision-making processes. To address these concerns, audit companies must proactively adopt ethical guidelines and assure compliance with applicable regulatory norms.

Firms should form internal committees to ensure that AI tools are utilised ethically. These committees can check AI systems for biases, discrimination, and other ethical issues (O'Neil, 2016). They should also guarantee that AI tools follow developing legislative frameworks and best practices in AI ethics (Brynjolfsson & McAfee, 2017).Firms should prioritise explainable AI, which ensures that auditors can comprehend and explain AI-driven findings. Transparency is vital for maintaining confidence with clients and stakeholders (Gunning, 2017).

Audit firms should establish procedures for conducting regular audits of AI systems in order to discover biases and errors that could jeopardise the audit process (Zhang et al., 2021). These assessments should involve both technical and ethical audits to assess the correctness, fairness, and transparency of the AI model (Zhang et al., 2021).

As AI usage in auditing grows, there will be a greater need for collaboration among audit firms, regulators, and industry leaders to ensure that AI is implemented appropriately. Audit firms should work with relevant regulatory agencies to guide the creation of legislation that addresses the unique issues brought by AI. Audit companies should collaborate with organisations like the International Auditing and Assurance Standards Board (IAASB) and the Public Company Accounting Oversight Board (PCAOB) to influence the development of AI-related auditing standards (Krause et al., 2020). This partnership can help verify that AI tools are used in accordance with audit best practices and regulatory standards.

Audit firms can work with other industry participants and technology companies to create common standards, guidelines, and tools for AI applications (Kokina & Davenport, 2017).

These consortia can encourage information sharing and ensure that AI use in auditing is transparent, equitable, and ethical (Kokina & Davenport, 2017). Audit firms can also work with other industry participants and technology companies to create common standards, guidelines, and tools for AI application. These consortia can encourage information sharing and ensure that AI use in auditing is transparent, equitable, and ethical.

Firms should promote innovation by funding research and development in AI. Creating separate teams for AI research can help organisations to investigate novel applications of AI in auditing while maintaining a competitive edge (Vasarhelyi & Kogan, 2015). Implementing AI necessitates a deliberate change management approach. Firms can prepare their staff for the transformation by conveying the benefits of AI, resolving any worries, and demonstrating how AI will augment, not replace, human judgement.

The use of AI in auditing offers both intriguing prospects and serious obstacles. Audit businesses must deliberately invest in employee training, technology infrastructure, and ethical principles, while also encouraging collaboration with regulators and industry leaders. Audit businesses may use AI to improve auditing procedures, increase productivity, and remain competitive in an ever-changing landscape by preparing their personnel, using relevant technologies, and building solid ethical and legal frameworks.

Future research

The study applies correspondence analysis, which is an exploratory method that cannot be applied to testing hypotheses as it involves subjective opinions. As a result, unlike positivist studies, this one does not try to produce a conclusion that can be applied universally (Maroun, 2014). It does not offer a quantifiable conclusion (Creswell, 2014; Moon & Blackman, 2014). Accordingly, the study does not aim to represent the opinions of every external auditor. To shed additional light on how the functions of AI contribute to prospective increases in audit quality, more interpretive research methods are thus needed.

To balance the expectations of all stakeholders, future research could also look at the contribution of AI from a different angle. For instance, audit committees and auditees could be consulted to find out how they believe AI will affect the calibre of audit services they receive from audit firms. Since audit committees and auditees are essentially the audit firms' clients and they select and collaborate with them as service providers, their opinions are highly valued.

Lastly, the study did not group the findings based on the respondents' firm sizes. According to Dikuua et al. (2023), there exists a disparity in the resources and capabilities of large and small audit firms. Therefore, future research must investigate if the perspectives on the influence of artificial intelligence on audit quality vary based on the size of audit firms. This is also an important factor to take into account because, according to ISQM1, a quality management system should be tailored to the needs and conditions of the company (IAASB, 2022).

References

Adeoye, O., Akintoye, R., Theophilus, A., Theophilus, A., & Olagunju, O. (2023). Artificial intelligence and audit quality: Implications for practicing accountants. *Asian Economic and Financial Review*, *13(1)*, 756-772. https://doi.org/10.55493/5002.v13i11.4861

Aduloju, K. (2014). Information Technology Managerial Capabilities and Customer Service Performance Among Insurance Firms in Nigeria. *SAGE Open*, *4(1)*, 4. https://doi.org/10.1177/2158244014561198

AFRC. (2023). *Effective Planning: The Key to High-Quality Audits* https://www.afrc.org.hk/en-hk/Documents/Publications/periodic-reports/2023_Audit_Focus_Effective_Audit_Planning.pdf

Agresti, A., & Wiley, I. (2002). *Categorical data analysis* (2nd ed.). Wiley-Interscience.

AICPA. (2019). The impact of artificial intelligence on audit and assurance services. *Journal of Accountancy*.

Al-Sayyed, S., Al-Aroud, S., & Zayed, L. (2021). The effect of artificial intelligence technologies on audit evidence. *Accounting*, *7(2)*, 281-288. https://doi.org/10.5267/j.ac.2020.12.003

Ardelean, A. (2013). Auditors' Ethics and their Impact on Public Trust. *Procedia - Social and Behavioral Sciences*, *92*, 55-60. https://doi.org/https://doi.org/10.1016/j.sbspro.2013.08.637

Arnold, C., & Kong, J. (2022). *Initial Steps and Key Resources for Small Firm Digitalization*. International Federation of Accountants Retrieved 05 December 2023 from https://www.ifac.org/knowledge-gateway/preparing-future-ready-professionals/discussion/challenges-initial-steps-and-key-resources-small-firm-digitalization

ASA. (2023). The Use of Artificial Intelligence (AI) in the Execution of Audits (Accountability State Authority of Egypt- ASA). *International Journal of Government Auditing 1*(1). https://intosaijournal.org/journal-entry/the-use-of-artificial-intelligence-ai-in-the-execution-of-audits/#:~:text=AI%20can%20study%20data%20and,audit%20strong%20and%20well%20supported.

Azizi, A. F., & Muliartha, I. K. (2018). Analisis Perencanaan Audit dan Kompetensi Auditor pada Kualitas Audit di Perwakilan BPKP Provinsi Bali. *E-Jurnal Akuntansi*, *25*(2), 851-876. https://doi.org/10.24843/EJA.2018.v25.i02.p02

Bendixen, M. T. (1996). A Practical Guide to the Use of Correspondence Analysis in Marketing Research.

Bijay, A. (2023). *AI in Auditing: Evaluating the Advantages and Disadvantages of Implementing Artificial Intelligence in Auditing.* Retrieved 18 February 2023 from https://www.crowe.com/np/insights/ai-in-auditing

Bowling, S. C. P. A. C., & Meyer, C. (2019). How we successfully implemented AI in audit. *Journal of Accountancy*, *227*(5), 26-28. https://search.proquest.com/docview/2241268791?accountid=15083

Brant E. Christensen, S. M. G., Thomas C. Omer, Marjorie K. Shelley. (2016). Understanding audit quality: Insights from audit professionals and investors. *Contemporary Accounting Research*, *33(4)*, 1363-1393. https://doi.org/https://doi.org/10.1111/1911-3846.12212

Brown, L., & Vasarhelyi, M. A. (2015). The future of audit: A perspective from the academic literature. *Journal of Emerging Technologies in Accounting*, *12*(2), 1-14.

Brynjolfsson, E., & McAfee, A. (2017). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W. W. Norton & Company.

Buhmann, A., Paßmann, J., & Fieseler, C. (2020). Managing Algorithmic Accountability: Balancing Reputational Concerns, Engagement Strategies, and the Potential of Rational Discourse. *Journal of Business Ethics*, *163*, 265-280. https://doi.org/10.1007/s10551-019-04226-4

Chan, S. W. S., Ip, S., Wan, C. F. C., & Yiu, H. F. D. (2018). *How would the emerging technology affect the future of auditing?* City University of Hong Kong]. https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=How+would+the+emerging+technology+affect+the+future+of+auditing%3F&btnG=

Chen, X., & Liao, S. (2020). Artificial intelligence in auditing and assurance services: An overview and research agenda. *Journal of accounting literature*, *45*, 1-20.

Christensen, B., Glover, S., Omer, T., & Shelley, M. (2015). Understanding Audit Quality: Insights from Audit Professionals and Investors. *Contemporary Accounting Research*, *33*. https://doi.org/10.1111/1911-3846.12212

Coffee, J. C. (2019). Why do auditors fail? What might work? What won't? *Accounting and Business Research*, *49*(5), 540-561. https://doi.org/10.1080/00014788.2019.1611715

CPA. (2020). *The data-driven audit: AI and automation's impact on audit and auditors' roles* https://www.cpacanada.ca/en/business-and-accounting-resources/audit-and-assurance/canadian-auditing-standards-cas/publications/data-driven-audit-ai-automation-impact

Creswell, J. W. (2014). *Research design: International student edition*. Los Angeles: SAGE.

Dalwai, T. A. R., Madbouly, A., & Mohammadi, S. S. (2022). An Investigation of Artificial Intelligence Application in Auditing. In B. Alareeni & A. Hamdan (Eds.), *Artificial Intelligence and COVID Effect on Accounting* (pp. 101-114). Springer Nature Singapore. https://doi.org/10.1007/978-981-19-1036-4_7

Danielle Lombardi, H. L. B.-L., Ivy Munoko. (2023). Using an Interactive Artificial Intelligence System to Augment Auditor Judgment in a Complex Task. *SSRN*. https://doi.org/https://dx.doi.org/10.2139/ssrn.4318689

DeAngelo, L. E. (1981). Auditor size and audit quality. *Journal of accounting and economics*, *3*(3), 183-199. https://doi.org/10.1016/0165-4101(81)90002-1

Dickey, G., Blanke, S., & Seaton, L. (2019). Machine Learning in Auditing. *CPA Journal*, *89*(6), 16-21. http://0-search.ebscohost.com.innopac.wits.ac.za/login.aspx?direct=true&db=f5h&AN=136901845&site=eds-live&scope=site

Dikuua, M. B., Maroun, W., Zijl, W. v., & Ram, A. J. (2023). Audit regulation and its relevance for audit quality in Namibia. *South African Journal of Economic and Management Sciences*, *26*(1), 4866. https://doi.org/doi:10.4102/sajems.v26i1.4866

Doey, L., & Kurta, J. (2011). *Correspondence analysis applied to psychological research* (Vol. 7).

Dresdner, H., & Fischer, D. (2020). Definitions and determinants of audit quality. *Journal of Corporate Accounting & Finance*, *31*. https://doi.org/10.1002/jcaf.22441

Elder, R., Akresh, A., Glover, S., Higgs, J., & Liljegren, J. (2013). Audit Sampling Research: A Synthesis and Implications for Future Research. *Auditing A Journal of Practice & Theory*, *32*, 99-129. https://doi.org/10.2308/ajpt-50394

Elliot, V., Paananen, M., & Staron, M. (2020). Artificial Intelligence for Decision-Makers. *Journal of Emerging Technologies in Accounting*, *17*, 51-55. https://doi.org/10.2308/jeta-52666

EY. (2018). *How artificial intelligence will transform the audit*. EY. Retrieved 29 November 2023 from https://www.ey.com/en_za/assurance/how-artificial-intelligence-will-transform-the-audit

EY. (2023). *EY launches artificial intelligence platform "EY.ai" and invests US$1.4 billion* https://www.ey.com/en_ch/news/2023/09/ey-launches-artificial-intelligence-platform-ey-ai#:~:text=use%20of%20AI.-,%22EY.ai%22%20combines%20leading%20EY%20technology%20platforms%20and%20AI,launch%20of%20the%20new%20platform.

Fedyk, A., Hodson, J., Khimich, N., & Fedyk, T. (2022). Is artificial intelligence improving the audit process? *Review of Accounting Studies*, *27*(3), 938-985. https://doi.org/10.1007/s11142-022-09697-x

Fonseca, L. (2020). *An Introduction to Artificial Intelligence: The Four Types of AI*. Retrieved 24 April 2020 from https://www.thedifferenceengine.tech/blog/2019/11/an-introduction-to-artificial-intelligence-the-four-types-of-ai

Francis, J. R. (2011). A framework for understanding and researching audit quality. *Auditing: A journal of practice & theory*, *30*(2), 125-152. https://doi.org/10.2308/ajpt-50006

Francis, J. R. (2023). What exactly do we mean by audit quality? *Accounting in Europe*, 1-11. https://doi.org/10.1080/17449480.2023.2247410

FRC. (2019). *Substantial increase in fines as FRC takes tough action to tackle poor quality audit* https://www.frc.org.uk/news-and-events/news/2019/07/substantial-increase-in-fines-as-frc-takes-tough-action-to-tackle-poor-quality-audit/

Gartland, D. J. (2017). *The importance of audit planning*. Daniel J. Gartland. Retrieved 28 November from https://www.journalofaccountancy.com/issues/2017/sep/importance-of-audit-planning.html

Gentner, D., Stelzer, B., Ramosaj, B., & Brecht, L. (2018). Strategic Foresight of Future B2B Customer Opportunities through Machine Learning. *Technology Innovation Management Review*, *8*, 5-17. https://doi.org/10.22215/timreview/1189

Gopal, L. (2023). *How is artificial intelligence used in auditing?* Nanonets. Retrieved 29/11/2023 from https://nanonets.com/blog/using-artificial-intelligence-in-audits/#:~:text=Data%20Analytics%3A%20AI%2Dpowered%20data,that%20may%20require%20further%20investigation.

Greenacre, M. J. (2007). *Correspondence analysis in practice (2nd ed.)*. CRC Press.

Greenman, C. (2017). Exploring the impact of artificial intelligence on the accounting profession. *Journal of Research in Business, Economics and Management*, *8*(3), 1451. https://commons.erau.edu/publication/826/

Guest, G., Namey, E. E., & Mitchell, M. L. (2013). *Collecting qualitative data: A field manual for applied research*. Sage.

Gunning, D. (2017). *Explainable artificial intelligence (XAI)*. DARPA.

Habib, F., Etesam, I., Ghoddusifar, S. H., & Mohajeri, N. (2012). Correspondence analysis: a new method for analyzing qualitative data in architecture. In *Digital Fabrication* (pp. 517-538). Springer. http://DOI 10.1007/s00004-012-0129-1

Hair, J. F., Jr., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th edition ; Global edition. ed.). Pearson.

Hassan, R. A. (2022). Artificial Intelligence (AI) in accounting & auditing: A Literature review. *Open Journal of Business and Management*, *10*, 440–465.

Hassani, H., Silva, E., Unger, S., Tajmazinani, M., & MacFeely, S. (2020). Artificial Intelligence (AI) or Intelligence Augmentation (IA): What Is the Future? *AI*, *1*, 1211. https://doi.org/10.3390/ai1020008

Heijden, v. d., & Ark , v. d. (2019). Correspondence analysis of sparse contingency tables. *Journal of the Royal Statistical Society Series C (Applied Statistics)*, *68*(5), 1234-1247.

Holm, C., & Zaman, M. (2012). Regulating audit quality: Restoring trust and legitimacy. *Accounting forum*, *36*(1), 51-61. https://doi.org/10.1016/j.accfor.2011.11.004

IAASB. (2009a). *International Standard on Auditing (ISA) 500, Audit Evidence*. IAASB.

IAASB. (2009b). International Standard on Auditing (ISA) 520, Analytical Procedures. In. IAASB.

IAASB. (2009c). ISA 200: OVERALL OBJECTIVES OF THE INDEPENDENT AUDITOR AND THE CONDUCT OF AN AUDIT IN ACCORDANCE WITH INTERNATIONAL STANDARDS ON AUDITING. In IAASB (Ed.), *INTERNATIONAL STANDARD ON AUDITING 200*. https://www.ifac.org/_flysystem/azure-private/publications/files/A009%202012%20IAASB%20Handbook%20ISA%20200.pdf

IAASB. (2009d). ISA 330: the auditor's response to assessed risk. In *SAICA Members' Handbook* (pp. 1-18). LexisNexis Pietermaritsburg. https://www.ifac.org/system/files/downloads/a019-2010-iaasb-handbook-isa-330.pdf

IAASB. (2009e). ISA 530: Audit sampling. In *SAICA Member's handbook*. LexisNexis Piertermaritsburg. https://www.ifac.org/system/files/downloads/a027-2010-iaasb-handbook-isa-530.pdf

IAASB. (2009f). ISQC1: Quality control for firms that perform audits and reviews of historical financial information, and other assurance and related services engagements. In *SAICA members' handbook*. LexisNexis Piertermaritsburg. https://www.ifac.org/system/files/downloads/a007-2010-iaasb-handbook-isqc-1.pdf

IAASB. (2015). *Enhancing Audit Quality in the Public Interest* https://www.irba.co.za/upload/IAASB-Invitation-to-Comment-Enhancing-Audit-Quality_Final%20Dec%202015.pdf

IAASB. (2019a). *Audit Evidence*. Retrieved 06 February 2024 from https://www.iaasb.org/system/files/meetings/files/20190311-IAASB-Agenda_Item_8-A-Audit-Evidence-Presentation-For-Posting_0.pdf

IAASB. (2019b). INTERNATIONAL STANDARD ON AUDITING 315 (REVISED 2019) IDENTIFYING AND ASSESSING THE RISKS OF MATERIAL MISSTATEMENT. In IAASB (Ed.), *International Standard on Auditing*. https://www.ifac.org/_flysystem/azure-private/publications/files/ISA-315-Full-Standard-and-Conforming-Amendments-2019-.pdf

IAASB. (2019). INTERNATIONAL STANDARD ON AUDITING 315 (REVISED 2019) IDENTIFYING AND ASSESSING THE RISKS OF MATERIAL MISSTATEMENT. In IAASB (Ed.), *International Standard on Auditing*. https://www.ifac.org/_flysystem/azure-private/publications/files/ISA-315-Full-Standard-and-Conforming-Amendments-2019-.pdf

IAASB. (2022). International Standard on Quality Management (ISQM) 1:Quality Management for Firms that Perform Audits or Reviews of Financial Statements, or Other Assurance or Related Services Engagements In *SAICA members' handbook*. LexisNexis Piertermaritsburg. https://www.ifac.org/system/files/downloads/a007-2010-iaasb-handbook-isqc-1.pdf

IESBA. (2021). *International Ethics Standards Board for Accountants (IESBA), 2021, Handbook for the*

International Code of Ethics for Professional Accountants www.ifac.org/_flysystem/azure-private/publications/files/IESBA-English-2021-IESBA-Handbook_Web.pdf

IFA. (2006). Code of professional conduct, South African Institute of Chartered Accountants Members' Handbook. In: LexisNexis Pietermaritsburg.

Institute of Directors Southern Africa. (2016). *KING IV*. https://www.adams.africa/wp-content/uploads/2016/11/King-IV-Report.pdf

IRBA. (2023a). *2022 PUBLIC INSPECTIONS REPORT ON AUDIT QUALITY* https://www.irba.co.za/upload/IRBA%202022%20Inspections%20Report%20Finals%20March%202023.pdf

IRBA. (2023b). *Minister of Finance gazettes maximum fines for auditor improper conduct*. IRBA. Retrieved 08 December from https://www.irba.co.za/news-headlines/press-releases/minister-of-finance-gazettes-maximum-fines-for-auditor-improper-conduct#:~:text=The%20maximum%20fine%20that%20may,is%20set%20at%20R15%2Dmillion.

Jaffer, F., Odendaal, E., & Theron, H. J. (2019). Auditors' evaluation of ethical leadership as part of management integrity. *Southern African Journal of Accountability and Auditing Research*, *21*(1), 99-109. https://hdl.handle.net/10520/EJC-197ef00597

Justice, C. (2020). *AI: The new power generation*. Retrieved 28 May 2020 from https://home.kpmg/xx/en/home/insights/2020/02/ai-the-new-power-generation.html

Ken, T. (2022). Embracing technology in the audit. *Journal of Accountancy*, *1*(1), 1. https://doi.org/https://www.journalofaccountancy.com/issues/2022/feb/embracing-technology-audit.html

Khan, H. (2021). Types of AI | Different Types of Artificial Intelligence Systems fossguru.com/types-of-ai-different-types-of-artificial-intelligence-systems. *9*, 50.

Kilgore, A., Radich, R., & Harrison, G. (2011). The relative importance of audit quality attributes. *Australian Accounting Review*, *21*(3), 253-265. https://doi.org/10.1111/j.1835-2561.2011.00141.x

Knechel, W. R., Staden, C., & Zerni, M. (2020). The impact of artificial intelligence on auditing and auditing standards. *International Journal of Auditing*, *24*(2), 183-202.

Kokina, J., & Davenport, T. (2017). The Emergence of Artificial Intelligence: How Automation is Changing Auditing. *Journal of Emerging Technologies in Accounting*, *14(1)*, 115–122. https://doi.org/10.2308/jeta-51730

KPMG. (2023). *AI's Role in Enhancing Trust in Financial Reporting and the Capital Markets*. KPMG. Retrieved 30 November from https://info.kpmg.us/content/dam/info/en/news-perspectives/pdf/2023/kpmg-ai-in-audit-survey-executive-summary.pdf

Krause, M., Martini, M., & Wiesen, D. (2020). Regulatory lag and the ethics of artificial intelligence: Perspectives from auditing. *Journal of Business Ethics*, *168*(4), 591-610.

Kshetri, N. (2021). AI, cybersecurity, and data privacy: Addressing the risks of artificial intelligence in auditing. *Journal of Information Privacy and Security*, *17*(2), 74-90.

Kudlats, J., Money, A., & Hair Jr, J. F. (2014). Correspondence analysis: A promising technique to interpret qualitative data in family business research. *Journal of Family Business Strategy*, *5*(1), 30-40. https://www.sciencedirect.com/science/article/pii/S1877858514000096

Lateef, Z. (2020). *Types Of Artificial Intelligence You Should Know*. Retrieved 27 May 2020 from https://www.edureka.co/blog/types-of-artificial-intelligence/

Law, K. a. S., Michael. (2020). How Does Artificial Intelligence Shape Audit Firms? *Nanyang Business School Research Paper*, 20-31. https://doi.org/http://dx.doi.org/10.2139/ssrn.3718343

Le, H. T. T., Tran, H. G., & Vo, X. V. (2021). Audit quality, accruals quality and the cost of equity in an emerging market: Evidence from Vietnam. *International Review of Financial Analysis*, *77*, 101798. https://doi.org/https://doi.org/10.1016/j.irfa.2021.101798

Leary, O. (2013). Emerging trends in knowledge discovery and decision support for the auditing profession. *Journal of Emerging Technologies in Accounting*, *10*(1), 1-17.

Lee. (2016). *KPMG recruits IBM Watson for cognitive tech audits, insights*. https://www.accountingtoday.com/news/kpmg-recruits-ibm-watson-for-cognitive-tech-audits-insights

Lehman, G. (2010). Interpretive accounting research. *Accounting forum*, *34*(3-4), 231-235. https://doi.org/10.1016/j.accfor.2010.08.007

Lehner, O., Ittonen, K., Silvola, H., Ström, E., & Wührleitner, A. (2022). Artificial intelligence based decision-making in accounting and auditing: ethical challenges and normative thinking. *Accounting, Auditing & Accountability Journal*, *35*, 109-135. https://doi.org/10.1108/AAAJ-09-2020-4934

Liao, F.-n., Zhang, C., Zhang, J.-j., Yan, X., & Chen, T.-x. (2024). Hyperbole or reality? The effect of auditors' AI education on audit report timeliness. *International Review of Financial Analysis*, *91*, 103050. https://doi.org/https://doi.org/10.1016/j.irfa.2023.103050

Maroun, W. (2014). Reportable irregularities and audit quality: Insights from South Africa. *Accounting forum*, *39*(1), 21-33. https://doi.org/10.1016/j.accfor.2014.03.002

Maroun, W., Turner, M., & Sartorius, K. (2011). Does Capital Gains Tax add to or detract from the fairness of the South African Tax System *South African Journal of Economic and Management Sciences*, *14*(4), 436-448. https://doi.org/10.4102/sajems.v14i4.131

Martin, K. (2019). Ethical Implications and Accountability of Algorithms. *Journal of Business Ethics*, *160*. https://doi.org/10.1007/s10551-018-3921-3

Meleshenko, S. S., & Usanova, D. S. (2014). Methodological Approaches to the Assessing of the Quality of Audit Sampling. *Mediterranean Journal of Social Sciences*, *5*. https://doi.org/10.5901/mjss.2014.v5n24p176

Michael Abresch, I. L.-J. (2023). *How we're adopting increasingly sophisticated digital tools and upskilling our people to use them profitably for our clients*. PwC. Retrieved 05 December from https://www.pwc.ch/en/insights/disclose/32/tomorrows-audit-today.html

Munoko, I., Brown-Liburd, H. L., & Vasarhelyi, M. (2020). The Ethical Implications of Using Artificial Intelligence in Auditing. *Journal of Business Ethics*, 1-26. https://link.springer.com/article/10.1007/s10551-019-04407-1

Munter, P. (2023). *The Importance of a Comprehensive Risk Assessment by Auditors and Management* https://www.sec.gov/news/statement/munter-importance-risk-assessment-082523#_ftn9

Nikolovski, P., Zdravkoski, I., Menkinoski, G., Dichevska, S., & Karadjova, V. (2016). The Concept of Audit Risk. *International Journal of Sciences: Basic and Applied Research (IJSBAR)*.

Noordin, N. A., Hussainey, K., & Hayek, A. F. (2022). The Use of Artificial Intelligence and Audit Quality: An Analysis from the Perspectives of External Auditors in the UAE. *Journal of Risk and Financial Management*, *15*(8), 339. https://www.mdpi.com/1911-8074/15/8/339

O'Neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy*. Crown Publishing Group.

Pardo, B. S. (2023). *AFRC Audit Focus: The importance of effective audit planning*. The Accountant Online. Retrieved 28 November from https://www.theaccountant-online.com/news/afrc-audit-focus-the-importance-of-effective-audit-planning/?cf-view

Parker, L. D. (2008). Interpreting interpretive accounting research. *Critical perspectives on Accounting*, *19*(6), 909-914. https://doi.org/10.1016/j.cpa.2007.03.013

Peterson,J.(2019). Failure Study. *CPA Journal*, *89*(3), 6-9. http://0-search.ebscohost.com.innopac.wits.ac.za/login.aspx?direct=true&db=f5h&AN=135250775&site=eds-live&scope=site

Pong, C., Fraser, I., Barlaup, K., Drønen, H. I., & Stuart, I. (2009). Restoring trust in auditing: Ethical discernment and the Adelphia scandal. *Managerial Auditing Journal*. https://doi.org/10.1108/02686900910924572

Puthukulam, G., Ravikumar, A., Sharma, R., & Meesaala, K. (2021). Auditors' Perception on the Impact of Artificial Intelligence on Professional Skepticism and Judgment in Oman. *Universal Journal of Accounting and Finance*, *9*, 1184-1190. https://doi.org/10.13189/ujaf.2021.090527

PwC. (2021). *How do automation and AI help build trust in financial reporting?* Retrieved 24 January 2024 from https://www.pwc.com/us/en/tech-effect/ai-analytics/artificial-intelligence-building-trust.html

Qi, Y., & Yuan, Q. (2023). Risk-preparedness mechanism and audit quality: Evidence from mandatory increase of professional indemnity insurance and professional risk fund. *China Journal of Accounting Research*, *16*(1), 100284. https://doi.org/https://doi.org/10.1016/j.cjar.2022.100284

Quadackers, L., Groot, T., & Wright, A. (2014). Auditors' Professional Skepticism: Neutrality versus Presumptive Doubt. *Contemporary Accounting Research*, *31*(3), 639-657. https://doi.org/https://doi.org/10.1111/1911-3846.12052

Raji, I., & Buolamwini, J. (2019). *Actionable Auditing: Investigating the Impact of Publicly Naming Biased Performance Results of Commercial AI Products*. https://doi.org/10.1145/3306618.3314244

Ram, A., Maroun, W., & Garnett, R. (2016). Accounting for the Bitcoin: accountability, neoliberalism and a correspondence analysis. *Meditari Accountancy Research*, *1*, 2-35. https://doi.org/10.1108/MEDAR-07-2015-0035

Ram, A. J. (2018). Taxation of the Bitcoin: initial insights through a correspondence analysis. *Meditari Accountancy Research*, *26*(2), 214-240. https://doi.org/10.1108/MEDAR-10-2017-0229

Rao, A., & Verweij, G. (2017). Sizing the prize: What's the real value of AI for your business and how can you capitalise. *PwC Publication, PwC*.

https://www.pwc.com/gx/en/issues/analytics/assets/pwc-ai-analysis-sizing-the-prize-report.pdf

Raphael, J. (2015). How artificial intelligence can boost audit quality. *CFO Magazine (CFO. com), June*, *15*. https://www.cfo.com/auditing/2015/06/artificial-intelligence-can-boost-audit-quality/

Raphael, J. (2017). Rethinking the Audit: Innovation Is Transforming How Audits Are Conducted - and Even What It Means to Be an Auditor. *Journal of Accountancy*, *223*(4), 29-32. https://www.questia.com/library/journal/1G1-491719177/rethinking-the-audit-innovation-is-transforming-how

Raschke, R., Saiewitz, A., Lennard, J., & Kachroo, P. (2018). AI-enhanced Audit Inquiry: A Research Note. *Journal of Emerging Technologies in Accounting*, *15*. https://doi.org/10.2308/jeta-52310

Reuters, T. (2023). *How do different accounting firms use AI?* Retrieved 29 November from https://tax.thomsonreuters.com/blog/how-do-different-accounting-firms-use-ai/#:~:text=The%20%E2%80%9CBig%204%E2%80%9D%20accounting%20firms,more%20advanced%20and%20insightful%20services

Reynoso, R. (2019). *4 Main Types of Artificial Intelligence*. Retrieved 24 April 2020 from https://learn.g2.com/types-of-artificial-intelligence

Rezaee, Z. (2004). Restoring public trust in the accounting profession by developing anti-fraud education, programs, and auditing. *Managerial Auditing Journal*, *19*(1), 134-148. https://doi.org/10.1108/02686900410509857

Ryan, C. (2019). *A shocking year for the audit profession*. Retrieved 26 May from https://accountingweekly.com/a-shocking-year-for-the-audit-profession/

Sardasht, M., & Rashedi, E. (2018). Identifying influencing factors of audit risk model: A combined fuzzy ANP-DEMATEL approach. *The International Journal of Digital Accounting Research*, *18*, 69-117. https://doi.org/10.4192/1577-8517-v18_4

Shimamoto, D. (2018). Why accountants must embrace machine learning. *Hentet fra: https://www. ifac. org/globalknowledge-gateway/technology/discussion/whyaccountants-must-embrace-machine-learning*.

Sreseli, N. (2023). Use of Artificial Intelligence for Accounting and Financial Reporting Purposes: A Review of the Key Issues. *American International Journal of Business Management (AIJBM)*, *6*(8), 72-83. https://doi.org/https://www.aijbm.com/wp-content/uploads/2023/08/I687283.pdf

Stockle, S. (2023). *All eyes on: Transforming the audit with AI*. KPMG. Retrieved 07 December from https://kpmg.com/xx/en/blogs/home/posts/2023/02/all-eyes-on-transforming-the-audit-with-ai.html

Sun, T., & Vasarhelyi, M. A. (2017). Deep Learning and the Future of Auditing: How an Evolving Technology Could Transform Analysis and Improve Judgment. *CPA Journal*, *87*(6). https://eds.b.ebscohost.com/eds/detail/detail?vid=0&sid=a4c94763-caaa-4f9c-a837-c61fa3942a49%40pdc-sessmgr01&bdata=JnNpdGU9ZWRzLWxpdmUmc2NvcGU9c2l0ZQ%3

Sung, E., Bae, S., Han, D.-I. D., & Kwon, O. (2021). Consumer engagement via interactive artificial intelligence and mixed reality. *International Journal of Information Management*, *60*, 102382. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2021.102382

Suresh, S., Sinha, N., & Prusty, M. (2020). Latent Approach in Entertainment Industry Using Machine Learning. *International Research Journal on Advanced Science Hub*, *2*. https://doi.org/10.47392/irjash.2020.106

Sutaria, N. (2020). Artificial Intelligences Impact on Auditing Emerging Technologies. *ISACA Journals*, *6*(1). https://www.isaca.org/resources/isaca-journal/issues/2020/volume-6/artificial-intelligences-impact-on-auditing-emerging-technologies

Ting, S., & Vasarhelyi, M. A. (2017). Deep Learning and the Future of Auditing: How an Evolving Technology Could Transform Analysis and Improve Judgment. *CPA Journal*, *87*(6), 24-29. http://0-search.ebscohost.com.innopac.wits.ac.za/login.aspx?direct=true&db=f5h&AN=123973396&site=eds-live&scope=site

Titman, S., & Trueman, B. (1986). Information quality and the valuation of new issues. *Journal of accounting and economics*, *8*(2), 159-172. https://doi.org/10.1016/0165-4101(86)90016-9

Topol, E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. *Nature medicine*, *25*(1), 44-56. https://www.nature.com/articles/s41591-018-0300-7

Tysiac, K. (2017). How to enable audit innovation. *Journal of Accountancy*, *223*(4), 33. https://search.proquest.com/docview/1886203177?pq-origsite=gscholar

Vasarhelyi, M. A., & Kogan, A. (2001). The role of continuous monitoring in audit: Current state and future potential. *Journal of Information Systems*, *15*(2), 63-85.

Vasarhelyi, M. A., & Kogan, A. (2015). The implications of artificial intelligence on the audit profession. *International Journal of Accounting Information Systems*, *21*, 1-15.

Watkins, A. L., Hillison, W., & Morecroft, S. E. (2004). Audit quality: A synthesis of theory and empirical evidence. *Journal of accounting literature*, *23*, 153. https://search.proquest.com/docview/216304484/fulltextPDF/A4D3675EE75A4B6DPQ/1?accountid=15083

Wolfe, J., & Sterna, S. (2020). Managing the Risks of Client Acceptance and Continuance. *CPA Journal*.

Wooten, T. C. (2003). Research about audit quality. *CPA Journal*, *73*(1), 48-50. https://search.proquest.com/docview/212330263

Xiao, T., Geng, C., & Yuan, C. (2020). How audit effort affects audit quality: An audit process and audit output perspective. *China Journal of Accounting Research*, *13*(1), 109-127. https://doi.org/https://doi.org/10.1016/j.cjar.2020.02.002

Zhang, S., Liu, X., & Zhao, Y. (2021). The impact of AI adoption on auditing practice: Opportunities and challenges. *Journal of Accounting Research*, *59*(3), 659-689.

Appendix A: Audit quality characteristics

Table I: Row and column labels
Audit quality characteristics (Column headings)
C1: Acknowledging the importance of resources and competency of the engagement team as well as the need for full compliance with ISA.
C2: A sense of legitimacy in the eyes of the informed public.
C3: A rigorous risk assessment process has been followed.
C4: The auditor's ability to understand the client and the key risks of the client's operations.
C5: The extent and coverage of substantive procedures and test of controls.
C6: The use of detailed analytics rather than high-level trend analysis.
C7: The amount of time available to perform audit evidence-gathering and evaluation tasks.
C8: The persuasiveness of the models used to obtain and evaluate audit evidence.
C9: The extent of testing.
C10: Informed judgements after consultation, supervision and review have been made in reaching the audit opinion.
C11: Audit work is performed in compliance with professional standards and applicable legal and regulatory requirements.
C12: Appropriate audit reports are issued.
Artificial Intelligence functional abilities (Row headings)
R1: AI systems can perform time-consuming repetitive tasks which previously required the auditor's effort.
R2: Identifying the level of risks of a given transaction as part of the risk assessment process.
R3: Enables auditors to devote their time to identifying and developing an audit approach for high-risk areas.
R4: Autonomous learning produces independent outcomes as it does not rely on historical data.
R5: Autonomous learning uses patterns and can be used as part of the risk assessment process to discover previously unforeseen risks.
R6: Assists auditors in understanding unstructured data and reveals complex interactions and behaviours obtained from various sources of structured and unstructured data.
R7: Makes 100% data testing possible.
R8: Machine learning is well suited for a broad range of problems that involve classification of data into categories, predicting outcomes and stratifying data sets.
R9: Certain audit procedures can be automated.
R10: Frees up time to exercise professional judgment and scepticism.
R11: Deep learning and machine learning can be used to support auditor's judgements and evaluate management's estimates by predicting outcomes.
R12: AI allows for triangulation by increasing the scope and type of data to be collected.

Appendix B: Participant Information Sheet

PARTICIPANT INFORMATION SHEET

Title of the study: The impact of artificial intelligence on audit quality.

Ethics clearance number: SOA-2023-04-32

Greetings, my name is Banzi, and I am an MCom Candidate at the University of the Witwatersrand. I would kindly like you to participate in my research project on the potential impact of artificial intelligence on audit quality.

You should only participate if you want to; choosing not to take part will not disadvantage you in any way. Before you decide whether you want to take part, I would like to explain why the research is being done and what your participation will involve. Please take the time to read the following information carefully and discuss it with others if you wish.

In this study, I am exploring the perceived relationship between the characteristics of audit quality and the functional abilities of artificial intelligence.

Artificial intelligence refers to technological systems that can perform cognitive activities such as reasoning, decision making and observation, akin to humans (Chan, Ip, Wan & You, 2018). Machine learning is a subset of artificial intelligence and is divided into supervised learning and unsupervised learning (autonomous learning) (Dickey et al., 2019).

If you kindly agree to participate, please complete the **'Correspondence Table' on the next tab**.

On the 'Correspondence Table' tab, you will find a table with 12 rows and 12 columns. The rows represent the functional abilities of artificial intelligence, and the columns represent the characteristics of audit quality. These functional abilities and characteristics arose from the review of relevant literature.

The order of the rows and columns has no importance. **Please mark with a '1' all those cells that you feel the functional ability of artificial intelligence will have a positive impact on the corresponding characteristic of audit quality.**

For instance, if you believe that a particular functional ability of artificial intelligence has a positive correlation with one or more characteristics of audit quality, mark each relevant cell with a '1'. If not, leave those cells blank. You may place as many '1s' as you feel appropriate or leave as many cells blank as you wish. There are no right or wrong responses, this research is only interested in your impressions.

If you decide to take part, your participation in this research study will last about 20 minutes. The completion of the research instrument takes place at your convenience, as it is an electronic instrument. Only the researcher will have access to the data. Your completion of the research instrument will be kept confidential. When results of the research study are shared, your name or anything else that could identify you will not be included.

If you decide to take part in the research study, it should be because you want to volunteer. You do not have to take part. You can stop being in the study at any time. You do not have to answer any questions if you do not want to. You will not get any direct benefits or payment if you choose to join the research study. You will not lose any services, benefits or rights you would normally have if you decide not to join. Taking part in the research study will not cost you anything.

The risks for this research study are no more than what happens in everyday life. This research study will be written up as a journal article. The article will be available on request. If you have any questions during or afterwards about this research study, feel free to contact me at the details listed below.

If you have any concerns or complaints regarding the ethical procedures of this study, you are welcome to contact the University Human Research Ethics Committee (Non-Medical), by telephone at +27(0)11 717 1408, email: hrecnon-medical@wits.ac.za.

Details	Researcher 1	Researcher 2
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Please kindly return your completed response via email to the researcher at:
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Appendix C: Consent form for participants in the research study

CONSENT FORM FOR PARTICIPANTS IN RESEARCH STUDIES

Please complete this form after you have read the Participant Information Sheet.

Title of the study: The impact of artificial intelligence on audit quality

Please kindly indicate your current occupation in the table below:

Occupation	Please kindly mark the applicable cell with a capital 'X'
Auditor in business/public practice	
Auditing regulator	
Auditing academic	

Please kindly note that returning a completed survey via email constitutes consent with the following:

• You understand that if you decide at any time during the research that you no longer wish to participate in this project, you can notify the researcher involved and withdraw from it immediately without giving any reason. Furthermore, you understand that you will be able to withdraw your data up to the point of submission of your responses.
• You understand that the information you have submitted will be published in a research article and that you can request a copy of the final article.
• You understand that your personal information will not be collected. Your identity will be kept confidential and will not be referred to directly in the final article.
• You agree that the information you provide may be anonymously used in other research projects.
• You agree that you have read both the notes written above and the participant information sheet and understand what the research study involves.

Thank you most sincerely for your participation!

Appendix D: Data collection instrument: Correspondence table

		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
	Audit quality is depend on: ⟶ Artificial intelligence functional abilities:	Acknowledging the importance of resources and competency of the engagement team as well as the need for full complaince with ISA	A sense of litigitimacy in the eyes of the informed public.	Rigorousness of the risk assement process.	The auditor's ability to understand the client and the key risks of the cient's operation.	The extent of coverage of substantive procedures and test of controls.	The use of detailed analytics rather than a high level trend analysis.	The amount of time available to perform audit evidence gathering and evaluation tasks.	The persuasiveness of the models used to obtain and evaluate audit evidence.	The extent of testing.	Informed judgements being made after consulation, supervision and review to form audit opinion.	Audit work being perfomed in compliance with professional standards, legal and regulatory requirements.	Appropriateness of audit reports issued.
R1	Performs time consuming repetitive tasks which previously required auditor's effort.												
R2	Identifies the level of risk of a given transaction as part of the risk assessment process.												
R3	Enables auditor's to devote their time to identifying and developing an audit approach for high-risk areas.												
R4	Autonomous learning produces independent outcomes as it does not rely on historical data.												
R5	Autonomous learning uses patterns and can be used as part of the risk assessment process to discover previously unforseen risks.												
R6	Assist auditor's to understand unstructured data and reveal complex interactions and behaviours obtained from various sources of structured and unstructured data												

	Audit quality is depend on: ⟶ Artificial intelligence functional abilities:	Acknowledging the importance of resources and competency of the engagement team as well as the need for full complaince with ISA	A sense of litigitimacy in the eyes of the informed public.	Rigorousness of the risk assement process.	The auditor's ability to understand the client and the key risks of the cient's operation.	The extent of coverage of substantive procedures and test of controls.	The use of detailed analytics rather than a high level trend analysis.	The amount of time available to perform audit evidence gathering and evaluation tasks.	The persuasiveness of the models used to obtain and evaluate audit evidence.	The extent of testing.	Informed judgements being made after consulation, supervision and review to form audit opinion.	Audit work being perfomed in compliance with professional standards, legal and regulatory requirements.	Appropriateness of audit reports issued.
R7	Makes 100% data testing possible.												
R8	Machine learning is well suited for a broad range of problems that involve classiffication of data into categories , predicting outcomes and stratifying datasets.												
R9	Certain audit procedures can be automated.												
R10	Frees up time to exercise professional judgement and sceptism.												
R11	Deep learning and machine learning can be used to support auditor's judgements and evaluate managements estimates by predicting outcomes.												
R12	Allows for triangulation by increasing the scope and type of data to be collected.												

Appendix E: Statistics for audit quality traits

Categories Columns Audit quality	Overall			Dimension 1 (x-axis)			Dimension 2 (y-axis)			Dimension 3 (z-axis)		
	mass	quality	inertia (%)	co-ord	sqcorr	contribution %	co-ord	sqcorr	contribution %	co-ord	sqcorr	contribution %
1	0,073	0,506	4,000%	0,179	0,14	1,300%	-0,137	0,061	1,000%	0,37	0,305	10,600%
2	0,056	0,193	3,900%	-0,067	0,016	0,100%	-0,114	0,034	0,500%	-0,282	0,143	4,800%
3	0,094	0,978	17,600%	-0,613	0,49	19,300%	0,701	0,476	33,900%	0,136	0,012	1,900%
4	0,097	0,926	10,000%	-0,561	0,743	16,600%	0,298	0,156	6,300%	0,149	0,027	2,300%
5	0,095	0,736	4,400%	0,323	0,552	5,400%	0,142	0,079	1,400%	-0,198	0,105	4,000%
6	0,108	0,491	5,800%	0,166	0,126	1,600%	-0,02	0,001	0,000%	-0,395	0,364	18,100%
7	0,096	0,936	13,200%	0,677	0,809	23,900%	0,14	0,026	1,400%	0,334	0,101	11,500%
8	0,078	0,837	7,600%	-0,307	0,233	4,000%	-0,252	0,117	3,600%	-0,62	0,486	32,000%
9	0,093	0,88	11,200%	0,633	0,816	20,400%	0,194	0,057	2,600%	-0,081	0,007	0,700%
10	0,071	0,94	13,700%	-0,354	0,158	4,900%	-0,89	0,742	41,300%	0,248	0,039	4,700%
11	0,066	0,513	4,600%	-0,035	0,004	0,000%	-0,326	0,279	5,200%	0,358	0,23	9,100%
12	0,074	0,474	4,000%	-0,252	0,289	2,600%	-0,225	0,171	2,800%	0,078	0,014	0,500%

Appendix F: Statistics for Artificial Intelligence themes

Categories Rows Artificial Intelligence	Overall			Dimension 1 (x-axis)			Dimension 2 (y-axis)			Dimension 3 (z-axis)		
	mass	quality	inertia (%)	co-ord	sqcorr	contribution %	co-ord	sqcorr	contribution %	co-ord	sqcorr	contribution %
1	0,078	0,897	16,700%	0,799	0,732	27,30%	0,277	0,065	4,400%	0,413	0,099	14,300%
2	0,067	0,87	15,100%	-0,602	0,393	13,20%	0,752	0,455	27,900%	0,201	0,022	2,900%
3	0,096	0,518	3,500%	-0,035	0,008	0,10%	0,2	0,202	2,800%	0,299	0,308	9,200%
4	0,063	0,698	4,000%	-0,291	0,331	2,90%	-0,211	0,129	2,100%	-0,345	0,238	8,100%
5	0,086	0,883	13,600%	-0,663	0,682	20,70%	0,417	0,201	11,000%	-0,012	0	0,000%
6	0,089	0,503	6,000%	-0,206	0,152	2,00%	-0,344	0,316	7,700%	-0,139	0,035	1,800%
7	0,083	0,641	7,900%	0,444	0,504	8,90%	0,011	0	0,000%	-0,324	0,137	9,300%
8	0,082	0,576	4,200%	0,001	0	0,00%	0,08	0,023	0,400%	-0,481	0,554	20,300%
9	0,088	0,931	9,900%	0,639	0,889	19,70%	0,153	0,038	1,500%	-0,063	0,004	0,400%
10	0,097	0,95	9,400%	-0,125	0,039	0,80%	-0,551	0,568	21,600%	0,517	0,343	27,800%
11	0,088	0,857	7,400%	-0,241	0,17	2,80%	-0,562	0,685	20,500%	0,035	0,002	0,100%
12	0,082	0,589	2,300%	0,185	0,298	1,50%	-0,019	0,002	0,000%	-0,255	0,288	5,700%