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A case study on the Big 4 Firms:

Impact of Artificial Intelligence on the work of external auditors

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Abstract

Recently, there are rising concerns with the possible disruptive effects of artificial intelligence (AI) in the auditing job. This paper aims to investigate the extent to which AI will transform the job of external auditors, specifically in the Big 4 firms. A general framework on auditing job domains is proposed to investigate if these tasks could be simplified or fully conducted by AI. The framework is then tested against the current Big 4 audit innovation and existing auditing and AI literature. The research shows that AI will moderately transform the work of Big 4 external auditors. AI will be involved in most of the audit process, except for steps which can be better executed by other technology or human interaction. Auditors will focus less on manual tasks and concentrate more on in-depth data analysis and high-risk areas. Thus, rather than replacing the job of the auditors, AI will augment auditors' work to provide enhanced quality and more efficient audits. To excel in an AI-driven future, auditors need to have advanced analytical skills, critical thinking and effective communication skills.

Keywords: audit artificial intelligence, Big 4 auditing, audit innovation

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1. Introduction

Artificial intelligence (AI) has been dubbed as the future (Schmelzer, 2019; Deming, 2020). According to Schmelzer (2019), AI could impact human's future in 4 main aspects: the way human works, lives, interacts with people and experiences the world, along with human's relationship with data. Technology slowly changes the nature of work and labour. As AI prices show a downward trend, one of the professions said to be at stake due to robotic process automation (RPA) is the accountant (Gass, 2018). A research by Frey and Osborne (2014) ranked bookkeeping, accounting and auditing clerks second among the jobs with the highest probability of being replaced by computerization.

According to Forbes, several business functions are now ready to embrace AI, and this includes accounting, finance, marketing, human resources and many other functions (Marr, 2020). A 2016 research by Accenture Consulting on 12 developed European countries supported this notion as AI is predicted to double the economic growth rates of those countries and boost their labour productivity by 2035 (Branon, 2016). It is no surprise that in 2017, Deloitte, PricewaterhouseCoopers (PwC) and Ernst & Young (EY) have started to deploy natural language processing (NLP) for document review which would otherwise take weeks if conducted by human auditors (Zhou, 2017). With the COVID-19 outbreak today which necessitates organizations to embrace digital transformation to function, there is no doubt that digital technologies will be the basic utility of the future and digital economy will be the way forward (Klasko, 2020). As such, accountants, especially in the Big 4 accounting firms, need to have proper planning to face the AI-enabled future due to the possible disruptive effects of AI (Deming, 2020) or otherwise, they might become redundant eventually.

This paper aims to focus specifically on the auditing field, a branch of accounting where the use of AI has drawn much discussion lately (Boillet, 2018; KPMG, 2018a; Zhou, 2017). It will be explored how AI will transform the work of auditors in the Big 4 accounting firms, namely Deloitte, PwC, EY and KPMG. These companies are the four largest accounting networks in the world (Statista, 2019) which audited 99% of the companies listed in Financial Times Stock Exchange (FTSE) 100 and 96% companies in FTSE 250 Index (Christodoulou, 2011). Being the market leaders, these companies have the financial capabilities and resources to undertake AI transformations. Moreover, they are most likely to be the first ones to start deploying AI innovation in the accounting field due to their networks and experiences. Therefore, the following research question is formulated:

"To what extent will artificial intelligence transform the job of external auditors in the Big 4 accounting firms?"

This research is socially relevant due to the following reasons. When Seidman (1959) discussed the future of accounting, he was concerned about how the accounting job domain could be altered in the future. This paper will raise the awareness of Big 4 auditors on the future of their jobs, including the necessary skills (and possibly new skills) they should focus on to fully take advantage of AI and expose them to new tasks developed from the data generated through AI. Moreover, this research will have implications on the accounting degree. The paper provides a reminder for educational institutions to restructure the accounting courses so it will fit the future job demands and include courses that would help future accountants to leverage on the various capabilities of AI.

In the past, some researchers have explored the future of accounting job (Seidman, 1959; Lafferty, 1985), which includes the future relevance of accounting, the scope of the job and ethics related to the profession. Plenty of papers also exist in the development of AI in the accounting domain (Baldwin, Brown & Trinkle, 2016; Kokina & Davenport, 2017; Greenman, 2017). These papers aim to analyze the implementation of AI in accounting and assess its effectiveness. Some papers also investigated how AI could assist in accounting research (Sutton, Holt & Arnold, 2016; Moll & Yigitbasioglu, 2019; Van den Bogaerd & Aerts, 2011). However, there is no single paper which tries to fit each aspect of auditing work with the capabilities of AI and observe if technology can fully perform each of the job requirements. This paper will fill in the missing gap in this area, thus providing a complete overview of how AI could transform the work of the auditors in large accounting firms. As such, this research is scientifically relevant.

In this paper, literature defining the development of AI, the auditing process and the relevance of AI implementation in accounting will be first discussed under the theoretical framework. Afterwards, a general framework on auditing job domains will be presented to investigate if these tasks could be simplified or fully conducted by AI. Next, the methodology part will explain how to test the proposed framework by studying a series of case studies of AI implementation in auditing as well as general AI capabilities. Under the results section, insights from the case studies will be presented and investigated against the current AI innovation implemented in Big 4 auditing. Lastly, the paper will end with a conclusion and discussions to show the limitations of the paper and future research suggestions.

2. Theoretical Framework

Firstly, some important terms used in this research will be defined. According to the American Institute of Chartered Public Accountants (CPA), an audit is the highest level of assurance service that a CPA performs. An audit aims to provide reasonable assurance to creditors, investors and other parties on the credibility of a firm's financial statement and non-financial information (American Institute of Chartered Public Accountants, n.d). The purpose of auditing is to compare "what is" with "what should be" (McNamee &

McNamee, 1995). Artificial Intelligence (AI) refers to a branch of computer science which studies the relation between computation and cognition (Barr, & Feigenbaum, 2014). AI is associated with the study of intelligent behaviours in artefacts, which includes the following behaviours: learning, reasoning, perception, communication and acting in complex situations (Nilsson, 1998). The upcoming sections will first delve upon auditing and artificial intelligence including their components in detail. Afterwards, the interaction between the two variables will be explored along with a general framework where different types of AI would be proposed to complement or fully perform the steps in the auditing process.

2.1. Auditing

In a company, different stakeholders may not be sharing the same objectives as the management. For instance, management typically aims for high payrolls and benefits (which are regarded as expenses to the company) whereas investors want high profits and dividends. In order to ensure that a company provides an accurate financial statement, an auditor is required to provide an audit opinion, which is an independent and expert opinion to ensure the fairness of the reports (Hayes, Wallage & Gortemaker, 2014). An audit report will enhance the validity of a company's financial statement as well as the reputation of the company itself (Ribstein, 2002). The International Auditing and Assurance Standard Board (IAASB) has developed International Standards on Auditing (ISA) to provide standard auditing practices across the world by presenting a generally accepted auditing standard (GAAS) (Hayes, Wallage & Gortemaker, 2014).

The practice of auditing could be traced back to around 3000 BC during the Mesopotamian era and was also evident in ancient China and Egypt. The word "audit" itself is taken from the Latin word "*audire*" which means "a hearing". Back then, an audit was conducted by reperforming the work of others to ensure its credibility. This was done by observing, counting and double-checking reports which is still the basis for auditing today (Teck-Heang & Ali, 2008; McNamee & McNamee, 1995). Modern auditing practices started after the Industrial Revolution when the Institutes of Chartered Accountants was founded in 1880 in the UK led to the formation of other similar institutes in the Western world. As companies grew more complex and financial scandals such as the City of Glasgow Bank (1883), *Afrikaansche Handels-Vereeniging* (1879), and Kingston Cotton Mill (1896) emerged, there was a rising demand for auditors and auditing policies (Hayes, Wallage & Gortemaker, 2014).

In the early 2000s, some of the biggest accounting scandals in history occurred, which involves large companies like Enron, WorldCom, Tyco and HealthSouth. At that time, Enron was one of the biggest US firms in terms of market capitalization. WorldCom was also the second-largest long-distance mobile network operator in the US, and they were found to capitalize expenses for personal uses (Agrawal & Chadha, 2005; Ribstein, 2002). Arthur Andersen (one of the largest accounting firms at that point which was part of the “Big Five”) who audited WorldCom was then convicted for cooperating with WorldCom and destroying fraud evidence (Smith & Quirk, 2004). Many investors lost confidence in the financial market and the reliability of auditors was questioned, followed by the collapse of Arthur Andersen. In response to the market situation, the US government stepped in and enacted the Sarbanes-Oxley Act of 2002 (SOX) which applies to all public companies listed in US stock exchange. The act necessitates auditor independence where auditor needs to restrict the type of non-audit services offered to their clients and required more detailed financial reporting, such as evaluation of internal controls in their annual reports. Moreover, the boards and audit committee in a company have to be independent of each other to prevent accounting fraud or earnings management scandals (Engel, Hayes & Wang, 2007).

2.1.1. Classification of auditing

According to Porter, Simon and Hatherly (2003), auditing could be classified based on their primary audit objectives and type of beneficiaries of the audit. Primary audit objectives could be classified into financial statements audits, operational audits and compliance audits. Type of beneficiaries refers to the receiving end of the audit services. Based on this, audits can be divided into internal audits and external audits. The different types of audit share the following characteristics: systematic examination of the evidence against criteria set and the publication of a written report to communicate the audit results. Financial statement audits and external audits constitute the external audit services provided by the Big 4 companies and thus are the focus of this research.

Classification based on primary audit objectives

Financial statement audit is defined as the examination of financial statements prepared by an entity’s management for its stakeholders to ensure that the information contained in the reports conform to the specific criteria. These criteria may differ between countries, such as the Generally Accepted Accounting Principles (GAAP) in the US, the International Financial Reporting Standards (IFRS) in the European Union and South America, and other national company laws such as in the case of Northern European countries. Companies need to provide evidence in support of their financial statement for the auditors to ensure the accuracy (Hayes, Wallage & Gortemaker, 2014; Porter, Simon & Hatherly, 2003).

Operational audit refers to a systematic evaluation and examination of specific operation(s) in an entity to improve its effectiveness and efficiency (Porter, Simon & Hatherly, 2003). Effectiveness can be defined as a measure of performance with reference to achieving its stated goals and objectives. Efficiency shows how well the resources were used to attain the goals. The two criteria do not have any specific standards as compared to financial statements’ IFRS or GAAP and therefore tend to consider more subjective opinions. This type of audit is not only limited to the accounting department, but also other functions like marketing, operations, productions and any other area that might require performance evaluation (Hayes, Wallage & Gortemaker, 2014).

Compliance audit is a type of audit which focuses on examining an entity's procedures to ensure that it is conforming to the rules and regulation set out by the management or regulatory body (Porter, Simon & Hatherly, 2003). Compliance audit can be conducted by an internal or external auditor who will then report to the management. While this type of audit is commonly associated with government auditors (i.e. auditing compliance of a bank with regards to capital reserve requirements), audits within the companies would include compliance audit based on internal control procedures (Hayes, Wallage & Gortemaker, 2014; Porter, Simon & Hatherly, 2003).

Classification based on type of audit beneficiaries

Auditors can be categorized into independent external auditors or internal auditors. External auditors are external parties which perform an audit on an entity based on the requirements proposed by the auditees. The primary objective of an external auditor is to audit financial statements of public and non-public companies. External auditors require a certification either from a professional accounting institute (such as Chartered Public Accountant (CPA) and Chartered Accountant (CA)) or government agency in order to perform the audit (Hayes, Wallage & Gortemaker, 2014). Internal auditors refer to auditors employed by an entity to examine its operating effectiveness. Their main objective is to audit internal controls and their scopes typically include operating and compliance audits. Most internal auditors are internal employees, although the practice of outsourcing internal auditors to public accountants have substantially increased in recent years (Swanger & Chewning Jr, 2001).

2.1.2. Auditing in Big 4

The Big 4 companies are made up of Deloitte, Ernst & Young, KPMG and PwC. In these firms, accounting and auditing make up approximately 50% of their income. These firms each have an international head office where global technologies, procedures and guidelines are shared. Moreover, due to their worldwide presence, each Big 4 firm typically audit the subsidiaries of its clients' member firms located in other countries (Hayes, Wallage & Gortemaker, 2014). Deloitte is currently the biggest accounting firm in the world with a revenue of 46.2 billion US dollars in 2019, followed by PwC with a 42.4 US dollars revenue, EY with a revenue of 36.4 billion US dollars and KPMG of 29.75 billion US dollars (Statista, 2019).

2.1.3. Audit Risks

There are inherent limitations in audit that may limit an auditor's ability to identify material misstatements. According to ISA 320, material misstatements refer to omission(s) in the financial statement, be it individually or in aggregate, which affects one's economic decisions taken on the basis of the information contained in the financial reports. Statement of Accounting Standards (SAS) 300 defines audit risk as "the risk that an audit would give an inappropriate audit opinion on the financial statement". Audits risks can be classified into three categories, namely inherent risk, control risk and detection risk (AICPA, 2004). The first two risks are difficult for external auditors to control, even though they can suggest improvement of internal control processes to keep the risks to their minimum. The higher the audit risks, the more evidence the auditor needs to gather in order to have reasonable assurance when providing an audit opinion (Hayes, Wallage & Gortemaker, 2014).

Inherent risk is defined as the risk of material misstatements in the absence of internal controls. Porter et al. (2003) categorized inherent risks based on its 3 different sources, which includes management integrity, account risk and business risk. The management integrity will indicate the extent to which the financial statements accurately reflect the actual financial performance. Account risk can happen due to the nature of certain accounts which are more susceptible to misstatements, be it intentional or due to human error. Business risk refers to the nature of the industry the business operates in and is largely affected by the prevailing economic condition (AICPA, 2006; Porter, Simon & Hatherly, 2003).

Control risk is defined as the risk of material misstatements which cannot be easily avoided or detected by the entity's internal controls. While some control risk cannot be eliminated due to the inherent limitations of internal controls, effective internal controls procedures will keep control risk to its minimum (Porter, Simon & Hatherly, 2003). Furthermore, appropriate audit process and techniques such as through risk assessment procedures and examining evidence from effective controls will help to ensure that this type of risk can be detected, if present (AICPA, 2006).

Lastly, detection risk refers to the risk where the auditors fail to recognize a material misstatement in the financial statement. AICPA (2006) cited that this could be due to inappropriate audit procedures, wrong application of audit procedures, insufficient audit evidence or misinterpretation of audit results. This can be prevented by allocating appropriate auditors, proper quality control and application of professional skepticism during the planning auditing process. On top of that, Porter et al. (2003) stated that detection risk could also be caused by sampling risk. As only a sample of the evidence is examined, the materially misstated transactions were not selected into the samples. As such, appropriate audit sampling needs to be set in accordance with statistical techniques so as to ensure to reduce the detection risk.

2.1.4. Audit Process Model

The standard audit process follows a systematic process which can be divided into 4 steps as shown in Figure 2.1.1. The client, in this case, refers to the auditee whereas the auditor refers to an accounting firm offering an auditing service. The audit process begins with determining the suitability of a client. This includes new clients or continuation of contracts with existing clients followed by determining both the acceptance of a client and by a client. In the next phase, an audit plan is created to understand the background of the client in order to determine the amount and type of evidence required to examine if the financial statements are free from material misstatements. Next, the auditor will assess the evidence provided with regards to the internal controls and the accuracy of the financial statements. After the audit procedures have been completed, the auditor will issue an audit opinion through publishing a formal letter (Hayes, Wallage & Gortemaker, 2014).

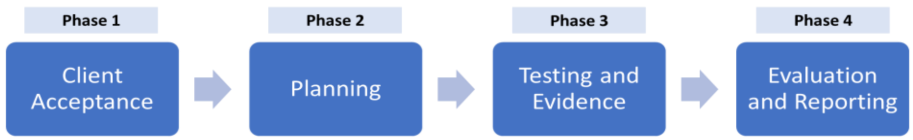

Figure 2.1.1: Standard Audit Process Model

Phase 1

The client acceptance phase begins with evaluating the client's background and the reason(s) for auditing to get an overview of the client's governance, internal controls and associated risks. This can be done by examining publicly available information, auditor's experience with the client and the information provided by the client (see Figure 2.1.2). Once the auditor accepts the client and the auditor confirms that they can meet the ethical requirements regarding the independence of auditors and the non-audited services they offer to the client (refer to SOX), the auditor will prepare a client proposal and select the staff to perform the audit. As the client accepts the auditor, the auditor will send an engagement letter to the client. An engagement letter is an agreement between the auditor and client regarding the audit procedures and related services (Hayes, Wallage & Gortemaker, 2014).

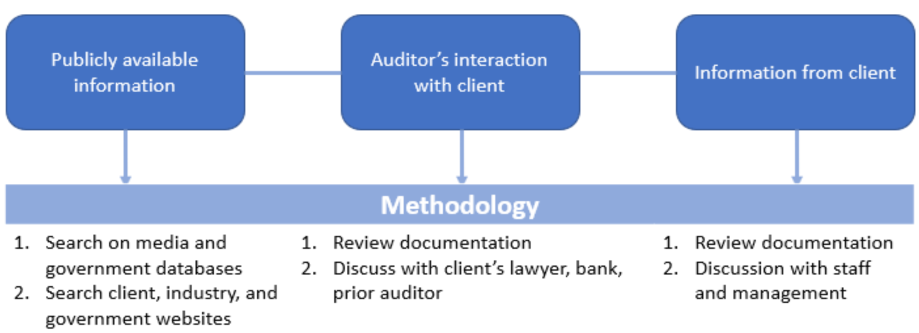

Figure 2.1.2: Evaluation of prospect client

Note: Adapted from "Principles of auditing: an introduction to international standards on auditing" by Hayes, R., Wallage, P., & Gortemaker, H., 2014, p. 155, Harlow: Prentice Hall.

Phase 2

After phase 1 is completed, audit planning begins. According to ISA 300, audit planning can be divided into two stages, namely developing a general strategy and creating an audit programme (audit plan) (IAASB, 2009a). An audit programme itself is the operationalization of the general strategy. Creating an audit plan begins with the auditor studying the client's business background, control environment and its internal control structure. To obtain a substantial understanding of the client, ISA 315 describes that risk assessments should be done through consulting the clients on their objectives and expectations towards its stakeholders, conducting analytical procedures of client's transactions (including a comparison of client's results with the market) and observing as well as inspecting the client's core activities, accounting policies, management reports, internal control manuals and other relevant documents (IAASB, 2009b). The information can then be used to identify potential audit risks (see 1.1.3. Audit risks for details) to the client.

Based on the audit risks, auditors can determine the materiality level. Materiality level can be defined as the degree of inaccuracy in the financial statements that is still considered acceptable based on the purpose of the financial statements. The higher the audit risks, the lower the material level, which means that the audit costs will be higher (Hayes, Wallage & Gortemaker, 2014). Currently, there is no single international standard for a materiality level and it typically differs per accounting firm. Common guidelines used by auditors include similar benchmarks like net income before taxes, total assets, total revenues and total equity and similar percentage ranges (Eilifsen & Messier Jr., 2015). Lastly, an audit programme which outlines the audit objectives, timing and audit procedures to obtain the required evidence will be created, including the details for material classes of transactions, account balances and transactions (Hayes, Wallage & Gortemaker, 2014).

Phase 3

This phase begins with the testing of internal controls, which is known as compliance testing which includes control tests of design (aims to test control effectiveness). This test is conducted to ensure that the internal controls information that the auditor intends to use have been complied with by the personnel of the client, thus the internal control strength can be established (Porter, Simon & Hatherly, 2003). Audit evidence for testing controls can be obtained through direct inquiries to the client's internal audit personnel, observing and reperforming the application of a specific control, inspecting documents or reports and tracing the information system to find related transactions for financial reporting (Hayes, Wallage & Gortemaker, 2014).

Once the controls have been tested, the auditor will perform substantive procedures to test the transactions and account balances. According to SAS 400, the greater the strength of the internal controls, the extent of the substantive procedures required can be reduced, though it cannot be completely eliminated (Porter, Simon & Hatherly, 2003). Moreover, the smaller the audit risk previously assessed, the lower extent of substantive procedures. Substantive procedures refer to the testing of the financial statements and its related disclosures. This test can be categorized into analytical procedures and test of details. Analytical procedures consist of examining accounting data, including financial and non-financial information, to find meaningful relationships and establish that the data contained in the financial statements are of reasonable value (reasonable testing). Common methods used are trend analysis over time, ratio analysis between financial accounts itself or with non-financial information. When there is a significant deviation from the expected value, further investigation is required to test if there is any material misstatement (Hayes, Wallage & Gortemaker, 2014). Test of details of transactions and balances is a test on the validity of the general ledger balance which is the constituent of a financial statement, where the overstatement or understatement, completeness, and validity of the transactions would be investigated. The test examines the details in high turnover accounts such as cash, account receivable and account payable. Various methods to gather audit evidence (audit procedures) is summarized under Table 2.1.

Table 2.1.1: Evidence-gathering techniques (audit procedures)

Technique	**Explanation**
Inquiry	Seeking explanation from a knowledgeable person inside or outside the entity
Observation	Observing processes or procedures performed by others
Inspection	Examining records, documents or tangible assets
Recalculation	Checking the arithmetic accuracy on source documents and accounting records; Performing independent mathematical methodology
Reperformance	Conducting independent execution of processes or procedures that were originally performed by the entity's internal controls
Confirmation	Corroborating information in the financial statements with external parties which are involved in producing the information
Analytical procedure	Conducting statistical procedures to find relationships between data in financial statements and non-financial information to identify inconsistent information or deviation from expected values

Note: Adapted from "Principles of auditing: an introduction to international standards on auditing" by Hayes, R., Wallage, P., & Gortemaker, H., 2014, p. 365, Harlow: Prentice Hall.

Phase 4

In this phase, the auditor will review the gathered evidence and draw a conclusion which will then be used to develop an audit opinion. Firstly, the auditor must review the contingent liabilities and commitment of the client. Contingent liabilities refer to a potential future obligation to an external party for an unknown amount resulting from a past event, such as pending litigation for patent infringement, product liabilities, product warranties and so on. Commitments are agreements by the client to hold on to a fixed set of conditions, regardless of the prevailing profit or economic situation. For instance, purchasing a product at a stated price in the contract. The auditor needs to enquire management, review legal working papers, examine letters of credit, review past tax returns and evaluate known contingent liabilities (Hayes, Wallage & Gortemaker, 2014; Porter, Simon & Hatherly, 2003).

Next, the auditor will review for subsequent events, which are the events occurring between the date of financial statement and the date of auditor's report described in ISA 560. The date of auditor's report is the day when the auditor has gathered appropriate audit evidence for forming an audit opinion (IAASB, 2009c). This includes adjusting events which can better explain the information in the financial statements at its date of release. This type of information should be incorporated in the financial statements so it will reflect the report as accurate as possible. Non-adjusting events that occur after the balance sheet date but can be considered material should not be adjusted in the financial statement but included as disclosure in a form of a note (Porter, Simon & Hatherly, 2003). According to SAS 500, procedures to identify subsequent events include inquiries with the management, examining minutes of board meetings, and reviewing relevant accounting records (AICPA, 2001).

Subsequently, financial statements and other report materials are reviewed to determine if the required information has been sufficiently disclosed. Next, once all the audit work has been completed, wrap-up procedures can be carried out. This consists of a supervisory review where senior auditors typically review the work of their subordinates, review of audit working papers, evaluation of audit findings for material misstatement and evaluation of the client's "going concern" assumption (Hayes, Wallage & Gortemaker, 2014). According to Financial Reporting Standard (FRS) 18, "going concern" means that the entity is to continue with its operational existence for the foreseeable future. This evaluation could be done through understanding the business risks, conducting analytical procedures and identifying mitigation plans for the problems identified. Once the wrap-up procedures have been completed, the auditor will report its important findings to the client's audit committee and eventually produce an audit report containing the audit opinion (Hayes, Wallage & Gortemaker, 2014; Porter, Simon & Hatherly, 2003).

2.1.5. Future of auditing

Over the years, auditing has been evolving from its traditional purpose of ensuring the credibility of the financial statements. Today, an auditor is also expected to provide value-added services like assessing business risks, detecting fraud and providing feedback on the entity's internal controls environment (Cosserat & Rodda, 2009). Accounting firms have also been investing in technological assets to improve their services, reducing reliance on substantive testing and focusing towards their qualitative risk assessments and analytical procedures to provide auditing with reasonable assurance (Eilifsen, Knechel & Wallage, 2001).

Since the early 2000s, continuous auditing (CA) has also transformed the auditing field due to the emerging trend of digitalization. CA is defined as a "systematic process to collect digital audit evidence as a basis to form an audit opinion of the accuracy of financial statements, under a paperless, real-time accounting system". Under real-time analysis, the evaluation phase of auditing is shortened as compliance testing can be performed simultaneously with substantive tests of details (Rezaee, Elam, & Sharbatoghlie, 2001). The positive benefits from CA are even more pronounced today since most large companies have been deploying enterprise resource planning (ERP) in their daily operations which makes obtaining audit evidence easier (Kuhn Jr & Sutton, 2010). As the computer advances over the years, it is expected that there will be more technology-based auditing techniques that will change the way auditing is performed (Percy, 1999).

In recent years, the development of SOX has led to an increase in emphasis on corporate governance as proven by various corporate government literature in accounting and auditing. Moreover, the issue of corporate social responsibility has been rising which pushes large companies to publish sustainability reports annually (Perrini, 2005; Hartman, Rubin & Dhanda, 2007). It is predicted that in the future, auditors will no longer only audit financial statements, but also non-financial information such as business conduct, efficiency and effectiveness of the entity's systems and other information that are demanded by other stakeholders to ensure proper governance is in place (Percy, 1997; Hayes, Wallage & Gortemaker, 2014).

2.2. Artificial Intelligence

2.2.1. Development of Artificial Intelligence

The concept of AI was conceived across many disciplines since the beginning of time, namely in the field of philosophy, science, mathematics and art (Buchanan, 2005). The very early stage of the basis of AI could be traced back to Aristotle (384-322 B.C.) where he proposed a type of deductive reasoning known as syllogisms (Nilsson, 1998). A syllogism is logical deductive reasoning derived from at least two premises that are claimed to be true (Smiley, 1973). This becomes the foundation of conventional computing logic which is based on binary choices (Nilsson, 1998). In the 13th century, Ramon Llull, a poet and philosopher, created a set of wheels, famously known as "Ars Magna", which allows one to obtain an answer to one's question, and these answers are generated through a combination of attributes from a set of lists. This was one of the first works in the computational theory, a field where a human makes use of logical reasoning to produce knowledge (Fidora, 2011; O'Reagan, 2008).

Major progress only occurred in the 19th century when the inventions of electronics and modern computers were prevalent. Simultaneously, the research on the human brain and neural networks were on the rise. One of the founders of Computer Science, Alan Turing, then asked: “Can machines think?”. In his paper, Turing contended the claim that machines can only do what they are instructed to do. Turing later discussed the three components of human knowledge and abilities, namely the initial state of the mind when one is born, the education that one received and other experiences one is subjected to. Rather than trying to develop a machine which has the intelligence of an adult human brain, Turing proposed the creation of a child-brain learning machine that can be “taught” to mimic human intelligence (Turing, 1988). The concept inspired early developments in the AI field, such as a chess-playing machine that can learn and compete with a human opponent (1951) (McCorduck, 2004).

The term “artificial intelligence” was then coined in 1956 by John McCarthy during the Dartmouth Conference. The conference aims to address any aspect of learning or feature of intelligence that can be simulated by a machine. In the conference, the logic theorist was introduced. It is dubbed as the first AI programme which is a programme specifically designed to perform automated reasoning (McCorduck, 2004; Crevier, 1993). In 1958, McCarthy developed LISP (derived from “LISt Processor”), which is a programming language based on predicate logic that are still widely used in AI today (McCarthy, 1960). In the 1960s to early 1980s, the development in AI peaked and led to the invention of innovation like general problem solver (GPS); Bobrow’s STUDENT program that can solve algebra word problems (Bobrow, 1964); DENDRAL, the first knowledge-based program which can devise scientific hypothesis (1977) (Lindsay et al., 1993) and so on.

DENDRAL eventually became the turning point that shifted AI towards knowledge-based systems from its initial systems based on logical inference and resolution theorem (Buchanan, 2005). In the 1990s, AI turned to a new paradigm, namely towards being an “intelligent agents” which “perceives its environment and takes actions which maximize its chance of success” (Russell & Norvig, 2003). This concept incentives researchers to look at specific problems and find solutions, even by learning from other disciplines, for example, statistics (such as the probability theory, Markov models, and Bayesian networks) and biology, which resulted in the creation of evolutionary algorithms (Pearl, 2014; Russell & Norvig, 2003).

2.2.2. Classification of Artificial Intelligence

Algorithms in AI advances throughout the years and have branched to many different types today. Ranging from speech recognition, data mining, medical diagnosis, to robotics, AI has been evident in many aspects of human lives. While there is no single fixed AI classification, researchers have tried to group AI based on different aspects, including the AI capabilities framework (Kaplan, 2015), AI approaches in problem-solving (Domingos, 2015), and the problem domains AI addresses (Agrawal, Gans & Goldfarb, 2018).

AI capabilities framework

According to AI capabilities framework, AI can be classified into three categories based on the level of intelligence developed, namely artificial narrow intelligence (ANI) or weak intelligence, artificial general intelligence (AGI) and artificial super intelligence (ASI). ANI is characterized by having a narrow range of abilities, where the AI developed till date could be classified into. This type of AI could either be reactive (responding to external stimulus) or have limited memory where it does what it is programmed to do. AGI refers to a machine which has the same level of intelligence as human. In order to realize this, AI researchers need to develop a conscious machine with cognitive capabilities based on the human brain, which is still debatable if it ever could be achieved. Another hypothetical goal of AI is to develop ASI, which is a machine that could surpass human capabilities. It is a self-aware AI model which adopts the theory of mind framework, a psychological theory which guides how mental states are attributed to the way human thinks and acts (Kaplan, 2015; Burgess, 2017).

The AI paradigms

The AI paradigms classify AI based on its different approaches to solve specific problems. These include symbolic, statistical and sub-symbolic approaches (Corea, 2018). The symbolic approach consists of AI which works based on logic and/or knowledge. Logic-based AI works on knowledge representation and problem-solving, whereas knowledge-based machines act in accordance to a large set of databases, information and rules (Minker, 2012; McCarthy, 2000). The statistical approach includes AI-based on mathematical tools, such as statistical methodology and machine learning. By leveraging on statistics, this type of AI could compare probabilities of scenarios and provides possible solutions. Machine learning attempts to use historical data to optimize future performance (Alpaydin, 2014). Sub-symbolic approaches include AI which is built on embodied intelligence and search engine optimization. Embodied intelligence relates to AI that utilizes engineered human capabilities, such as interaction, perception and visualization, whereas search engine optimization AI acts as a search function in order to find multiple solutions to a query (Corea, 2018).

AI problem domains

AI is also classified by the different type of problem(s) it focuses on. This consists of the following spectrums: reasoning, knowledge, planning, communication and perception. These domains are not necessarily disintegrated as certain machines work in overlapping domains. Reasoning refers to the AI used for problem-solving. Knowledge-focus AI aims to provide information and understand the human world. Planning AI are those which are capable of attaining the set of goals it is instructed to, whereas AI in the communication domain can process languages and communicate. Lastly, AI which is able to transform sensory inputs (visuals, sound, touch) into useful information can be categorized in the perception domain (Agrawal, Gans, and Goldfarb, 2018).

AI knowledge map

Referring to Agrawal, Gans and Goldfarb (2018) as well as Domingos (2015), Corea (2018) combined different ways of classifying AI into an AI knowledge map. His model of AI knowledge map has been simplified and presented in Figure 2.2.1. The map uses AI paradigms as its x-axis while AI problem domains is on the y-axis. The figure shows that some type of AI display multiple characteristics, thus they overlap in different AI problem domains and/or paradigms.

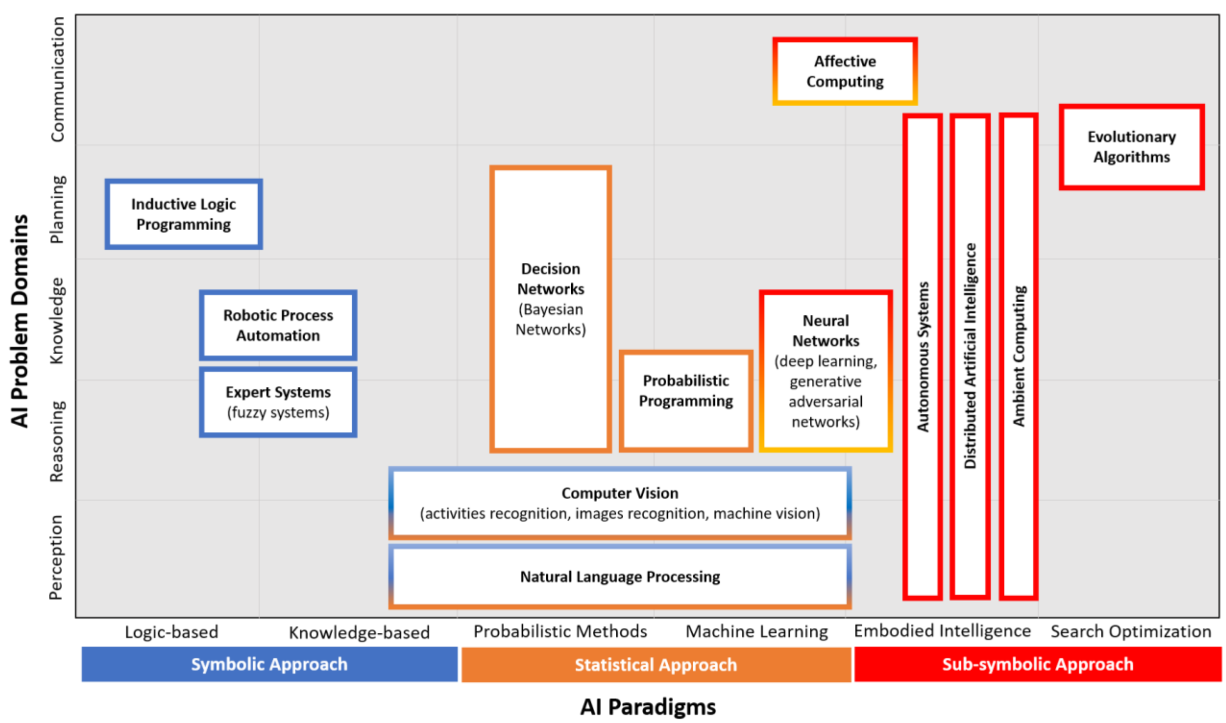

Figure 2.2.1: AI knowledge map.

Note: Adapted from "AI Knowledge Map: how to classify AI technologies" by Corea, F., 2018, Aug 22. Retrieved from https://www.forbes.com/sites/cognitiveworld/2018/08/22/ai-knowledge-map-how-to-classify-aitechnologies/#494cf7787773

General applications of AI using symbolic approach include inductive logical programming, robotic process automation and expert systems. Inductive logical programming (ILP) refers to tools which can generate hypotheses based on a given set of data through computational logic. The system is based on the properties of inference rules and convergence of algorithms. Rather than providing a deductive answer from the logical code generated by the user, ILP generates a conclusion from its background knowledge and the instances (Muggleton & De Raedt, 1994). An application of ILP is the program "CART" which generates decision trees based on the scenarios given (Breiman et al., 1984). Robotic process automation (RPA) are machines or systems capable of performing an action in the same way that a human does. RPA works in accordance with a structure data and typically follows a process map that has been coded in the RPA tool language for each of its action. Commercial RPA vendors such as AutomationEdge, Blue Prism and UiPath have experienced a surge of demand in recent years due to its potential cost-cutting that RPA brings to companies (Van der Aalst, Bichler & Heinzl, 2018). Expert systems are defined by AI that aims to perform a decision-making process in a way a human does through hard-coding using the LISP programming language. The system relies on ruled-based systems where variables are mapped into a continuous value between 0 to 1 instead of the digital logic of binary choices (either 0 or 1) (Jackson, 1998). A famous example would be MYCIN, a medical diagnosis system through descriptions of symptoms (McCorduck, 2004).

Applications of AI that combines both symbolic and statistical approaches are natural language processing (NLP) and computer vision. NLP is a field of AI that relates to the natural language data, which includes language generation, language understanding and machine translation. It aims to make use of human language and translate it into meaningful insights (Chowdhury, 2005). Some examples would be translation machines like Google translate, the speech assistants Siri and Google Alexa and text analytics software (Tableau, n.d.). Just like NLP, computer vision AI also aims to recognize patterns of a visional input (activities, images recognition or machine vision) into useful information. Sometimes, the machines can also make a decision based on the information observed (Szeliski, 2010). Computer vision has played a major role in the creation of self-driving cars and applied for facial recognition technology as well as the predictive maintenance system in the manufacturing industry (Marr, 2019).

Other AI with statistical approaches are decision networks and probabilistic programming. Decision networks utilize the concept of Bayesian networks where decisions are mapped based on its probabilistic relationships into networks that allow for sequential decisions (Corea, 2018). In probabilistic programming, the machines were given pre-defined probabilistic models which are then used to make an inference in each scenario. The machine is typically applied in a situation with many uncertainties, for example, in predicting stock prices, providing movie recommendations and diagnosing computer problems (Corea, 2018).

Some AI combines statistical and sub-symbolic approaches, such as neural networks and affective computing (affective learning). Neural networks are based on the concept of human neurons, where there are inter-connected processors called neurons, each producing "a sequence of real-valued activations". Neurons can get activated through their sensors which perceive the environment or through their connections with other neurons. Deep learning is a sub-field of neural networks which aims to build these connections to derive deeper insights (Schmidhuber, 2015). An application of deep learning is found in Recaptcha, a website security service that utilizes human knowledge in distinguishing texts and images to train machine algorithms. Affective learning refers to AI which is trained to recognize, interpret and simulate human emotions. This includes studying human facial expression, tone of voice, gesture, and micro-expression which are then translated into human emotions through machine algorithms. Companies like BBC, Disney and Coca Cola Company have deployed affective learning in their marketing domain to gain insight on customer perceptions towards their advertisements (Marr, 2016).

AI which uses sub-symbolic approaches includes autonomous systems, distributed AI, ambient computing and evolutionary algorithms. Autonomous systems are AI that combines the element of robotics and intelligent systems. Instead of performing automatic tasks, these robots can detect their physical environment and act accordingly if any changes occur (Corea. 2018; Langston, 2019). Distributed AI (DAI) utilizes the multi-agent systems where it aims to solve complex problems, typically using a large data size, through distributing them into autonomous "agents" which would interact with one another. This type of AI has been deployed in devising trading strategies today (Corea, 2018; Weiss, 1999). Ambient computing are physical devices that detect, perceive and react (subtly) to a human presence. It aims to support the daily lives of human being in an uninstructive way. The applications include smart home, smart car and street camera surveillance (Cook, Augusto & Jakkula, 2009). Evolutionary algorithms are defined as "stochastic search methods that have been applied successfully in many search, optimization and machine learning problems" (Alba & Tomassini, 2002). It is based on the evolutionary mechanism, a concept inspired by biology. It follows the notion of natural selection where "the fittest" candidate solution is chosen (Corea, 2018).

2.2.3. Future of Artificial Intelligence

The development of AI so far could be explained through Figure 2.2.2 below. As previously explained in Chapter 2.2.1, AI experienced a steep advancement from the 1940s until 1980s. However, since the late 1970s, the funding on AI from the US government was stopped as AI was not able to meet one of its highly promised goals, namely machine translation. This period was known as the "AI winter". The failures to provide a translation which were initially thought to be straightforward raised criticisms and instilled doubts if AI could ever solve challenging human problems (Buchanan, 2005; McCarthy, 1990). This results in stagnation in AI development until the new paradigm shift of thinking towards AI in the 1990s. According to Menzies (2003), if technology has something to offer, it will not remain in "Trough of disillusionment" (see Figure 2.2.2) but it will rise back to a new activity level.

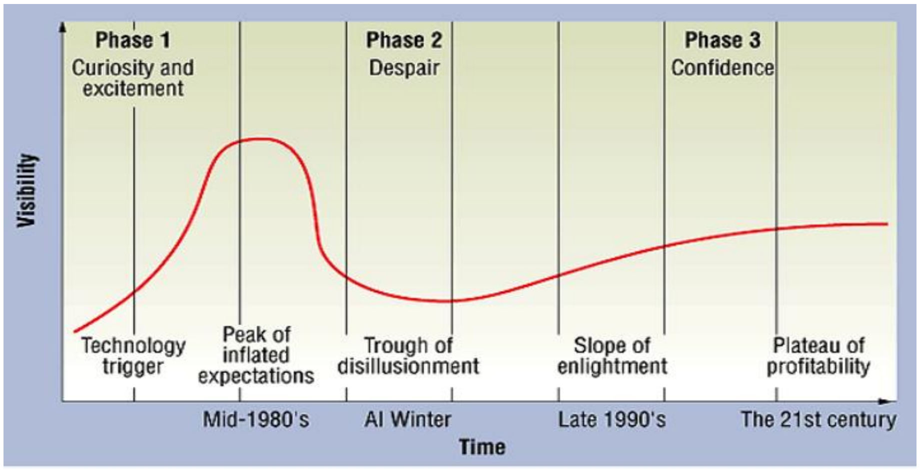

Figure 2.2.2: The hype curve of AI.

Note: Adapted from "21st Century AI: Proud, Not Smug" by Menzies, T., 2003, *IEEE Intelligent Systems, (3)*, p. 19.

Furthermore, Figure 2.2.2 shows that AI innovation is predicted to reach a constant rate in the 21st century. However, the curve likely does not consider the possibility of a financial crisis, which is currently happening today due to the COVID-19 pandemic. According to Schumpeter's creative destruction theory (1942), economic crisis can give rise to new business models, enterprises and even industries that could transform the economy which is otherwise known as "innovation". Recession can also act as a catalyst for growth. For instance, when the world started to recover from the Great Depression, Alexander Field, a historical economist claimed it to be a decade with the greatest technological progress in the century (Field, 2003). Following the same line of thought and noting for the massive scale of the economic crisis caused by the pandemic today, AI innovation could increase steeply in the coming years, thus resulting in AI advancements in an unprecedented rate.

Currently, the opinion on the future of AI varies greatly. A survey conducted on 550 AI experts shows that 41% of the respondents believe that an AI which can simulate learning and every aspect of human intelligent could never be developed. The same percentage of respondents believed that this could happen, but likely in more than 50 years from now (Müller & Bostrom, 2016). On the other hand, Kurzweil (2014), predicted that such a machine would appear by the year 2029. He derived such conclusion from Moore's Law, which claims that computer processor speeds will double every two years. Another research also predicts that AI can overtake certain human abilities in the coming years, aligning with the concept of artificial super intelligence (ASI) previously explained. For instance, AI will be better than human in writing a high-school essay by 2026, writing a best-selling book by 2049 and even replace a surgeon by 2053 (Grace et al., 2018).

Perhaps, as molecular biology and neuroscience research shows more in-depth insights on how human brain thinks, processes speech and reacts to a certain stimulus, an AI that better simulate human behaviour like artificial general intelligence (AGI) and ASI could indeed be developed. Algorithms need to go hand in hand with the sciences to understand how much AI can progress in the future. Nonetheless, the ethical issue concerning AI with human intelligence overtaking humans might be a problem and should be thought upon before considering such development.

2.3. Implementing Artificial Intelligence in Big 4 Auditing

According to Beasley, Carcello and Hermanson (2001), the top five audit deficiencies come from insufficient audit evidence, inability to maintain professional work attitude, failure to exercise a sufficient level of professional skepticism, incorrect application of US GAAP and improper design of audit programme. In order to minimize such human error, there is a need to have good control in place. Based on Merchant's (1982) management control model, the first step to determine the best control for an organization is to examine if a human can be avoided through automation or centralization, thus opting for control problem avoidance.

As previously explained, the end-goal of AI is to create artificial general intelligence (AGI) and hypothetically, artificial super intelligence (ASI). AGI is an AI which has the ability to perform tasks at the same level as human whereas ASI refers to AI which can outperform human capabilities (Grace et al., 2018). Some authors claimed that once AGI is achieved, AI systems will slowly take over humans in carrying tasks, leading to a process called "intelligence explosion" (Bostrom, 2014; Good, 1966). In this case, human jobs, including auditing, will then be affected. This is especially possible since many researchers have previously claimed auditing as a job with emotionless methods of algorithmic reasoning due to its systematic audit process (Guénin-Paracini, Malsch & Paillé, 2014; Francis, 1994). Therefore, based on the audit process model explained under chapter 1.1.4. and characteristics of different AI under chapter 2.2.2., the following general framework is developed to predict the type of AI that can be utilized for auditing work in the future.

2.3.1. General Framework

Table 2.3.1: General framework which fits the capabilities of AI with auditing works

Audit Process	**Potential AI type(s)**
Phase 1: Client Acceptance	
1. Evaluation of client's background and reason for auditing	
• Search on publicly available information	Evolutionary algorithms
• Interaction with client, previous auditor, legal team	-
• Document review	Natural language processing
2. Check ethical requirements regarding the independence of auditors and the non-audited services they offer to the client	

• Check through the audit firm’s database	Evolutionary algorithms
3. Provide an engagement letter to the client	
• Use a general engagement letter template and fill in with agreed terms between the auditor and client	Robotic process automation
Phase 2: Audit Planning	
1. Obtaining a substantial understanding of the client & audit risk assessments	
• Consulting the clients on their objectives and expectations towards its stakeholders	-
• Conducting analytical procedures of client’s transactions	Deep learning; Probabilistic programming
• Inspecting the client’s core activities, accounting policies, management reports, internal control manuals and other relevant documents	Deep learning; Inductive logic programming
2. Determine the materiality level	
• Determined based on audit risk and general guidelines in the audit company	Deep learning; Expert systems; Bayesian networks
3. Develop an audit programme	
• Outlines the audit objectives, timing and audit procedures to obtain the required evidence	Robotic process automation
Phase 3: Testing and Evidence	
1. Testing of internal controls	
• Direct inquiries to the client’s internal audit personnel	Affective learning
• Observing and reperforming the application of a specific control	Computer vision; Robotic process automation
• inspecting documents or reports	Natural language processing
• tracing the information system to find related transactions for financial reporting	Evolutionary algorithms; Natural language processing
2. Performing substantive procedures	
• Analytical procedures: examining accounting data, including financial and non-financial information	Inductive logic programming; Bayesian networks; Deep learning
• Test of details of transactions and balances	Probabilistic programming; Bayesian networks; Deep learning
3. Gathering audit evidence	
• Inquiry, recalculation and confirmation	Affective learning; Deep learning
• Observation, re-performance	Computer vision; Robotic process automation
• Document inspections	Natural language processing

• Analytical procedures	Inductive logic programming; Bayesian networks; Deep learning
Phase 4: Evaluation & Reporting	
1. Review the contingent liabilities and commitment of the client	
• Enquire management	Affective learning
• Review legal working papers, letters of credit, past tax returns	Natural language processing
• Evaluate known contingent liabilities	Deep learning
2. Review for subsequent events	
• Enquire management	Affective learning
• Examine minutes of board meetings	Natural language processing
• Review relevant accounting records	Natural language processing
3. Review financial statements and other report materials to determine if the required information have been sufficiently disclosed	
• Review relevant accounting records and reports	Natural language processing
4. Wrap-up procedures	
• Supervisory review	Deep learning
• Review of audit working papers	Natural language processing
• Evaluation of audit findings for material misstatement	Deep learning
• Evaluation of the client's "going concern" assumption	Inductive logic programming; Expert systems; Deep learning
5. Final reporting	
• Report important findings to the client's audit committee	-
• eventually produce an audit report containing the audit opinion	Robotic process automation

3. Methodology

To find an answer to the research question, the methodology is divided into two parts. Firstly, it is crucial to understand how much AI has been utilized today specifically in Big 4 auditing. Therefore, the research begins with examining existing information of the current audit innovation in Big 4 firms. The information will be obtained directly from each Big 4 firm website to ensure that they are up-to-date and accurate. Keywords such as "audit innovation", "audit technology", and "audit artificial intelligence" will be used to find the relevant information.

The next part aims to evaluate the possible AI innovation that Big 4 firms might undertake in auditing in the coming years. Various literature on AI application in auditing and relevant general AI application will be studied with reference to the general framework (see Table 2.3.1). Combining the keywords of the specific audit process and the potential AI type(s) proposed under the framework, for instance, "information search" and "evolutionary algorithms", existing literature on the topic will be studied to understand how the AI can aid auditing. This also includes AI type that has not been utilized in Big 4 auditing but has potential use(s) in certain audit steps as indicated in the framework. In this case, the feasibility of the AI during an audit process will be examined. More general keywords like "auditing", "audit innovation", and "computer-assisted audit" will also be paired up with all the AI type to ensure representative results in this research. To complement previous research studies, the future focus of audit innovation in Big 4 firms will also be evaluated from the Big 4 websites to predict the extent of improvement of the current AI implemented. Lastly, if it is concluded that AI will indeed transform auditing work in Big 4 firms, existing literature on skills for AI-driven future will be examined to provide a full picture of the future audit works.

To ensure the reliability of this research, the paper that will be studied on AI application in auditing or in general will be carefully selected based on its journal impact factor. This means that only auditing and artificial intelligence journals with high impact factors, which indicate they are of high quality, will be used in the analysis of this research. Besides, all the steps taken regarding the choice of keywords explained earlier in this chapter will also ensure the representativeness and reliability of this research.

4. Results

4.1. Current Audit Innovation in Big 4 Auditing

Today, Big 4 firms have branched out their audit innovation to include different AI systems and advanced technology as discussed below. There are two approaches that Big 4 firms take in deploying AI in their operations. The first one would be to select a broad range of AI capabilities from a small number of vendors, like in the case of KPMG with Microsoft and IBM. The second approach would be to combine different cognitive technologies from various vendors in order to create the "best of breeds" which is well represented by Deloitte (Kokina & Davenport, 2017).

<u>KPMG</u>

KPMG classifies its audit innovation into three main pillars, namely digital automation, predictive analytics and cognitive technologies. These features are manifested through KPMG Clara, an intelligent audit platform created through collaboration with the most advanced tech companies today, which utilizes systems like Microsoft Azure and IBM Watson. The platform is rooted in KPMG's audit methodology and international auditing standards, while it aims to "empower KPMG professionals to see things with greater clarity and generate deeper and clearer insights". As such, KPMG auditors can work smarter and deliver a better audit quality through enhanced analytical capabilities. Moreover, KPMG Clara includes algorithms based on statistical models which allow the analysis of an entire population rather than using sampling techniques. This allows identification of anomalies in the business and provides more rooms for the auditors to focus on these risks and the implications to the business (KPMG, 2018b). In 2020, KPMG Clara Workflow has been deployed to replace its predecessor, eAudIT, an activity-based workflow and electronic file which is essential to measure audit engagement process and for audit documentation (KPMG, n.d.).

KPMG Clara is based upon different types of AI. For instance, IBM Watson is a cognitive computing technology which is built based on natural language processing (NLP), inductive logic programming (ILP) and deep learning (High, 2012). Using IBM Watson, a large amount of financial data can be analyzed to detect inconsistent information, as opposed to assessing only a sample of data like in traditional auditing. Microsoft Azure is a cloud computing service which allows real-time data analysis. Microsoft Azure works on the basis of a machine learning which supports its ability of predictive analysis (Barnes, 2015). Besides, robotic process automation (RPA) also plays a part in audit steps like reconciliations, audit confirmation, and generation of emails; as well as gathering audit evidence by collecting information of an organization that are not integrated into one system and applying a basic order of data (KPMG, 2019).

KPMG also relies on cognitive technology which focuses on evidence gathering through natural language processing and optical character recognition on financial documents. KPMG (2018b) defines cognitive technology as an element of AI which requires human interpretation and cognitive judgement to process the information and deliver the outcome. Afterwards, through deep learning, machine learning and predictive analysis, hypotheses that support decision-making will be generated, which will then have to be evaluated by human auditors to fully reap the benefits of the systems (KMPG, 2016).

Ernst & Young (EY)

EY groups its audit innovation into AI, blockchain and drone technology. EY's investment in AI mainly focuses on deep learning, machine learning and automation. With AI, EY aims to analyze data through advanced pattern recognition to digitally assist their auditors. The most prominent features include analyzing and extracting information from unstructured data like images, contracts and invoices to gather audit evidence as well as analyzing a large population of data to accurately identify risks and respond to potential material misstatements due to fraud (Ernst & Young, n.d (a)). Machine learning, in this case, includes natural language processing for document reviews and data extraction from contracts (Ernst & Young, 2018).

EY further developed EY Helix and EY Canvas to utilize automation in order to improve audit efficiency (Ernst & Young, n.d (a)). EY Helix is a global audit analytics platform aims to optimize analytical-driven audit so auditors can focus on data analysis rather than data collection. EY Helix started with EY Helix General Ledger Anomaly Detector (GLAD) which is a machine learning based on expert systems that evaluates the flagged entries supplied by the auditors and provide recommended action based on the analysis. The system's algorithms are exposed to EY auditors' knowledge based on previous clients, including their business, accounting policies and governance. The more audit engagements EY Helix handles, the better will the algorithms be in its detection methods (Ernst & Young, n.d (b)). Today, EY algorithms have been trained to provide relevant questions for auditors to derive insights for each type of data. On top of that, EY Helix has branched into analyzers of other parts of audit components, such as inventory, trades payable, mortgage and audit scope (Ernst & Young, n.d (d)). EY Canvas is a digital audit cloud platform which connects the auditors with their client and digitalizes the end-to-end audit process. The platform allows real-time monitoring of engagements, streamline communication with clients, less administrative procedures and improved project management, thus improving audit transparency and enhanced audit quality (Ernst & Young, n.d (c)).

The blockchain and drone technology complement AI in the auditing process. The blockchain technology, known as EY Blockchain Analyzer, aims to facilitate auditors in gathering an organization's entire transactions from multiple ledgers and reconcile the data into the EY client books. Afterwards, the data will be further evaluated through predictive analytics built through deep learning, such as trend analysis and identification of outliers. EY Blockchain Analyzer can also perform transaction analysis, such as tax calculation and capital gains calculation in accordance with the national law tax (Ernst & Young, 2019). The drone technology aims to assist auditing in the testing phase. The use of drones can assist observations of inventories and other procedures performed, which is accessible to the auditor real-time and from a distance (Ernst & Young, n.d (a)).

Deloitte

Deloitte has a global audit platform known as Deloitte Omnia. The platform aims to amplify the skills, knowledge and experiences of Deloitte auditors through its collaboration with cognitive technology, risk-based workflows and advanced analytics so as to provide enhanced audit quality and value-added audit services. The platform allows centralization of project management, streamline of data retrieval, targeted testing through analytics, and leverages on AI to automate manual processes and generate insights (Deloitte, n.d. (a)). To complement Deloitte Omnia, Deloitte deploys blockchain technology which provides easy access to structured data which become the input for machine learning and advanced data analytics. Moreover, drones with remote-sensing and advanced imagery is currently being invested for observations of inventories at remote locations and asset inspections (Deloitte, n.d. (c)).

Deloitte uses a variety of AI application in auditing. Through machine learning, Deloitte utilizes predictive analytics so the auditors can better able evaluate the client's "going away" assumption and provide better insights to the client. The cognitive technology further allows a thousand of contracts in different languages to be read and detects key terms. Deloitte also utilizes deep learning to ensure that the algorithms can generate predictions with better accuracy and improved insights after every audit engagement. In 2015, Deloitte won the audit innovation of the year for developing Argus, a cognitive audit innovation tool that learns from every human interaction and leverages advanced machine learning as well as natural language processing in identifying and extracting accounting information from a given data (Deloitte, 2016). In analyzing audit evidence, Deloitte makes use of natural language processing, optical character recognition and machine learning. Besides, robotic process automation is employed to conduct processes and cognitive tasks (Deloitte, n.d. (c)).

PricewaterhouseCoopers (PwC)

PwC audit key technologies are Halo, Aura and Connect. Halo is a data auditing technology which utilizes data and visualization from internal and external information of the client to identify business risks, direct audit work and generate insights for the client. Halo is also designed to test information reliability provided by the client where a large population can be tested at once and the accuracy improves with each analysis due to its deep learning algorithms. Over the years, Halo has grown to include features like journals (identification of high risks transactions and process inefficiencies), general ledger revenues (process streamline revenue testing), audit testing, risk assessments and investment valuation tools. The system is fully automated which enables real-time analysis and fast process (PwC, 2019).

Halo is supported by Aura, a global enterprise resource planning system to ensure the quality and consistency of audit at each stage. Aura plays a pivotal role during the audit planning as the system assists in audit risks identification and allows PwC global network to approach audit risks efficiently and in a systematic manner. Aura focuses on the business, the client's strategic trends, macro trends and the business risks to derive its audit risks. It allows real-time monitoring and can be accessed by multiple auditors at the same time, preventing work duplication. Moreover, Connect platform is a collaborative audit workflow tool between PwC auditors and the clients for a streamline, real-time communication. When a document is missing, an automatic message will be sent to the client, thus making the process more efficient. The platform further automates audit schedules which saves time (PwC, n.d.).

The key technologies are complemented with other AI-driven tools like Count, PwC's confirmation system, PwC extract platform and robotic process automation. Count is an app which can accurately measure stock counts in a short time. Besides Count, PwC also uses drones on inventory observations. PwC confirmation system allows confirmation to be done quickly and securely on the web whereas PwC extract platform allows data to be extracted securely from the client's system to the audit platform and transformed into a readable format. Robotic process automation has been deployed to automate transactional processes to reduce the workload of the client for the audit process (PwC, n.d.).

Current state of audit innovation in Big 4 firms

Based on the audit innovation currently put in place by KPMG, EY, Deloitte, and PwC, it is observed that the firms are using common technology for different audit processes to enhance their audit quality and improve efficiency. Table A in Appendix summarizes the different type of AI and the function(s) they serve during the audit process. On top of that, complementing technology used is also presented in the table to provide a full picture of the current state of technology in Big 4 auditing. In Appendix, Table B also shows the current level of AI innovation in each Big 4 firm for each audit step.

4.2. Future of AI in Big 4 Auditing

4.2.1. Current and potential future applications of AI in auditing

Expert systems

The early application of AI in auditing largely revolved around expert systems. Gillet and Vasarhelyi (1993) developed an expert system audit automation tool called ADAPT, which aims to aid auditors in creating an audit programme. ADAPT's objectives are to create a sufficient but not excessive audit evidence plan and to do so in the most optimal manner, meaning that its cost-effectiveness is enhanced. ADAPT system maintains knowledge about financial statement assertions, audit procedures and audit programme planning. Based on the client information and requirements supplied by the auditor, the programme will assess the audit risks and generate possible audit procedures which can then be modified if necessary, allowing the auditor to be in control. Moreover, expert systems can determine the material level, evaluate internal controls and provide "going concern" judgement (Baldwin, Brown & Trinkle, 2006).

The use of expert systems for audit planning is also echoed by Bedard et al. (1994), which focuses on the risk identification and analysis portion. This is because these tasks are relatively unstructured and require the understanding of quantitative and qualitative data, which makes decision-assisting expert systems suitable to aid the process. However, the use of expert systems in auditing eventually received much criticism as it generates recommendations based solely on the assessment method programmed to its algorithms, which is not user neutral as different auditors will offer different recommendations based on their ways of working (O'Leary, 2003). Over the years, such a problem has slowly been reduced as algorithms can be exposed to experiences and patterns via deep learning to generate more neutral results.

Bayesian networks

In a paper by Dusenbury, Reimers and Wheeler (2000), it is concluded Bayesian decision networks is a suitable framework to design the audit risk model. Audit risk model shows that overall audit risks are determined by inherent risk, control risk, analytical procedures risk (Chapter 2.1.3) and allowed test-of-details risk. The last risk refers to the amount of acceptable risks set by the auditors after considering other risk levels in order to achieve the desired overall audit risk. Bayesian networks are suitable as the audit risk components are conditionally related and sequentially determined, which fits the nature of probabilistic sequential decision making of Bayesian networks. On top of Bayesian decision networks, neural networks (deep learning) needs to be deployed to ensure that the audit risk model can recognize patterns based on experience and mimic the processing of human brain better (Ramamoorti, Bailey Jr & Traver, 1999). According to Hunton and Rose (2010), the application of Bayesian networks is also evident in the Big 4 today, such as the examples of KPMG's KRisk system and PwC's FRisk system.

Natural language processing

Natural language processing (NLP) plays a crucial role in document reviews, which highly constitutes communication in the auditing domain. The use of NLP in accounting could be traced back since the early 2000s when NLP started to be deployed for classifying financial statement contents which were proven to be successful (Fisher, Garnsey, & Hughes, 2016). NLP makes data extraction more efficient as it only takes a few minutes to review a document, which will otherwise take hours if done by human auditors. NLP could scan through written documents like invoices, contracts, meeting minutes and reports to identify keywords and extract relevant accounting information from the data. NLP is also being developed to transform unstructured data such as speech and images into digital information which makes data processing easier. Currently, image inspection is not much used in the auditing process, however, in the future, it might be useful in terms of analyzing certain types of inventory (Kokina & Davenport, 2017).

Deep learning

Deep learning aims to mimic the neural networks of a human brain in the way human processes input and conducts decision-making. Today, deep learning has been evident in many stages of the audit process, such as assessing the possibility of management fraud (Issa, Sun & Vasarhelyi, 2016), forecasting fraudulent financial reporting (Bell & Carcello, 2000), determining materiality level, providing a firm's "going concern" assumption (Koh, 2004), and supplying insights and recommendations to auditors in forming an audit opinion (Issa, Sun & Vasarhelyi, 2016). However, Issa, Sun & Vasarhelyi (2016) argued that deep learning which exists today is still in a development phase which still requires a lot of improvements before it is able to simulate human cognitive capabilities. Therefore, deep learning can be used for supervised learning but not yet able to replace human in decision-making. Nonetheless, as the knowledge base of deep learning gets expanded through various training dataset, it would be able to process structured and unstructured data without any human intervention. Thus, deep learning could aid NLP in conducting automated contract and paperwork reviews as well as analysis of financial statements.

Robotic process automation

Robotic process automation (RPA) has many potentials throughout the audit process. During the client acceptance phase, RPA can be used to collect the client's background information from exogenous sources and generate a client-specific engagement letter (Issa, Sun & Vasarhelyi, 2016). RPA can also verify the accuracy of mathematical calculations in the financial statements, review journal entries, and conduct full automation of manual tasks like payment transaction testing, including extraction of relevant data for subsequent substantive testing (Kokina & Davenport, 2017). In general, human still needs to handle the unstructured tasks like formatting the data into a structured format, before passing on the systematic tasks to the robots. The robots will then convert the input into an output based on the algorithms they have been programmed to, for instance, identifying errors, creating a report, or retrieving information from the system. The use of RPA has been said to improve speed and accuracy as it can operate continuously for 24 hours a day and conduct a large volume of work at once (Lacity & Willcocks, 2017).

Computer vision

Computer vision can be useful in audit planning as well as testing and evidence phase of the audit process. During the observation of the client's internal control system, instead of physical observation, drones can be utilized to record video footage which can then be analyzed for anomalies. Computer vision can be installed in the drones for pattern recognition and visualization methods for risk identification (Issa, Sun & Vasarhelyi, 2016). For instance, in PwC Poland, drones have been expected to fully conduct the audit examination of assets. Moreover, the use of computer vision combined with drone technology could also support automated data collection for testing control as the sensor tracking capability of computer vision can measure inventory per hour. This means that computer vision is useful for continuous auditing as it is able to collect audit evidence continuously (Appelbaum & Nehmer, 2017; Brown-Liburd & Vasarhelyi, 2015).

Inductive logic programming

One of the strengths of Inductive logic programming (ILP) is its ability to process a wide variety of background knowledge as compared to other types of attribute-based learning. While the use of ILP in auditing has not been much explored in the accounting field, it has been successfully applied in the science field, such as for predicting the mutagenicity of chemical compounds and classification of water quality based on its physical attributes (Bratko & Muggleton, 1995). Based on the existing applications, it is possible that ILP (through combination with Bayesian networks) could be useful for tasks with similar characteristics in auditing, such as determining materiality level, detecting fraud and classifying transactions in the financial statements.

Probabilistic programming

Similar to ILP, there appears to be little research on the application of probabilistic programming in auditing. Most research present today focuses on the capabilities of probabilistic programming in data analysis, action and activity recognition, reasoning as well as planning. This includes the use of probabilistic programming in DNA sequence analysis, inferring metabolic pathways, event recognition in camera surveillance and information retrieval from the web (De Raed & Kimmig, 2015). Thus, probabilistic programming shows potential capabilities in aiding audit process for searching client's information, conducting predictive analysis, observing control performances, and detecting fraud.

Affective computing

The use of affective computing in auditing could potentially occur during auditor's interaction with clients or when decoding pictures and videos gathered for audit evidence. Advanced affective computing can recognize facial expressions, body gestures and listen to human voices, and then based on that identify various information that has been programmed into its algorithms. For instance, it can detect the possibility of lying and determine the time and location of a given picture. This technology can, therefore, help to provide assurance against fraud (Issa, Sun & Vasarhelyi, 2016; Agarwal et. al., 2018). This type of emotion elicitor system could be based on Sequence Check Theory, which draws emotion decision tree based on the attributes presented at each node.

A challenge currently faced based affective computing researchers are the lack of database to train the system. Just like most other AI systems, deep learning will also be required to supply the system with the right information to ensure that it can interpret human emotions accurately (Luo, 2012). There is still a need for more research in the study of human actions and adaptation to different scenarios in order to generate a machine that can well recognize human behaviour.

Evolutionary algorithms

Evolutionary algorithms have the potential to detect fraud and conduct advanced information search. According to Baldwin, Brown and Trinkle (2006), evolutionary algorithms can be used in the classification of audit tasks, such as assigning a particular debt as a collectable or bad debt and if a transaction can be deemed as legitimate or questionable. This is supported by Welch et al. (1998) which claimed that evolutionary algorithms are suitable to model auditors' decision behaviour in fraud detection settings.

Alden, Bryan, Lessley and Tripathy (2012) further proved that the combination of evolutionary algorithms and modern estimation of distribution algorithms could provide an accurate financial statement fraud detection as compared to the traditional detection method which is based on the logistic regression model. In this manner, evolutionary algorithms appear to be a suitable technology to trace the information system in finding related transactions for financial reporting. Besides, evolutionary algorithms can play a part in search engine optimization (Fonseca & Flemming, 1995; Michalewicz & Schoenauer, 1996). which is useful for information search when gathering the client's background and audit evidence.

4.2.2. Audit innovation focus in Big 4 auditing

Currently, KPMG's future focus is to develop a cognitive technology which can process unstructured data from the non-traditional sources like social, digital and printed media. This is so following the increasing trend that investors are basing the decision on unstructured data such as reputation, customer experience and economic indicator (KPMG, 2018b). According to "Audit 2025: The Future is Now" report published by KPMG, large companies in the US demand for a more forward-trending view of risks and data derived from the audit so they can run their business better and improve their risk management. Nearly half of the respondents also highlight the need for more transparency during the audit process (KPMG, 2017).

Similar to KPMG, EY aims to invest more in deep learning to analyze unstructured data in untraditional formats, such as emails, social media posts and even audio files from conference calls. Such data processing will help to produce more in-depth insights, reduce manual works and improve the algorithms of deep learning used to analyze information. Moreover, EY will explore the blockchain technology to execute transactions automatically and real-time. By using a real-time distributed ledger system, more anomalies can be detected on a daily basis, thus increasing the audit efficiency (EY, 2017).

In the future, Deloitte audit services aim to generate better insights from the auditing process to provide the clients with process improvements recommendations and accurate risks identifications for potential disruptions in the client's business (Deloitte, n.d. (c)). Deloitte will also focus on blockchain technology, which they dubbed as a potential transformative analytical tool to move towards continuous auditing, as blockchain derivative transactions are predicted to rise in the coming years (Deloitte, n.d. (b)). Furthermore, Deloitte global audit innovation team will continue to deploy "best of breed" approach in their innovation by integrating various systems, rather than choosing a single-source solution (Deloitte, n.d. (c)).

PwC's future focus is on exploring other potential application of robotic process automation and developing AI capabilities in terms of enhanced audit analytical capabilities like AI prediction and AI anomaly detector. For instance, in 2019, PwC won Audit Innovation of the year by developing Cash.ai, a system that automates end-to-end cash audit by reading, understanding and testing client's cash balances and bank documents. Besides, PwC is also looking into blockchain technology and other potential uses of drones in making the audit process more efficient and produces enhanced audit quality (PwC, n.d.; PwC, 2019)).

4.2.3. Analysis of Future AI involvement in Big 4 Auditing

Table 4.2.1. below indicates the potential AI involvement in external auditing process provided by the Big 4 firms in the future. The prediction is derived based on current AI involvement in Big 4 auditing (Chapter 4.1.), previous research (Chapter 4.2.1.), and the future focus of each Big 4 in audit innovation (Chapter 4.2.2). If AI is not feasible in the audit step, another more suitable type of technology might be proposed on the "Is AI involved in the audit step?" column, if any. The AI involvement in the audit step is colour-coded based on the extent of involvement as follows:

No involvement
(AI plays no role in the audit step)
Moderate involvement
(AI plays some roles in the audit step, however human action is required)
High involvement
(AI plays major roles in the audit step, human action is optional)

Table 4.2.1: Prediction of Future AI capabilities in Big 4 auditing

Audit Process	**Is AI involved in the audit step?**
Phase 1: Client Acceptance	
1. Evaluation of client's background and reason for auditing	
• Search on publicly available information	
• Interaction with client, previous auditor, legal team	
• Document review	
2. Check ethical requirements regarding the independence of auditors and the non-audited services they offer to the client	
• Check through the audit firm's database	Blockchain technology
3. Provide an engagement letter to the client	
• Use a general engagement letter template and fill in with agreed terms between the auditor and client	
Phase 2: Audit Planning	
1. Obtaining a substantial understanding of the client & audit risk assessments	
• Consulting the clients on their objectives and expectations towards its stakeholders	
• Conducting analytical procedures of client's transactions	
• Inspecting the client's core activities, accounting policies, management reports, internal control manuals and other relevant documents	

2. Determine the materiality level

- Determined based on audit risk and general guidelines in the audit company

3. Develop an audit programme

- Outlines the audit objectives, timing and audit procedures to obtain the required evidence

Cloud computing

Phase 3: Testing and Evidence

1. Testing of internal controls

- Direct inquiries to the client's internal audit personnel
- Observing and reperforming the application of a specific control
- inspecting documents or reports
- tracing the information system to find related transactions for financial reporting

2. Performing substantive procedures

- Analytical procedures: examining accounting data, including financial and non-financial information
- Test of details of transactions and balances

3. Gathering audit evidence

- Inquiry, recalculation and confirmation
- Observation, re-performance
- Document inspections
- Analytical procedures

Phase 4: Evaluation & Reporting

1. Review the contingent liabilities and commitment of the client

- Enquire management
- Review legal working papers, letters of credit, past tax returns
- Evaluate known contingent liabilities

2. Review for subsequent events

- Enquire management
- Examine minutes of board meetings
- Review relevant accounting records

3. Review financial statements and other report materials to determine if the required information have been sufficiently disclosed

- Review relevant accounting records and reports

4. Wrap-up procedures

- Supervisory review
- Review of audit working papers
- Evaluation of audit findings for material misstatement
- Evaluation of the client's "going concern" assumption

5. Final reporting • Report important findings to the client’s audit committee • eventually produce an audit report containing the audit opinion	

From the table, it can be seen that AI will be involved in most of the audit process, except for steps which can be better executed using other platforms like blockchain technology or cloud-computing, or directly through human interaction. While it is predicted that some activities like document reviews and information search can be automated with AI, other audit steps will likely require human actions to process the insights generated by the AI to ensure its validity and accuracy. The review process on AI accuracy can be lessened each year as deep learning makes AI algorithms more precise with each engagement. It appears that AI will largely reduce the burden of auditors in terms of evidence gathering, audit sampling, manual testing and data reviews, so they can focus more on analyzing insights supplied by the AI to further assist the client’s business operations, focus on the high-risk areas and improve fraud detection. The current auditing standard might also evolve to fit the effect of disruptive technology in the field, such as the adoption of continuous auditing (Issa, Sun & Vasarhelyi, 2016).

Therefore, rather than replacing the job of the auditors, AI will augment auditors’ work to provide enhanced quality and more efficient audits. This claim is also supported by a research from Abdolmohammadi (1999) which claims that auditing job can be divided into 39 per cent of structured tasks, 41 per cent of semi-structured tasks and 20 per cent of unstructured tasks. This means that while AI can play a major role in up to 39 per cent of the structured tasks which are easy to replicate, human actions are still required for the rest of the work. Moreover, the rise of AI innovation also means that the focus of external auditing jobs will change over the years towards data-driven, digital audit approach which necessitates new skills for future Big 4 auditors. Hence, it can be concluded that AI will transform Big 4 auditing works to a moderate extent.

4.2.4. Skills required for AI-Driven Auditing

According to a survey by the World Economic Forum (2015), 75 per cent of the respondents believed that by 2025, 30 per cent of the corporate audit work will be fully conducted by AI. As auditing becomes increasingly automated, there will be less emphasis on manual tasks like data extraction and physical reviews, but more towards understanding insights from data and its underlying assumptions so as to provide more in-depth analysis. Moreover, it is expected that they will focus more on other high risks areas to better understand their clients’ business, help improve client’s risk management and deliver enhanced audit quality (Deloitte, 2017; KPMG, 2017). With this, auditors need to have complex problem-solving skills to excel in their jobs (Agarwal et al., 2018).

Auditors must learn to work alongside the intelligence machines and have adequate big data knowledge and advanced analytical skills to interpret the insights and recommendations provided by the technology, in order to improve their performances and results (Kokina & Davenport, 2017). They need to exercise professional judgements and skepticisms even more with the output provided by these machines, as these technologies do not possess such capacity and the world is constantly changing (Jarrahi, 2018). Moreover, according to "Audit 2025: The Future is Now" report by KPMG (2017), auditors need to develop excellent communication skills and critical thinking with the clients since this would be the tasks that are not likely to be replaced by technology. They need to communicate effectively and ask the right questions to help identify and assess critical issues, thus delivering value-added audit services.

5. Conclusion

This research has looked into capabilities of different type of AI and tested their feasibility in the specific steps of an audit process, as presented through the general framework under Chapter 2.3.1. By studying the websites of Big 4 firms, information about current AI innovation in Big 4 auditing was obtained. Afterwards, this information was compared with Big 4 future innovation focus along with existing literature on AI implementation in auditing and general AI applications which can potentially be adopted in the auditing process.

The research shows that while AI involvement in Big 4 auditing process today is rather small, it is showing a developing trend towards a moderate extent (Table B in Appendix). Today's existing audit innovation includes AI like natural language processing (NLP), deep learning, inductive logic programming, expert systems, Bayesian networks, robotic process automation, probabilistic programming and computer vision. These AI work in complementary with other technology such as blockchain, enterprise resource planning, drones, cloud-computing, data visualization tool, and optical character recognition (Table A in Appendix).

Furthermore, the results predict that in the future, AI will be moderately involved in Big 4 auditing works and completely take over structured tasks (Table 4.2.1). Tasks like document reviews, information search and producing engagement letter can be fully automated with AI. Some types of AI that are currently not deployed in audit process today also shows potentials to aid some audit steps, such as affective learning in client interaction; and evolutionary algorithms in fraud detection and advanced information search. Thus, as AI increasingly automates audit works, future Big 4 auditors can focus less on manual tasks like data extraction and concentrate on in-depth data analysis for enhanced audit quality and provide value-added audit services to the clients.

Therefore, the research question "To what extent will artificial intelligence transform the job of external auditors in the Big 4 accounting firms?" is answered. AI will transform the work of Big 4 external auditors to a moderate extent. This is because AI will be involved in most of the audit process, except for steps which can be better executed using other platforms like blockchain technology or cloud computing, or directly through human interaction. AI will largely reduce the burden of auditors in terms of evidence gathering, audit sampling, manual testing and data reviews, so they can focus more on analyzing insights supplied by the AI to further assist the client's business operations, focus on the high-risk areas and improve fraud detection. In order to excel in the future AI-driven auditing Big 4, Big 4 auditors need to have sufficient big data knowledge, advanced analytical skills and know how to communicate effectively and think critically. Moreover, there is a need to exercise more professional judgements and skepticisms in handling insights supplied by the AI in order to produce an accurate audit opinion.

There are several limitations encountered while conducting this research. Firstly, while this paper highlights the benefits of AI and assesses their potentials in the auditing process, the paper did not look into the costs of AI implementation and its associated risks. As such, this paper does not fully address the limitations of the use of AI in auditing. Moreover, the results of this research could not show a complete and detailed depiction of AI innovation in Big 4 firms due to the limited information that these firms provide publicly. In this era where audit innovation is prevalent, using a specific type of AI could be a competitive advantage for the firm, and thus they do not share this information unless requested by clients. On top of that, Big 4 firms often use non-technical terms to explain their audit innovation which is easier to understand for the general public. For instance, the phrases "machine learning" and "predictive analytics" which constitutes a different type of AI were commonly used in the Big 4 websites. This makes it difficult to precisely identify the type of AI that the firms are deploying. Lastly, the term "artificial intelligence" itself causes a drawback. What constitutes AI is constantly changing due to the AI effect phenomenon. As machines turn increasingly capable, technology that become common will no longer be considered as AI anymore (McCorduck, 2014). For example, some of the Big 4 firms no longer consider robotic process automation as AI but as other type of technology.

The following suggestions can be delved upon for further research. Future research can investigate the cost-benefit analysis of AI implementation in Big 4 auditing to accurately predict if these firms would indeed implement these technologies in the future. Moreover, this research also shows that Big 4 firms are not just focusing on AI, but also on other audit innovation like drones, cloud-computing and blockchain. While these topics were touched upon briefly in this paper, more research is required to focus on these topics to understand how they will affect the work of auditors, especially as they play complementing roles with AI. Future research can also involve AI experts and Big 4 auditors to fully understand the logic behind how each AI works and the extent to which they will progress in the future audit. All these suggestions will provide more insights into the technology-driven future of external auditing works in the Big 4 firms.

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Appendix

Table A: Current audit innovation in Big 4 firms

Technology	System(s)	Function(s) in auditing process
AI	Natural language processing (NLP)	1. Document review 2. Data extraction
	Deep learning	1. Detect anomaly in financial or non-financial information 2. Advanced pattern recognition 3. Analysis of structured and unstructured data 4. Predictive analytics 5. Financial calculation
	Inductive logic programming; Expert systems; Bayesian networks	1. Generation of hypothesis for audit risks assessments 2. Generate relevant questions for in-depth data analysis
	Robotic process automation	1. General ledger reconciliation 2. Counting of inventory 3. Audit confirmation 4. Generate emails to clients 5. Gathering audit evidence into a single platform 6. Automate client's transactional process
	Probabilistic programming	1. Investment valuation 2. Predictive analytics 3. Identification of process inefficiencies 4. Identification of business risks and risky transactions
	Computer vision	Technology utilized for drones: 1. Remote sensing 2. Advanced imagery
Others	Blockchain	1. Transactional analysis 2. client's data consolidation for easy access
	Enterprise resource planning	1. Activity-based audit workflows 2. Centralized audit project management
	Drones	1. Observation of inventories in remote locations 2. Observation of control performance activities
	Cloud-computing	1. Digitalize end-to-end audit process 2. Streamline communication with clients 3. Secure data transmission from the client's system to auditor's system
	Data visualization tool	1. Real time monitoring of audit process 2. Easier analysis of audit evidence and client's financial information
	Optical character recognition	1. Convert images or documents into text data

Table B below indicates the current involvement of AI in external auditing process provided by the Big 4 firms. If AI is not applicable, another more suitable type of technology (if any) is written on the “Is AI involved in the audit step?” column. The AI involvement in the audit step is colour-coded based on the extent of involvement as follows:

No involvement
(AI plays no role in the audit step)
Moderate involvement
(AI plays some roles in the audit step, however human action is required)
High involvement
(AI plays major roles in the audit step, human action is optional)

From Table B, it can be seen that the AI implementation in Big 4 auditing today is mostly moderate or absent, with some high involvement of AI in document reviews and inspections steps. This shows that today’s AI involvement in Big 4 auditing is small, though it is showing a developing trend towards a moderate extent.

Table B: Current state of AI innovation in Big 4 firms

Audit Process	**Is AI involved in the audit step?**
Phase 1: Client Acceptance	
1. Evaluation of client’s background and reason for auditing	
• Search on publicly available information	
• Interaction with client, previous auditor, legal team	
• Document review	
2. Check ethical requirements regarding the independence of auditors and the non-audited services they offer to the client	
• Check through the audit firm’s database	Blockchain technology
3. Provide an engagement letter to the client	
• Use a general engagement letter template and fill in with agreed terms between the auditor and client	
Phase 2: Audit Planning	
1. Obtaining a substantial understanding of the client & audit risk assessments	
• Consulting the clients on their objectives and expectations towards its stakeholders	
• Conducting analytical procedures of client’s transactions	
• Inspecting the client’s core activities, accounting policies, management reports, internal control manuals and other relevant documents	
2. Determine the materiality level	
• Determined based on audit risk and general guidelines in the audit company	
3. Develop an audit programme	

- Outlines the audit objectives, timing and audit procedures to obtain the required evidence

Cloud computing

Phase 3: Testing and Evidence

1. Testing of internal controls
   - Direct inquiries to the client's internal audit personnel
   - Observing and reperforming the application of a specific control
   - inspecting documents or reports
   - tracing the information system to find related transactions for financial reporting

2. Performing substantive procedures
   - Analytical procedures: examining accounting data, including financial and non-financial information
   - Test of details of transactions and balances

3. Gathering audit evidence
   - Inquiry, recalculation and confirmation
   - Observation, re-performance
   - Document inspections
   - Analytical procedures

Phase 4: Evaluation & Reporting

1. Review the contingent liabilities and commitment of the client
   - Enquire management
   - Review legal working papers, letters of credit, past tax returns
   - Evaluate known contingent liabilities

2. Review for subsequent events
   - Enquire management
   - Examine minutes of board meetings
   - Review relevant accounting records

3. Review financial statements and other report materials to determine if the required information have been sufficiently disclosed
   - Review relevant accounting records and reports

4. Wrap-up procedures
   - Supervisory review
   - Review of audit working papers
   - Evaluation of audit findings for material misstatement
   - Evaluation of the client's "going concern" assumption

5. Final reporting
   - Report important findings to the client's audit committee
   - eventually produce an audit report containing the audit opinion