The implications, applications, and benefits of emerging technologies in audit

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Abstract
Technological innovation has given rise to the possibility of implementing emerging technologies to potentially improve business operations. Audit firms, as businesses, could utilise emerging technologies to address several challenges the audit profession currently faces. This paper performs a qualitative analysis of prior literature concerning the potential implications and applications of the use of emerging technology in the audit process and the benefits audit firms can realise from using emerging technology. Using emerging audit technology in the audit process could automate many repetitive, mundane tasks and assist with performing analytical reviews on large datasets, thereby improving audit quality and efficiency. This paper adds value firstly by highlighting the potential for technological innovation within the audit process and how this innovation could supplement the traditional audit processes and procedures audit firms currently use and secondly, by incorporating emerging technologies into the audit process and highlighting key benefits that can be derived by shifting away from manual processes.

Introduction
Rationale for audit firms to implement emerging technology
Over the past decade, the world has experienced an exponential increase in technological innovation. Building on the foundations created from digital systems developed during the Third Industrial Revolution, technological innovation in computing has allowed computers to manipulate and analyse data more timeously and effortlessly allowing emerging technologies (Hashimoto et al., 2018) to be used in many positive ways (Beata, 2018; Schwab, 2016; Veerankutty et al., 2018). These emerging technologies may improve the efficiency and effectiveness of operations when applied within a business context (Beata, 2018; Schwab, 2016; Veerankutty et al., 2018). As more businesses use increasingly sophisticated technology, auditors will need to adopt these emerging technologies not only to offer an assurance service in line with the expectations of their clients (Alles, 2015) but also to allow auditors to respond adequately to the risks associated with their clients using more complex technology (Alles, 2015; Appelbaum et al., 2017). Amid the pressures currently faced by the audit profession to improve the quality of its services (Botic, 2018; Harris, 2016) and reduce audit fees (Asthana et al., 2018) despite resource constraints (Persellin et al., 2019) and time constraints (Ferguson, 2016; Persellin et al., 2019), many audit firms have turned to emerging technologies to improve audit quality and efficiency (Harris, 2017). As such, this has prompted audit firms, particularly the 'Big 4' audit firms, to invest substantial resources into developing and implementing emerging technology in their audit processes (Deloitte, 2020; EY, 2020; KPMG, 2020; PwC, 2019).

Research question
This paper provides a detailed qualitative analysis for interrogating the following two research questions:

"Firstly, what are the implications and applications of emerging technologies such as artificial intelligence (AI) (including data analytics) and robotics process automation in the audit process? Secondly, how have these emerging technologies improved the overall audit effectiveness and efficiency?"

The scope restriction for emerging technology in the research questions is based on emerging technology most commonly covered in prior literature and mainstream media. Other emerging technologies may exist, but they have not been specifically considered in this paper.

Before answering the research question, several broad terms are first defined and where necessary, elaborated on, to provide the context within which these terms are used in the paper. The terms "artificial intelligence", "robotic process automation" and "big data" are defined below.

Definitions
Artificial intelligence

The Institute of Electrical and Electronics Engineers Standards Association Corporate Advisory Group defines AI in the *IEEE Guide for Terms and Concepts in Intelligent Process Automation* (2017) as a mixture of cognitive automation, machine learning, reasoning, hypothesis generation and analysis, natural language processing, and intentional algorithm variations that produce comprehension and analysis equalling or surpassing the competence of humans.

AI allows computers to perform tasks that require human intelligence such as problem-solving, recognition of text, speech and images, reasoning and learning by equipping the computer with the ability to think like a human and adapt to their environment as necessary (Copeland, 2020).

AI can be categorised into four further sub-divisions consisting of machine learning, artificial neural networks, natural language processing and computer vision (Hashimoto et al., 2018).

Machine learning is defined in the *IEEE Guide for Terms and Concepts in Intelligent Process Automation* (2017:14) as:

"Detection, correlation, and pattern recognition generated through machine-based observation of human operation of software systems along with ongoing self-informing regression algorithms for machine-based determination of successful operation leading to useful predictive analytics or prescriptive analytics capability."

By focusing on how machines learn from past patterns appearing in data, machine learning allows the machine to perform future tasks more efficiently and effectively (Alpaydin, 2016; Hashimoto et al., 2018).

Many other AI applications have been developed due to an artificial neural network's ability to function like a human brain in receiving, processing, and responding to information (Deo, 2015; Hashimoto et al., 2018). Artificial neural networks therefore replicate the human brain in a computer.

Natural language processing allows computers to understand language, whether written or spoken. Natural language processing has been used in applications such as search engines (for example, Google), speech and document categorisers and virtual assistants such as Apple's Siri (Quarteroni, 2018).

Computer vision equips computers with "human sight" and allows them to recognise and understand visual aids such as images and videos. Applications of computer vision include fingerprint recognition, motion capture, surveillance, optical character recognition and machine inspections (Szeliski, 2011).

Robotic process automation

The *IEEE Guide for Terms and Concepts in Intelligent Process Automation* (2017:11) defines robotic process automation as:

"A preconfigured software instance that uses business rules and predefined activity choreography to complete the autonomous execution of a combination of processes, activities, transactions, and tasks in one or more unrelated software systems to deliver a result or service with human exception management."

Simply put, robotics process automation allows robots to perform tasks by following a set of rules (Moffitt et al., 2018).

Big data

"Big data" has no official definition (Favaretto et al., 2020; Gandomi & Haider, 2015) but most definitions tend to include any combination of three characteristics, namely volume, velocity and variety of information that require financially economical, innovative processing to provide increased understanding, the ability to make decisions and the automation of processes (Gartner, 2012).

Favaretto et al. (2020) elaborate on the concepts of volume, velocity, and variety. Although there is no common understanding of what is considered "big" for data by today's standards, volume typically refers to the size of the dataset. Velocity refers to data that is created and processed at an exponential rate, while variety acknowledges that data may consist of financial and non-financial information (such as images and videos) derived from numerous sources such as social media and administrative platforms. Typically, the size of the dataset is considered the most important aspect of "big data" but Gandomi and Haider (2015) argue that all three characteristics hold equal prominence.

Definitions for "big data" from other reputable organisations and bodies are presented below and for the most part, have common characteristics:

"Large, diverse, complex, longitudinal, and/or distributed data sets generated from instruments, sensors, Internet transactions, email, video, click streams, and/or all other digital sources available today and in the future." (National Science Foundation, 2012:2).

"Data that challenge existing methods due to size, complexity, or rate of availability." (National Science Foundation, 2014:3).

The European Commission (2016:1) refers to "big data" as:

"Large amounts of different types of data produced from various types of sources, such as people, machines or sensors. This data could be climate information, satellite imagery, digital pictures and videos, transition records or GPS signals. Big data may involve personal data: that is, any information relating to an individual, and can be anything from a name, a photograph, an email address, bank details, posts on social networking websites, medical information, or a computer IP address."

Lastly, the Association of Certified Chartered Accountants (2020) defines big data as very large collections of information that may be examined to discover associations and meaning, in particular relating to people.

Certain definitions for "big data" extend the definition to include characteristics related to versatility, vitality, exhaustivity and extensionality (Favaretto et al., 2020).

Other definitions of "big data" sometimes refer to the techniques used to analyse the dataset (Favaretto et al., 2020). However, Salijeni et al. (2018) refer to those techniques under the term "big data analytics" thus distinguishing the techniques from the nature of the data.

For this paper, "big data" refers to data exhibiting the characteristics of volume, velocity and variety as described by Favaretto et al. (2020), and consistent with Salijeni et al. (2018), the definition will be used separately from the techniques used to analyse it.

Research design

This paper answers the research questions by first outlining the methodology used in this paper. A literature review follows, discussing possible applications of emerging technology by audit firms and, where necessary, how it is applied in the audit process. Key benefits to audit firms, the audit industry, and the audit process from using emerging technology are then discussed in detail.

As technology continues to evolve, new applications are routinely created allowing numerous benefits to be realised. This poses a challenge in attempting to thoroughly address this paper's research question. Given the practical limitations, this paper highlights and analyses the key benefits most identified, allowing a more thorough, relevant, and valuable review to be performed. Where necessary, counterclaims to the key benefits are also highlighted to provide a more complete analysis of the prior literature.

The conclusion then presents an overall analysis, the paper's limitations, and areas for future research.

Methodology

The paper used directed content analysis to provide greater clarity on the use and benefits of emerging technology on the auditing profession, audit firms and the audit process. While the goal of directed content analysis is usually to extend theory (Hsieh & Shannon, 2005), in this case, prior literature was used to collate, summarise, and analyse studies to help focus future research questions.

The sample selection began with an online search of the Google Scholar and University of Cape Town library databases. All papers and published reports on emerging technology in audit were identified. The abstracts of these studies were then scrutinised to ascertain whether they contained information relevant to this paper. As research relating to emerging technology is still gaining prominence, where necessary, online searches for supplementary information were accessed from the websites of reputable sources such as the 'Big 4' audit firms and professional accounting bodies. The selected literature was then reviewed in terms of the two research questions of this paper.

Literature review
Introduction
This literature review briefly discusses how emerging technology can be used in the audit process. The key benefits associated with audit firms using emerging technology is then highlighted and analysed in more detail.

Audit implications and applications
Audit implications
The International Auditing Assurance Standards Board (IAASB) has acknowledged the rapid rate at which technology is changing, particularly concerning big data and how it may impact the performance of an audit (IAASB, 2016). ACCA (2015) has also acknowledged the impact that big data will have on the audit industry and has called for audit firms to redesign how they perform their audits by using modern technology.

In performing an audit, ISA 200 requires the auditor to exercise professional judgement (IAASB, 2009). Audit methodologies have incorporated this requirement but have been developed on the premise that humans — not machines — exercise professional judgement. However, as certain tasks become automated, this may necessitate adjusting the audit plan to incorporate the shift from manual to automated tasks (Kend & Nguyen, 2020). This may then involve performing additional testing on the operating effectiveness of controls of the algorithms and decision processing used in machine learning (Kend & Nguyen, 2020). In essence, there could be a greater emphasis on auditing the machine (Zhang, 2019).

Audit applications
There are three broad areas of the audit where emerging technology could assist by either automating the task or providing the auditor with the necessary information needed to perform the task:

Aspects of the audit related to work processes and workflows.

Aspects of the audit that resulted in recurring judgements that are largely based on the information available to the auditor.

Judgments that are very different amongst auditors causing auditors to either disagree or not arrive at the same conclusions (Moffitt et al., 2018).

High volume structured and mundane tasks (such as the two areas identified by Moffitt et al. (2018) above) are ideally suited to be automated by robots (Cohen et al., 2019; Moffitt et al., 2018). These would include tasks such as performing reconciliations, matching documents for control and substantive testing (Moffitt et al., 2018), matching or transferring data from one source to another (Cohen et al., 2019; Cooper et al., 2019; Kend & Nguyen, 2020), and filtering and extracting specific data fields from a larger dataset (Cohen et al., 2019). Other robotics applications include the use of drones to perform inventory counts (Kend & Nguyen, 2020).

AI, however, can be used in all three areas of the audit identified by Moffitt et al. (2018). AI is typically best employed to automate tasks that would require the auditor to draw a conclusion based on the evidence gathered. These tasks do not require the use of professional judgement to perform being typically low-risk tasks that could be performed by an average person, even one without an auditing background, who can follow simple but clear instructions. An example of such an activity would include counting the number of inventory items appearing in an image or extracting certain terms from a contract. Once the AI has completed the task, the auditor can then review the results for errors and make any adjustments necessary (Zhang, 2019). When professional judgement is required to perform a task, AI is a useful tool for providing the auditor with the information needed to be used as the basis for the auditor to

arrive at an appropriate judgement. However, the final interpretation of the information is left to the auditor. AI is, therefore, a useful tool for enhancing auditors' professional judgement, not replacing it, thereby improving audit quality (Zhang, 2019).

Popular applications of AI in the audit process include, but are not limited to:

A virtual assistant developed as a conceptual model by Li and Vasarhelyi (2018) that can be used in audit brainstorming meetings for information retrieval and risk assessment purposes.

The use of natural language processing for automated contract analysis for risk assessment and performance of audit procedures (Zhaokai and Moffitt, 2019).

The use of algorithms and machine learning to analyse large datasets (Jiali & Khondkar, 2017; Kend & Nguyen, 2020). This has implications for risk assessment and gathering audit evidence.

Drones using computer vision to identify items to perform an inventory count (Christ et al., 2019).

AI has the potential to be used in even greater ways as AI subfields can be combined with other advances in computing (Deo, 2015), which could lead to even more opportunities for AI to be used within the audit space.

Key benefits

The benefits facing an audit firm from implementing emerging technologies into the audit process are extensive. The use of AI and big data may result in audits being more effective, both in terms of audit quality and cost (Jiali & Khondkar, 2017; Zhang, 2019). The factors that contribute to improving audit effectiveness and efficiency are elaborated on below.

Analysing large data sets

ISA 200 recognises the inherent limitations of an audit. One of those limitations is that it is impractical to audit all the available information due to time, cost, and resource constraints. Consequently, where necessary, auditors will use audit sampling techniques. However, there is an unavoidable risk that the financial statements may not be free from material misstatements, despite auditors performing their audit following the ISAs, as items not selected as part of the sample are not tested and may contain material misstatements (IAASB, 2009). Computer-assisted audit techniques (CAATs) assist auditors to perform many facets of an audit, such as sample selection for testing (Christensen et al., 2015; Salijeni et al., 2018). Although the use of big data analytics in the audit process is still in its infancy, analytics has routinely been used within the audit space before the development and use of big data analytics (Salijeni et al., 2018). However, existing analytical techniques utilising CAATs have several limitations in terms of the statistical techniques that can be performed (Brown-Liburd et al., 2015). Furthermore, CAATs are not able to integrate non-financial data from external sources such as social media networks and newspaper articles (Brown-Liburd et al., 2015). The use of AI in data analytics allows auditors to overcome these limitations and analyse larger, more diverse data sets (Brown-Liburd et al., 2015). This therefore reduces the risk of auditors not testing items that may contain material misstatements.

The limitation has, among others, allowed auditors to provide only reasonable assurance. As auditors have the ability to audit much larger samples, if not 100 percent, of their clients' data, they are also able to provide a greater level of assurance (Harris, 2017; Jiali & Khondkar, 2017; Kend & Nguyen, 2020; Salijeni et al., 2018). Big data analytics may allow auditors to perform more credible and effective audits (Alles, 2015) as audit practitioners are able to analyse real-time data of their client's transactions (Jiali & Khondkar, 2017; Kend & Nguyen, 2020). Auditors will also be able to collect information relating to external parties (such as newspapers, emails, social media platforms etc.) from sources other than the accounting records (Jiali & Khondkar, 2017). This enables auditors to increase the sufficiency of the audit evidence they collect, and which may be used to identify risk indicators or misstatements which would previously have been undetected when examining only financial data.

By testing 100 percent of the population, auditors are not only able to offer a greater level of assurance but are also able to address one of the limitations of the current audit process created by sampling and thus improve overall audit quality (Kend & Nguyen, 2020).

Machine learning has helped auditors to analyse big datasets as the machine learns subtle patterns in the larger dataset and is able to apply the same logic to similar cases (Dickey et al., 2019). Machine

learning thus makes it possible to analyse larger datasets as more indirect and complex patterns and multivariate effects, including those that may have been previously overlooked, are identified compared to the conventional statistical analysis technique performed by humans and computers (Hashimoto et al., 2018; Obermeyer & Emanuel, 2016). Machine learning thus allows previously inaccessible data to be analysed as current technology lacks the technological advances to analyse larger, complex datasets (Obermeyer & Emanuel, 2016). This then allows auditors to perform their audit work in a more focused manner (Dickey et al., 2019) and make better judgements (Zhang, 2019).

Improved accuracy

Zhang (2019) and Moffitt et al. (2018) state that robots can perform repetitive and rules-based tasks more efficiently and with far fewer errors than humans. Natural language processing and image recognition have also advanced to the stage where their capabilities are almost as accurate as a human's (Zhang, 2019). These automated tasks allow the audit to be performed more efficiently, but more importantly, when combined with a review by the auditor, could produce results that are as reliable as manual processes (Zhang, 2019).

Focusing on high-risk areas rather than performing mundane tasks

Technology allows auditors to spend a greater portion of their time on the audit applying their minds to more complex, subjective areas of the audit as mundane and repetitive tasks can now be automated, freeing up the auditor's time that would previously have been allocated to the performance of mundane tasks (Harris, 2017; Kend & Nguyen, 2020).

Reducing the time spent on tasks

If larger datasets are analysed using traditional statistical techniques, this requires a significant time investment for auditors to perform the necessary testing. Reducing the time spent on audit tasks reduces audit costs. Alles (2015) claims that auditors may decrease the costs associated with their audits by using big data analytics. The use of big data analytics improves the overall efficiency of the audit (Salijeni et al., 2018).

There are some concerns that emerging technology may hamper efficiency. Audit practitioners express concern regarding the substantial time required upfront to ensure the technology operates effectively and to address any 'teething problems' (Kend & Nguyen, 2020).

Other efficiency concerns may arise from the ability to examine entire data sets potentially resulting in auditors 'over-auditing' (Kend & Nguyen, 2020) or highlighting patterns within the data which appear to indicate that the financial information contains misstatements and would thus require the auditor to respond expending time and effort, when in fact the patterns represent outliers (Salijeni et al. 2018).

These may lead to an increase in costs as auditors have to spend more time addressing these efficiency concerns (Salijeni et al. 2018).

Improved fraud detection

Fraud detection may also be more effective by using big data analytics as both financial and non-financial information can be analysed. For instance, phone calls, emails and meetings of management and directors can be analysed more thoroughly for patterns or links with financial information to detect instances of fraud (Jiali & Khondkar, 2017). Big 4 respondents expressed views in favour of using big data analytics as it highlights suspicious, high-risk areas that auditors should focus on (Dagilienė & Klovienė, 2019).

Using AI offers many benefits by improving effectiveness and efficiency in the audit process, but these benefits must be weighed up against the threats to the audit industry (Kend & Nguyen, 2020).

Conclusion

The paper's objective of analysing how emerging technology is used in audits and the positive effects audit firms can realise from its use was answered through the two research questions. More specifically, what are the implications and applications of emerging technologies in the audit process and how have these emerging technologies improved the overall audit effectiveness and efficiency? This analysis makes two meaningful contributions: Firstly, the analysis highlights the potential for technological innovation within the audit process and how this innovation could supplement traditional

audit processes and procedures currently used by audit firms. Secondly, incorporating emerging technologies into the audit process highlights the key benefits that can be derived by shifting away from manual processes, wherever possible. These key benefits include an improvement to audit effectiveness and efficiency by reducing the time spent on tasks, allowing auditors to spend more time auditing high-risk areas by automating routine, mundane tasks which would previously have had to be performed by auditors, thereby reducing errors, improving fraud detection and equipping auditors with the ability to audit large datasets, if not all of their clients' data, thereby potentially allowing auditors to express a higher degree of assurance and reduce the risk of not testing items that may contain material misstatements.

Limitations and areas for future research

The paper focused on highlighting and analysing the key benefits rather than the threats associated with audit firms using emerging technology. As such, no analysis was performed as to whether audit firms should invest in emerging technology by contrasting whether the benefits outweigh the threats. Given the emerging nature of the technology, research in this area provides limited empirical evidence of the benefits associated with using emerging technology in the audit process (Salijeni et al., 2018).

Future research could empirically test whether incorporating emerging audit technology results in improved audit effectiveness and efficiency. A quantitative analysis of individual benefits may improve the understanding of key benefits associated with using emerging technology in the audit process. When contrasted with a quantitative analysis of the individual costs, this could aid the decision as to whether the audit profession should implement emerging technology.

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