CPA Australia Global Research Perspectives Program

Building analytics capability for audit efficiency and effectiveness: A need analysis for digital transformation

Final Report

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Executive Summary

Emerging technologies and digital transformation have become pervasive in the contemporary society and business world. Big data and analytics tools are all around us. They have become an essential part of social and organisational lives. Auditing practices are no exception to this ongoing trend of technological adoption and transformation. In parallel with the explosion of technological change, the accounting profession has been keeping pace with innovation and the adoption of technologies in audit. This research project improves the understanding of audit analytics, emphasises the significance of adopting analytics tools, and suggests how to enhance auditors' data analytics and professional capabilities.

Using mixed-method (combining quantitative and qualitative approaches) for data collection and analysis, this study addresses the questions of *(1) what exactly are the analytics tools and technologies adopted by the audit firms in Australia?; (2) how data analytics, audit analytics, machine learning and artificial intelligence are helping audit firms to meet clients changing demands in the current big data-driven environment; and (3) how data analytics, audit analytics, machine learning and artificial intelligence are helping audit firms to manage risk and gain efficiency in audit processes?* In doing so, it contributes to the role of technologies and digital transformation of auditing in the era of big data and analytics. It explores the implications of data analytics, audit analytics, machine learning and artificial intelligence for developing audit efficiency with an aim to find the potential for risk management to inform the future of audit practice. This exploratory research has two objectives. To begin, determine where the need for audit data analytics comes from, how auditors are innovating or embracing analytics for audit practise, and what advantages are being realised as a result of analytics. Second, what difficulties are provided by developing technologies such as audit data analytics, and how are these risks affecting auditee and regulator relationships.

This research delivers on the objectives of understanding the adoption of analytics technologies by audit firms. It sheds light on the contemporary audit environment, emerging technologies, and digital transformation that helping audit firms to manage audit risk and gain efficiency. The findings show the most effective means of analytics to further its use in audit plans and processes to meet the demands from clients and changing technological environment. The key findings of this research show how technology and digitalisation (re)shaping the audit practice in Australia, and how audit firms seeking to build analytics capability by innovating and adopting data analytics, audit analytics, machine learning and artificial intelligence technologies. To then end, key recommendations relate to what, why and how accounting profession and researchers need to engage with emerging areas of audit technologies and digital transformation.

1. Introduction

1.1 Significance of the study

Big data is all around us which has become common in the contemporary business environment (McKinsey, 2018). PricewaterhouseCoopers (PwC) aims to devote US$12 billion in areas such as artificial intelligence and cybersecurity, and create 100,000 new jobs by 2026 to meet the demand on emerging technology (The Wall Street Journal, 2021). The data analytics, audit analytics, artificial intelligence, machine learning, and artificial intelligence technologies have been developed and applied in many areas of business and social life ranging from driver-less cars to efficient energy management systems in homes. These technologies have been developed to capitalise on the big data environment for real-time decision making. Audit firms and audit practices are riding these waves globally (Vasarhelyi et al., 2015). the audit process is set to go through a further digital transformation due to analytics capability, deep learning, and audit automation (Appelbaum et al., 2017). All these technologies can collect and analyse both structured data (accounting and financial information) and unstructured data (emails, social media, audio files, video files etc.). For example, machine learning can help audit firms undertake complex audit tasks in more detail and collect new and complementary evidence (Yoon et al., 2015) from financial and non-financial datasets. Due to the adoption of new technologies, audit firms are supposed to gain efficiency in their audit processes to improve the quality of their audits. However, there is a lack of empirical evidence particularly from Australia as to how and to what extent both big and small audit firms are leveraging these technologies to gain efficiency and effectiveness.

1.2 Opportunities for new knowledge

Audit firms and the whole business environment are being reshaped by big data and analytics (McKinsey, 2018). To satisfy the demands of audit clients that operate in this changing environment, audit firms in Australia are increasingly adopting data analytics, audit analytics, artificial intelligence, machine learning and artificial intelligence technologies in their audit practice. Big data analytics and audit data analytics have become the currency of business (Sun et al., 2022), and new advancements in these technologies promise audit firms more efficiency and effectiveness in their auditing and analytical procedures (Appelbaum et al., 2018; Vasarhelyi et al., 2015). These technologies also promise to provide high levels of assurance through the collection of robust evidence (Yoon et al., 2015) and thorough audit procedures (Appelbaum et al., 2017). However, empirical study is needed to determine whether and to what degree these audit data analytics tools are being used and assisting audit firms in Australia in meeting client demand, changing data environments, and technology adoption.

1.3 Scope of the study

The research focuses on identifying the most effective means of data analytics to further its use in audit processes to meet the demands from clients and changing assurance environment. This project will highlight data analytics, audit analytics, artificial intelligence, machine learning and artificial intelligence technologies which auditors are using and can be used to gain the expected efficiency and effectiveness. This shed lights on what types of new audit evidence can be gathered and analysed through new data analytics, audit analytics, artificial intelligence, machine learning and artificial intelligence capabilities and how new audit procedures need to be developed to cope with the data analytics, audit analytics, artificial intelligence, machine learning and artificial intelligence capabilities of clients.

1.4 Objectives of the study

Everyday auditors and the audit firms are working to help their clients with assurance. It is the explosion of big data of their clients has created the need for audit firms to adopt data analytics, audit analytics, artificial intelligence, machine learning and artificial intelligence technologies. That's why audit firms need to continue investing in new technologies to create the best value for them and their clients. To do that audit firms needs to know what best practices and what new technologies or processes are required to developed or invest in. Hence, this project's objectives are three-fold: (1) to understand how data analytics and automation technologies are helping audit firms to improve audit process and minimise risk; (2) to explore how audit firms using data analytics, audit analytics, artificial intelligence, machine learning and artificial intelligence for industry assessment, risk analysis, audit tests, and confirmation; and (3) to investigate whether audit firms are seeing efficiency and effectiveness gains through the use of data analytics, audit analytics, artificial intelligence, machine learning and artificial intelligence.

1.5 Research questions

Despite the fact that this study is theoretically motivated and grounded in the relevant literature our research questions are exploratory as our goal is to uncover the usages of technology and practices of data analytics in audit by identifying and configuring different perspectives in relation to institutional and contingency factors surrounding innovation and adoption of technology.

(1) what exactly are the data analytics, audit analytics, artificial intelligence, machine learning and artificial intelligence technologies adopted by the audit firms in Australia?;

(2) how are data analytics, audit analytics, artificial intelligence, machine learning and artificial intelligence helping audit firms to meet clients changing demands in the current big data-driven environment; and

(3) how are data analytics, audit analytics, artificial intelligence, machine learning and artificial intelligence helping audit firms to manage risk and gain efficiency in audit processes?

1.6 Methodology

Using a mixed-method of combining quantitative and qualitative approaches (Malina et al., 2011) this study collected data from various sources including online survey, interviews, focus group discussions and review of audit reports and academic literature over a two year period (January 2020- December 2021). To develop a robust understanding of the adoption of analytics and technologies in audit practices and how the influence of institutional and contingency factors connects audit firms and their work with the wider technological environment in the Australian audit sector, a mixed-method approach was adopted. It has been argued that by collecting a broad range of data on the same phenomenon, the researcher can improve the accuracy of their analysis and findings (Hoque et al., 2013; Jick, 1979). In this research strategy, different methods complement each other and, in turn, offer the potential for rigorous and robust research in management accounting (Grafton et al., 2011; Hopper and Hoque, 2006). Following this argument, this study employs mixed method or data-triangulation approach for validation and between-cross case triangulation (Creswell, 2003; Creswell and Plano Clark, 2007; Hoque et al., 2013; Tashakkori and Teddlie, 2003). A total of 127 survey included in the study out of 189 responses received as 62 were invalid or unusable for analysis. Auditors from the three audit firms participated in a total of 20 online interviews using MS Teams. Two focus group discussions conducted to gather data so that we could map the technological adoption, concerns and opportunities by combining findings from mixed-method approach.

1.7 Contributions

This project contributes to the role of new technologies and role digital transformation in external auditing in Australia in the era of big data. It explores the implications of DA, ML and AI for developing audit efficiency and effectiveness with an aim to find the potential for changes to radically alter the current and future of audit practice. Key focus areas are the use of analytics technologies by audit firms in modern audit environment; emerging technologies that help audit firms to manage audit risk; and digital transformation of audit plans/processes to gain efficiency and effectiveness in a technology-driven business environment. The findings of this research show how emerging technologies and digitalisation reshaping the audit practice in Australia and globally, and why accounting and auditing researchers should engage with research in new technologies of audit data analytics. First, this exploratory research contributes by illustrating from where the need and demand for audit data analytics comes from, how auditors are innovating or embracing analytics technologies for auditing, and what advantages are being realised as a result of analytics.

Second, what difficulties are provided by audit firms developing their own technologies such as audit data analytics, and how are these risks affecting auditee and auditor-auditee relationship. This study makes an incremental contribution to the accounting literature by using diverse theories and research methods. First, it interprets and explains multiple roles of audit analytics using theoretical triangulation (Hopper & Hoque, 2006; Hoque et al., 2013) of institutional, contingency, and innovation theories of socio-technical systems: maintaining organisational efficiency, increasing operational effectiveness, developing dynamic capability, and managing external legitimacy. As a result, this study adds to the audit scholarship and practice by providing empirical evidence that the availability of new technologies influences auditors' choice of data analytics or audit analytics as a risk and performance management tool for programme audits. The methodological triangulation, which is described in more detail below, aids in the collection of data and the explanation of audit analytics technologies, usages, causes, requirements, difficulties, and managers' views of the frequency and complexity of analytics systems. Second, in terms of adding to the accounting technique literature, this study used a mixed method approach to gather and analyse data using both quantitative and qualitative methodologies over a 12-month period, including a survey, interviews, documentary data, and focus group discussion. Using different types of data (Creswell 2009; Creswell and Plano Clark, 2007), we were able to combine inductive and deductive thinking to address the research problem by identifying determinants of audit analytics adoption and usage in the audit sector (Creswell 2009; Creswell and Plano Clark, 2007).

1.8 Policy and practice implications

The new knowledge will help audit firms to assess the benefits of available data analytics technologies and they can find which ones are better to meet the clients internal and external environment. The new knowledge from this study will help audit firms to optimize their audit plans and processes. In addition, accounting professional bodies need to recognise the need for building audit data analytics capability not only for adoption but also for innovation and controlling technology. Technologies are not proxies for professional expertise or professional judgements. Technologies must be used in conjunction with professional judgement.

2. Literature on audit analytics

When audit analytical methods are paired with audit methodologies, judgement, technological developments, digital audit tools, and new techniques may be a beneficial contribution to the audit practice (Appelbaum et al., 2017, 2018; Brown-Liburd et al., 2015; Gepp et al., 2018; Hamdam et al., 2022: Khansalar et al., 2015). Data analytics, machine learning, and artificial intelligence are increasingly digitally transforming auditing procedures (Alles, 2015; Cao et al., 2015; Vasarhelyi et al., 2015). For example, artificial intelligence can enhance audit inquiry where audit bots can be used to inquire with client managers about unexpected or unusual transactions that can be identified through continuous auditing (Raschke et al., 2018; Zhang et al., 2015). Further, text analysis can be used to analyze client responses, both from a content perspective and to identify potential attempts to persuade the auditor to support the client's position.

Audit data analytics enables auditors to collect more evidence in order to provide more comprehensive reports on estimations projections, going concern, fraud detection, and managing risks (Alles, 2015; Yoon et al., 2015). As audit data analytics becomes a more important part of business operations, auditors will be able to use contemporary analytical techniques to track the success of client management (Cao et al., 2015). Prior research found that audit data analytics allow auditors use techniques to computationally determine available actions, their consequences, and/or alternatives, given the complexities, rules, and constraints of the engagement. Because of analytics, deep learning, and audit automation, the audit process, for example, is poised to undergo additional digital change. All of these systems can gather and analyse both structured (accounting or financial data) and unstructured data (emails, social media, audio files, video files etc.) (Vasarhelyi et al., 2015). Audit firms are expected to gain efficiency in their audit operations as a result of the use of new technology, therefore improving the quality of their audits (Braun and Davis, 2003). However, there is a paucity of empirical information on how and to what degree both large and small audit firms use these technologies to improve efficiency and effectiveness.

Furthermore, current analytics tools demonstrate their versatility by performing a broad range of activities, from evaluating keywords and patterns in complex digital documents to extracting accounting-related data from a number of sources, including sales, contracts, and invoices. For example, analytics tools can spot abnormalities in a company's financial records, such as abnormally elevated turnover or disbursements for unusually high transactions (Rapoport, 2016), as well as find unexpected trends in the data. Firms have also begun to use robotic process automation software (also known as audit bots) to minimise the amount of time auditors spend on repetitive and routine activities (Cooper et al., 2019). However, the degree of maturity in the use of Generalised Audit Software (GAS) in Australia is at the low level (Smidt et al., 2019). Although, there is a great deal of opportunity for incorporating technologies for enhanced audit inquiry within auditing processes (Janvrin et al., 2008), specifically for textual analytics.

In the risk assessment process of an external audit, audit data analytics plays a bigger role. The new technology can make even more cost-effective improvements, such as real-time inventory analysis, which lowers the cost of acquiring confirmation proof and allows modern auditors to do their jobs more quickly (Brown-Liburd et al., 2015; Dai and Vasarhelyi, 2016). Although the technological revolution is swiftly attacking different fields' possibilities, there is still ambiguity regarding challenges and consequences (Alles and Gray, 2016; Earley, 2015; Kruskopf et al., 2019; Nwachukwu et al., 2021). Brown-Liburd et al. (2015) discusses the challenges that auditors encounter when incorporating big data and audit analytics supported by various analytical tools. Brown-Liburd et al. (2015) raised questions about implications big data and analytics on audit judgment by addressing the issues of information overload, information relevance, pattern recognition, and ambiguity. The study calls for future research to address related issues to examine the practice of analytics and technologies in auditing. Thus, what is the attitude of existing auditors or audit firms, and how are they adopting and using audit data analytics, and how are they using audit data analytics to increase efficiency and improve effectiveness in their audit practice warrant new research.

According to Gepp et al. (2018) and Schmidt et al. (2020), there is considerable pushback to audit data analytics methods being used. Although insights from audit partners suggests that several top audit firms have begun to implement new technology tools and approaches in practise it mostly due to clients growing use of analytics (Appelbaum et al., 2018). On the other hand, Gepp et al., (2018) found a consensus in their study that some emerging technologies are underutilised in auditing. One probable explanation for this apprehension is that auditors are not sure which technologies and techniques to use for evidence collection and analytical procedures (Appelbaum et al., 2018). External Audit Analytics (EAA) framework is proposed by Appelbaum et al. (2018) to identify gaps, to provide motivation for new research, and to classify and outline the main topics addressed in the literature on analytics for audit procedures and audit engagement. Another explanation is that auditors hesitant to utilise these new approaches, or the technology their audit clients are using are far ahead (Appelbaum et al., 2017).

While audit data analytics provide exciting new potential and benefits for auditors, they also pose distinct difficulties and challenges (Alles and Gray, 2016; Earley, 2015; Krahel and Titera, 2015; Tiberius and Hirth, 2019). Analysing deep learning to audit procedures, Sun (2019) highlights the challenges faced by auditors, accounting firms, regulators, and accounting educators in promoting wider adoption of deep learning in auditing. One of the notable challenges for auditors and regulators is how to develop an efficient and cost-effective information sharing within audit firm while preserving data privacy and security (Sun, 2019). Thus, many researchers and practitioners see emerging technologies as a threat to the status quo of the accounting and audit profession, with the potential for the emergence of new audit risks (specifically detection risks). Auditors must weigh the benefits of new technology against the appropriate use of data, and then assess any unexpected effects or audit risks (Kend and Nguyen, 2020). As new auditing technologies become more common, academic and professional expertise will need to grow in order to handle the possibilities and challenges that these technologies now bring to the audit practice and to the accounting profession in general. By considering recent technological developments in auditing, this study responds to calls for a more in-depth exploration of what and how analytics and technologies are adopted and diffused as a response to growing emergence of big data and analytics.

3. Research design and method

This project uses a mixed method or data-triangulation (Creswell, 2009) approach involving field-based interviews, online survey data, focus group discussions and review of documents. There are several call in the literature that recognise the potential of case-based research to supplement survey research. This project spans over a 12-month period to develop a robust understanding of the adoption of audit analytics in audit practices and how the influence of institutional, contingency and innovation factors connects auditors with the social-technical and vice-versa in the Australian context. In the social sciences, mixed methods research has a long history (Creswell, 2009). There are several studies that use a mixed method approach in accounting, as well as methodological articles that investigate the features of this research approach. It has been argued that by collecting a broad range of data on the same phenomenon, the researcher can improve the accuracy of their judgments and contribute to theoretical refinement. Despite the fact that this study is theoretically motivated and grounded in the relevant literature three research questions are exploratory as the goal is to uncover audit analytics and other big data analytics and values by identifying and configuring different perspectives from auditors in relation to institutional, contingency and innovation factors. This comprehensive research approach has captured social, organisational, and institutional aspects of auditing and data analytics practices and the complex interplay of different institutional and socio-technical factors. The approach has primarily focused on the experience of the auditors through the focus group discussions, online survey and interviews about the design, implementation and use of analytics in auditing.

3.1 Data collection

The field research has five distinct but interrelated stages to extract extensive descriptions of innovation, adoption, and practices from descriptive analysis from the focus group, survey and interview to further validation goals.

3.1.1 Documentary evidence

To begin, a wide range of organisational and institutional papers on the innovation and diffusion of big data analytics and/or audit analytics, including annual reports and auditor reports for the years 2019-2020, were studied and analysed. Audit reports created as a direct response and result of larger institutional elements such as audit standards, legislation, and reporting obligations that were introduced in Australia are among the publicly available records. In terms of documentation data, websites, media stories, newspaper articles, social commentary, and audit firm websites have all been studied, in addition to audit and annual reports. Both electronic and printed materials were examined for this aim.

3.1.2 Focus group one

The goal of this focus group discussion was to gather data so that we could map the difficulties and opportunities for navigating cost concerns by combining study findings. Ten senior audit managers from three audit firms (two big four and one medium-large non-big four) participated in a focus group discussion on their perceptions and experiences with innovation and analytics diffusion in their businesses. This offered a chance to get input on the study goals, topics, and design that had been developed throughout the literature review and document analysis stages. The participants were invited to a casual yet constructive online group discussion (because to Covid-19-related travel and social distance restrictions). Participants from Melbourne and Sydney, Australia, used MS Teams as a virtual conference room. The focus group was an efficient way to communicate essential information with individuals who are using analytics for their audits, as well as provide a social venue for some stimulating debates. The researcher moderated the group discussion so that all participants could freely express their opinions on big data analytics, audit analytics, analytics-systems, risk management, efficiency gains, and how these emerging practises relate to strategic decisions, control, and performance management in their organisations. The attendees discussed current trends, advantages, difficulties, and possibilities in the areas of audit engagement management, risk management, enhanced transparency, future investment, and performance measurement concerns encountered by auditors. Our field data has benefitted from audit managers' practical feedback and ideas, which have assisted researchers in refining and further developing theoretical models for survey and interview questions in order to extract useful empirical findings.

3.1.3 Online survey of auditors

The pilot survey questionnaire was created using existing research, document analysis, and focus group discussions with audit managers from three different audit firms. Due of the Covid-19 epidemic, responses from the focus group discussion recommended that an online survey might be more suitable. I then designed and analysed the surveys using Qualtrics (a vendor-provided web platform that the researchers' university subscribed to). The survey was pilot tested by two managers from audit firms and three academics from the researchers' business school and an international business school in order to enhance the design and focus the content. The online survey was carried out using online platforms. The surveys were distributed using Prolific and Amazon AMturk (vendor-provided online platforms). The participants came from all six Australian states and two territories (New South Wales, South Australia, Tasmania, Queensland, Victoria, and Western Australia and the Australian Capital Territory and the Northern Territory). The online survey began on June 1, 2021, and ended on December 31, 2021. There were 189 replies in total, but 62 of them were invalid or unusable for analysis, thus only 127 were included in the descriptive analysis. Auditors from various levels within the firms (audit partner, director, senior manager, audit manager, senior and junior auditors who are involved with the use of technology and analytics in audit related tasks and decision making) as well as from various types of audit firms participated in the survey (Big Four, large, medium, and small-sized firms).

3.1.4 Interview-based case studies

Based on survey results, three audit firms were chosen for in-depth qualitative case studies as part of a mixed method or data-triangulation approach (Creswell, 2009) to address "how" and "why" questions in connection to big data analytics and audit analytics system innovation and diffusion. I used the same framework for each case while gathering case materials and presenting evidence, and I drew a single set of conclusions from cross-case analysis (Yin, 2019). The goal is to mobilise knowledge from each individual case before aggregating it by comparing and contrasting them. The findings of our study revealed the extent to which firms use analytics in their audit systems and procedures, but they did not explain how or why auditors make sense of them at an organisational level. Based on the survey results, an interview protocol was created. The case studies added to the evidence of the effects of the changing environment, the emergence of technologies, competitiveness, auditors' need for and perception of analytics for evidence/information intensity and elaborateness, and motivations for the development or improvement of analytics systems within audit firms. From the researcher's contact, the interviewees were identified. Auditors from the three businesses participated in a total of 20 online interviews with MS Teams. Interviews took up a total of 26 hours. The interviews ranged from 60 to 90 minutes in length. None of the interviews and focus group discussions were audio recorded at the request of the participants, although comprehensive notes were recorded from each.

3.1.5 Focus group two

At this point, the field study's preliminary findings were given to a focus group of five managers from three audit firms, who were asked for confirmation and comment on the draught findings, as well as ideas for future research that would better meet their practical requirements.

3.2 Data analysis

To evaluate the data, I used a mixed methodology analysis (Creswell, 2009; Creswell and Plano Clark, 2007) while referring to Miles, Huberman, and Saldana's (2013) methodologies of qualitative analysis. I first conducted a detailed examination of the data through a variety of descriptive statistics, determining the frequency distributions of values for various groups, and testing for normality and homogeneity of variance. I then computed descriptive statistics (means, medians and standard deviations) for each variable. In addition, I calculated the minimum, maximum and range for both types of variables. Missing, extreme and variable distributions were explored. Then, utilising Broun and Clarke's (2006) methodologies as a general guide, we applied a theory-driven mixed-method coding process to categorise the reduced material. The researcher read the documents, survey results and interview and focus group transcripts to become acquainted with the separate and complete data set as a foundation for triangulated interpretation. After completely familiarised with the quantitative and qualitative data, the data were further evaluated using coding procedures, allowing the researchers to focus on the data's contents.

4. Results

4.1 Findings from literature review

To take stock of existing understanding and practise of data analytics and new technologies in auditing, a thorough examination of the relevant literature and archival document analysis was performed. This study is based on data analytics studies published in academic and practitioner publications in accounting and auditing during the previous 25 years, as well as audit reports and commentary from 2019 to 2021. The study is based on a quantitative (quantitative) and qualitative (thematic/narrative) examination of relevant literature. To begin, determine which subjects, contexts, techniques, and theories are covered, as well as how unique these features are from management accounting research in general. Second, a narrative overview of key findings from diverse research. I utilised a three-dimensional model to analyse the literature: the opacity/transparency of data analytics models, the usage of explanatory or predictive modelling, and structured or unstructured data.

Big data and data analytics have lately emerged as a major and timely study subject in current auditing research, according to the findings. Despite the fact that big data is not a new concept, it has recently resurfaced as a focus for auditing academics and practitioners. This, I believe, is due in part to the huge growth of unstructured data originating mostly from non-traditional sources such as social media and internet publications. I also notice that the majority of research papers focus on normative (what should be) rather than analytical or theoretical frameworks for analytics or machine learning in auditing. The lack of evidence from practice-focused case/field studies on technological innovation, adoption, and implementation of data analytics and machine learning approaches in auditing is highlighted in this analysis.

Reviewing the literature, I have noticed a latent theme in much of the literature addressing a tension between the immense possibilities for effectiveness and efficiency improvements in auditing by using data analytics and the extent that auditors seem to harvest fruitful outcomes for their organization, for themselves, and their profession. Some researchers explicitly address this tension, (see Arnaboldi, Busco, & Cuganesan, 2017) who argue that accountants may be sidelined by marketers who lead the digital transformation in organizations. Knudsen (2020) find that accountants must compete in horizontal power struggles because digital platforms distribute power to platform owners. There seems to be something peculiar with the combination of AI and accountants/auditors that is not captured in functionalist analyses, and which cannot be completely explained with opaque AI methodology. As Quattrone (2016) argues, the extensive use of data analytics in accounting and auditing will put accountants and auditors either in the driver's seat or in the passenger seat depending on how they take control over data analytics innovations.

It is also noteworthy that bulk of this data is in unstructured format. To better appreciate the role of data analytics in auditing it is imperative to note the difference between structured and unstructured data sources. Traditionally, accounting information that supports decision-making was an output of structured data stored in relational databases. When data is stored in a structured format the data can be organised and analysed in additional ways that are typically not available with unstructured data. Big Data consists of 90% unstructured data retrieved from video, images, audio and textual files and interpretation of this data can immensely enhance the quality of accounting information (Warren et al, 2015).

To answer the question 'what differentiates Big data from conventional data gathered with the invent of computers' one must understand the 3 V's that define Big Data – Volume, Variety and Velocity. Big data 'Volume' is massive and exceeds the processing capacity of conventional database system; 'Velocity', which is the speed at which it is gathered is extremely high and 'Variety', is the different formats in which data is stored is widely varied. This makes 'Big Data' go beyond the capabilities of the traditional data processing systems; therefore, it is imperative to choose an alternative way to process it. Big Data can include anything from documents, to photos, to videos, to sensor data which is structured and unstructured (Franks, 2014).

A variety of machine generated data and sensor-detected data may be analysed and used to make key decisions. Pickard et al (2013) in their article demonstrate how Embodied Conversational Agents (ECA) can augment audit interviews traditionally held by humans and enhance quality of accounting information. ECA is an autonomous computer interface capable of human-like interactions such as interviews and is capable of conversing verbally and non-verbally with humanlike manners and affective responses for a more complete picture. This is an example of how audit interviews held traditionally as video recordings combined with vocalic and linguistic elements can create a more complete picture and give insights into company's health. Hobson et al (2010) in their research provide evidence of how vocal markers of cognitive dissonance are useful for detecting financial misreporting. They used speech samples of CEOs during earnings conference calls and generated vocal dissonance markers using automated vocal emotion analysis software and found positive association between misreporting and vocal dissonance markers generated by the software. This is an enhancement to the traditional audio recording and can emanate additional data and insights into financial misreporting. Textual data is a fast-growing collection of unstructured data in the form of emails, web pages and social media. The Sarbanes-Oxley Act requires that companies archive email to use as a resource for deterring fraud. Using Bayes model to predict whether archived email messages contain disgruntled communications, Holton's research provides insights into how to use this information to detect and deter fraud, which is unlikely to be revealed in a traditional fraud audit.

The review highlights a set of underdeveloped research areas and indicates that a variety of research questions in auditing field that can be addressed through this CPA funded research project. To bridge this gap, I am developing an analytical framework for research. I argue that accounting and auditing researchers and practitioner can utilize this framework for future research study or to enhance the decision-making capacity of auditors in practice.

4.2 Findings from survey

4.2.1 Auditors profile

The profile of auditors and audit companies is shown in Table 1. The majority of the participants are female and between the ages of 57 and 44 (75%). Most of the participants are from VIC (46%) followed by NSW (33%) and QLD (22%), and work in audit companies as Partners (14%), Directors (16%), Senior Managers (31%), and Managers (21%).

Table 1: Auditors and Audit Firms Profile

Gender	**N (%)**
Male	57 (44.88)
Female	70 (55.12)
Age	**N (%)**
18-24 years	4 (3.15)
25-34	55 (43.31)
35-44	46 (36.22)
45-54	12 (9.45)
55-64	10 (7.87)
Location	**N (%)**
VIC	46 (36.22)
NSW	33 (25.98)
QLD	28 (22.05)
ACT	3 (2.36)
SA	2 (1.57)
TAS	2 (1.57)
Others	13 (10.24)
Type of Firms	**N (%)**
Big Four	48 (37.80)
Large	41 (32.28)
Medium	33 (25.98)
Small	5 (3.94)
Position	**N (%)**
Partner	18 (14.17)
Director	21 (16.54)
Senior Manager	40 (31.50)
Manager	27 (21.26)
Senior Auditor	12 (9.45)
Staff Auditor	9 (7.09)

4.2.2 Adoption of audit data analytics technologies

The Table 2 presents the types of technologies adopted by the audit firms under the study. The table reflects terms and descriptions provided to the respondents by the researcher in the survey instrument to reduce misunderstanding from the respondents. As these terms can mean different things to different audit professionals. For the definitions and descriptions provided to the respondents of the terms used in Table 2 is provided in Appendix A. These terms, definitions and descriptions are collected from the findings of systematic literature and audit report review which was part of this study. In addition, there was one open ended question (under the option "other") as free text responses in the survey to capture additional terms and technologies not provided by the researcher.

Table 2: Adoption of analytics technologies

Analytics Technologies	**Percentage**	**Frequencies**
Text Mining (TM).	19.69%	25
Process Mining (PM).	22.05%	28
Support Vector Machines (SVM).	3.94%	5
Artificial Neural Networks (ANN).	11.81%	15
Genetic Algorithm (GA).	22.05%	28
Analytic Hierarchy Process (AHP).	15.75%	20
Pattern Recognition Technology (PRT)	23.62%	30
Natural-language processing (NLP).	16.54%	21
Predictive Modelling (PMO).	29.13%	37
Predictive Analytics (PAS)	18.90%	24
External Audit Analytics (EAA).	35.43%	45
Market Information Data Analysis System (MIDAS).	25.20%	32
Accounting Quality Model (AQM)	28.35%	36
Others: Business Analytics, Statistical Analysis, Quantitative Analysis, Mathematical Models, Computer-based Models, CaseWare IDEA	24.41%	31

As shown in the table, audit analytics technologies are most commonly used for analytical procedures (35.43%), followed by predictive modelling, which is used in analysing and evaluating big data in the audit assessment of fraud risks (29.13%), and Accounting Quality Model (28.35%), also known as RoboCop for the financial services industry to scan routine regulatory fil. Market information data analytics systems came in second (25.20%), followed by pattern recognition technology (23.62%), Genetic Algorithm (22.05%), Process Mining (22.05%), and predictive analytics (18.90%), which includes predictive and probability models, forecasts, statistical analysis, and scoring mods. Other (24.41%) technologies used by the auditors include Business Analytics, Statistical Analysis, Quantitative Analysis, Mathematical Models, Computer-based Models, and CaseWare IDEA.

4.2.3 Motivations for audit data analytics

The variables that drive audit companies to use audit data analytics are listed in Table 3. As can be seen from the table, the most important motivation is to increase audit efficiency (mean = 4.24), followed by improving audit quality (mean = 4.18), increasing the reliability of financial statement information (mean = 4.08), increasing the likelihood of accounting error detection (mean = 4.07), and freeing up auditor time to focus on tasks that require audit judgement (mean = 4.07).

Table 3: Motivations for adopting audit data analytics

Audit firms' motivations for adopting audit data analytics	Mean	Std	Count
Auditors are more likely to embrace audit analytics through client pressure rather than as a market opportunity.	3.26	1.11	127
Audit analytics reduce costs during data collection and analysis.	3.71	0.97	127
Audit analytics improve the efficiency of financial statement audits.	4.24	0.9	127
Audit analytics improve the quality of financial statement audits.	4.18	0.89	127
Audit analytics increase the likelihood of accounting error detection.	4.04	0.94	127
Audit analytics will free up auditor time to allow them to make better professional decisions/judgments.	3.96	0.99	127
Audit data analytics improve the efficiency of financial statement audits through automation/computerization	4.07	0.98	127
Audit data analytics reduced the need for human labor to perform routine/repetitive work.	3.86	1.1	127
Audit data analytics will improve the reliability of the financial statement information.	4.08	0.92	127

4.2.4 Roles of audit data analytics for risk assessment in audit engagements

Table 4 shows how audit data analytics may help with risk management during audit engagements. As can be seen from the table, audit analytics play a critical role in improving efficiency in a variety of areas, including performing detail tests (mean = 4.22), identifying audit failures by highlighting any transaction that deviates from a standard business process (mean = 4.09), and identifying and assessing the risks of material misstatement of the financial statements.

Table 4: Role of audit data analytics in relation to risk assessment

Role of audit data analytics in relation to risk assessment in audit engagements	Mean	Std	Count
Audit data analytics identify and assess the risks associated with accepting/continuing an audit engagement.	4.02	0.83	127
Audit data analytics identify and assess the risks of material misstatement of the financial statement due to fraud and testing for fraud regarding the assessed risks.	4.03	0.96	127
Audit data analytics identify and assess the risks of material misstatement through understanding the entity and its environment.	3.89	0.96	127
Audit analytics perform effective substantive analytical procedures in response to the assessment of the risks of material misstatement.	3.95	0.89	127
Audit data analytics identify audit failures by highlighting transactions that deviates from a standard business process.	4.09	0.93	127
Audit data analytics improve efficiency by performing effective tests of details.	4.22	0.89	127

4.2.5 Benefits and opportunities of audit data analytics

Table 5 illustrates the benefits of using audit data analytics in auditing. The audit analytics give some benefits to auditors, audit procedures, and audit objectives by giving valuable capacity for monitoring market events and seeking out financial statement fraud (mean = 4.23), as can be shown in this table. Following that, audit data analytics improves the objectivity of audit evidence (mean = 4.21), adds greater value to audit clients (mean = 4.15), and assists audit clients in decision-making (mean = 4.04), all of which might have a significant influence on financial statement quality. Furthermore, audit data analytics will help auditors estimate client lawsuit risks as a significant component of audit pricing (3.92), and audit firms will be able to capture a sequential causational process in real time (mean = 3.90).

Table 5: Benefits of audit data analytics

Benefits of using audit data analytics in audit engagements	Mean	Std	Count
With audit data analytics, audit firms will have the capability of capturing a sequential causational process on a real-time basis.	3.9	0.97	127
Audit analytics create more value for audit clients	4.15	0.87	127
Audit data analytics are helping audit clients in the decision-making process which could have a material impact on financial statements quality.	4.04	1.03	127
Audit data analytics are beneficial for assessing client litigation risks as a critical component of audit pricing.	3.92	0.97	127
Audit data analytics applications are useful for monitoring the market event to seek out financial statement fraud.	4.23	0.77	127
Audit data analytics benefits by improving interactions between key stakeholders like management, audit committee, governance teams and the engagement team.	3.88	0.96	127
Audit data analytics benefits the objectivity of the audit evidence.	4.21	0.83	127

Table 6 shows how audit data analytics may be used to improve efficiency and effectiveness while also altering the way some audit activities are typically performed. As can be seen from the table, audit analytics are critical in improving efficiency and effectiveness in many areas of audit tasks, including continuous auditing (mean = 4.16), embracing the wider and deeper data availability and analysis of the modern era to create a more thorough audit (mean = 4.15), quality improvement by increasing the coverage of testing transactions by (mean = 4.15), and quality improvement by increasing the coverage of testing transactions by (mean = 4.15). Furthermore, audit data analytics allows for the updating or revision of auditing standards (mean = 4.11).

Table 6: Opportunities of audit data analytics

Opportunities of audit data analytics in audit engagements	Mean	Std	Count
Audit data analytics is a valuable complement to traditional audit evidence due to its enhanced capabilities.	4.01	0.85	127
Audit data analytics facilitate continuous auditing.	4.16	0.83	127
Audit data analytics can contribute to audit quality improvement by increasing the coverage of testing transactions by include whole population instead of sample data.	4.14	0.93	127
External audit practice becomes more standardised because of audit data analytics.	3.82	0.98	127

Due to audit data analytics, professional auditing standards need to be updated/revised.	4.11	0.91	127
Audit data analytics have applications in reducing the amount of primary detection error.	3.87	0.83	127
Audit analytics offer a variety of analytical techniques that are based on aggregated historical trends.	3.91	0.92	127
Audit data analytics are useful for exception prioritisation in addition to exception detection.	3.88	0.88	127
Audit data analytics are useful to pay attention to cognitively complex tasks such as in-depth regression analysis.	4.03	0.87	127
Audit analytics are useful in embracing the wider and deeper data availability and analysis of the modern era to create a more thorough audit.	4.15	0.9	127
With audit data analytics, audit firms can include their own quantifications for materiality determination as a supplement to the audit opinion.	3.82	0.96	127
Audit data analytics tools contribute immensely to the auditor's understanding of the client environment.	4.03	0.96	127

4.2.6 Challenges of audit data analytics

Table 7 presents opportunity for audit data analytics. The two key factors are that accounting professional bodies need to offer more education or training on the use of big data analytics or audit analytics to auditors (mean = 4.51) and the risk of cyber security threat is a challenge of using audit data analytics in audit engagements (mean = 4.12). The other challenges are that auditing profession faces a severe supply-side issue of adequately trained auditors who can use audit data analytics systems (mean = 3.82), followed by evaluation and integration of unstructured big data with traditional audit evidence (mean = 3.77) and data privacy is a challenge to utilising audit data analytics as audit evidence due to internal and external unauthorized use of data. (mean = 3.74).

Table 7: Challenges of audit data analytics

Challenges of audit data analytics, machine learning and artificial intelligence in audit engagements	**Mean**	**Std**	**Count**
With large volumes of information available from big data, audit data analytics can impact information processing biases and human cognition limitations, potentially leading to suboptimal auditing judgments.	3.51	1.1	127
Veracity (conformity to truth) presents a challenge for the use of audit data analytics in auditing.	3.51	0.95	127
The auditing profession faces a severe supply-side issue of adequately trained auditors who can use audit data analytics systems.	3.82	1.03	127
Information overload gained from audit data analytics, can prevent an audit team from following up on every error uncovered over the course of an audit engagement.	3.56	1.07	127
Evaluation and integration of unstructured big data with traditional audit evidence is one of the challenges of adopting audit data analytics.	3.77	0.89	127
Information privacy is a challenge to utilising audit data analytics as audit evidence due to internal and external unauthorized use of data.	3.74	0.98	127

Accounting professional bodies need to offer more education/training on reducing the challenges of audit analytics.	4.51	0.75	127
The risk of cyber security threat is a challenge of using audit data analytics.	4.12	1.06	127

Overall, The results of the survey presented above indicated the extent to which audit data analytics are adopted by auditors and their firms; however, the descriptive statistics could not explain how and why they adopted these technology, and what are the main challenges based on specific organisational contexts.

4.3 Findings from interviews

The thematic analysis of interview-based case studies has identified a number of themes that emerged from the discussions with the respondents from the surveys and case study firms about the adoption, role and implications of technologies in audit practice. This illustrates how thematic analysis of qualitative data contextualises to provide nuances about various types of potential opportunities and challenges of audit data analytics. The themes are presented below.

New technologies are shaping audit in Australia. The interview participants have confirmed the survey responses that new technologies are emerging frequently and transforming audit practice through the technologies of blockchain, cloud, robotics process automation, data and text mining, natural language processing (NLP), artificial neural networks (ANN), and genetic algorithms (GA). Auditors play an important role in identifying risk in clients' business operations. For example, in auditing wine manufacturers which has complicated supply chain, auditors can use blockchain to check on potential authenticity issues or sourcing issues or modern slavery issues.

"The world of auditing in Australia is changing rapidly. The audit world has transformed moving from manual tools to digital tools. This change has significantly improved the analytical capacity of auditors to identify risks, detect anomalies, highlight weakness or potential fraud…"

"Blockchain is an electronic ledger systems sits in the cloud but provides permanent and immutable records of financial transactions..."

"Through the blockchain we can review or check all transactions in the chain, particularly our clients' supply chain and logistics…"

The blockchain making things easier and faster and improving efficiency through faster access and processing of data and effectiveness through improving reliability and accuracy…"

Technologies provides opportunities for significant improvements in audit by offering dynamic capabilities and abortive capacity which leads to audit efficiency and effectiveness. The proliferation of big data and technologies of analytics machine learning and artificial intelligent has become part of contemporary audit practice. Rather than relying on sampling techniques audit firms can now review and test the entire population. In addition, the technology has enabled audit firm to engage with continuous auditing (Zhang et al., 2015). Auditors can also identify risks emanating from the concentration of suppliers or over dependence of one supplier from a particular region. Instead of using sampling for testing auditors can analyse all transitions.

"Machines can be taught to identify new sources of quantitative and qualitative data…"

"Machines can learn like humans but can handle much more voluminous datasets which are essential for audit"

"Machine learning can generate artificial intelligence to speed up the audit processes…"

"Audit data analytics and audit technologies can provide competitive advantage for small audit firms in rapidly changing business environment…."

"Data analytics and machine learning technologies are enabling us to examine entire population rather than representative sampling which increase the chance of detecting anomalies. In addition, we can perform audit tests in more specific and directed manner…."

The new technologies can generate artificial intelligence which then can automate audit tasks and building modern analytical models for deeper and sophisticated analysis. The auditors who embed technologies in their audit enjoy more seamless and transparent interactions with their audit clients. With new technologies in hand auditors can investigate new datasets which leads to new insights, which then transforms entire audit process.

"Use of data analytics for machine learning and artificial intelligence can identify data outside of audited firm, mobilise auditors' resources to get new insights from the new datasets, and help transforming audit planning, risk assessment and sampling processes…"

"Natural-language processing (NLP) along with other machine learning, robotics, and artificial technologies play an important role in improving our audit quality as it allows auditors to go deeper at the granulated level with advanced data analytics"

"Our dynamic risk assessment (DRA) provides insights related to risks that can enhance resource allocation, strategic decision-making, judgement, and agility in audit planning and testing processes…"

Although data analytics and emerging technologies of data analytics, machine learning, and artificial intelligence has the capacity to improve audit efficiency and effectiveness it is not without risks. Fear of emerging risks such as behavioural, ethical and professional judgemental (Brown-Liburd et al., 2015; Hamdam et al., 2022; Munoko et al., 2020) issues as well as human biases from machine learning driven by technology are the most acute among the respondents:

"Machine learning offers speed in audit, but at the end auditors need to contextualise and make judgement. Otherwise, we will gain efficiency at the expense of effectiveness.".

"Overreliance or overfitting of new technologies can be problematic as the machine pick and choose idiosyncrasies or eccentricities in the data that are not representative of the real and natural world…. human understanding and judgment are still critical components in audit…machine learning needs to work as complementary but not reducing human relevance…"

"The scope and implications of data analytics technology varies significantly. This variability represents that there are opportunities as well as threats and risks…".

"The ways machine can gather data can breach regulatory conditions and it can cross the ethical and confidentiality boundary between auditors and auditees…"

"We need to understand and recognise the biases in machines and the ways in which they learn…"

Overall, auditors perceive that auditing always has been about data analysis. However, the tools of data analysis have changed due to the new technologies which are complimentary for procedures and evidence collection in contemporary big data environment (Yoon et al., 2015).

"Auditing always has been about data analytics but how data is collected, analysed, used in professional decision-making and judgement have changed due to new technology and these are the areas where auditors require to develop new skills…"

"The most important aspect of audit data analytics is the analytic mindset… analytical mindset is recognising when/how data analytics can address auditing questions…at the same time getting the question right is the key to any data analytics function…"

"For technologies to work in audit practice, critical thinking skills are required for auditors to be able to interact with big data…to discover new sources of data--- to comprehend the process needed to extract , clean and prepare the data before using appropriate data analysis and visualisation tools considering of data dimensions – veracity, velocity, variety, and volume---are essential for ensuring quality of audit data analytics…auditors need to recognise what is meant by data quality, completeness, reliability, or validity for audit evidence and decision..."

The auditors expect that data analytics tools such as visualisation can reduce the cognitive load on auditors because of the voluminous datasets and complexities of clients business processes (Hamdam et al., 2022). The analytics and visualisation can help to integrate and communicate vast and complex information in an effective manner for audit judgements and decision-making. To this end, the auditors are more concerned about the opportunities for positive impact and enhanced professional judgement (Brown-Liburd et al., 2015) compared to the challenges that arises from the new technologies for auditing. There are other factors and themes that emerged after triangulating data and findings from various sources which are presented below.

4.4 Overall findings from surveys and interviews

The three-case studies (1, 2, 3) summary findings (Table 8) provide triangulation of findings from surveys and interviews to illustrate the complex and dynamic relationships that exist between audit data analytics and clients demand, new business opportunity, competitiveness, development and improvement of appropriate analytics models and regulatory systems as per the need of the audit firms and their clients. In addition, it highlights the organisational and environmental level factors that driving audit data analytics innovation and adoption at a deeper level.

Table 8 - Factors influencing analytics practices in three case organisations

Factors/drivers	Case study 1	Case study 2	Case study 3
Client pressure	4	4	4
Funding/investment	4	3	4
Competition for new clients	4	4	4

Auditing regulation	4	4	4
Audit expectations	3	4	3
Clients' analytics environment	4	4	4
Financial performance measurement	4	4	4
Non-financial performance measurement	2	2	2
Audit risk management	4	2	1
Financial management	4	3	2
Technological advancement	3	4	1
Audit firms' organisational culture	4	4	4
Audit firm's top management/leadership style	4	4	4
Audit firm's management's strategic orientation	4	4	4
Partners/directors orientation to technology	4	3	4
Opportunity for non-audit services	2	3	0

Note: Scale: 4 = very high impact; 3 = high impact; 2 = reasonable impact; 1 = low impact; and 0 = no impact

Client-side demands, competition for new clients, opportunity for non-audit consulting services, audit expectations, and technological advances, according to the cross-case study findings, are key factors influencing the adoption of audit data analytics in the audit practise. Client expectations are that auditors will not only reinvigorate their own audit technology but will also be able to manage and traverse the client's own technological developments. This suggests a conflict between customers and their auditors over differing viewpoints on the auditors' own technology. While this may be true in many situations, the current study indicates that audit data analytics have been pushed by the degree of rivalry amongst larger auditors (in particular). After that, the study discovers that technical demand is driven not just by audit services, but also by consultancy (non-audit) services. However, the speed at which external auditors must proceed may be determined by client demand (whether generated by audit or non-audit services). Client demand and partner/directors' personal interest and attitude towards audit data analytics serve as important drivers for small audit firms. As table five shows, Big Four auditors were most worried about cost absorption, while customers questioned whether they should pay for these extra services.

5. Summary conclusions and recommendations

The goal of this exploratory mixed-method research was to learn more about how audit data analytics are used in Australian auditing and to add to the inventory of exploratory knowledge in this field. The study illustrated that the emerging domain of audit data analytics is critical to contemporary auditing process where auditors adopting data analytics and new technologies. The data analytics and technologies of machine learning, artificial intelligence, and robotics have transformed audit practice in Australia in the ways in which they are transforming other sectors and industries. The research projects contributed to the role of existing and emerging technologies and digital transformation of auditing in the era of big data and analytics. It explored the implications of business analytics, machine learning and artificial intelligence for developing audit efficiency and effectiveness with an aim to investigate the potential for changes to radically alter the future of audit practice. Key focus areas covered are the use of technologies by audit firms in audit environment; emerging technologies that help audit firms to manage audit risk; and digital transformation of audit plans and review processes to gain efficiency and effectiveness in a technology-driven business environment. The findings of this research showed how technology and digitisation shaping the audit practice in Australia, and why accounting researchers, professional and accounting bodies should engage with the technological issues in audit practice. Drawing on the study's findings the following policy, practice and general recommendations are made to improve the positive implications of audit data analytics technologies:

1. Diverse drivers motivate the adoption of audit technologies so one size fits all policy will limit the full potential of audit analytics capability. Hence, any policy or regulation related to audit analytics need to be principles-based not rule-based.

2. The audit firm should not adopt technologies predominantly to reduce costs or increase revenues.

3. The audit firms had not yet figured out how integrate include audit data analytics into their structures, and that dependence on shared services inside those structures will be a component of audit's growth.

4. Since audit data analytics implementation is important not just for Big Four auditors, but also for non-Big Four auditors, audit regulators, and audit committee members, as they all contribute to the success of audit data analytics implementation and usage in the audit business.

5. Auditors must believe that they have given more intriguing audit-related duties to perform rather than just ticking boxes with the help of new technologies, which will need intellect, critical analytical abilities, and professional judgement.

6. Auditors, auditees and accounting professionals need to recognise that technologies do not operate in vacuum. All technologies of data analytics, machine learning and artificial intelligence reflect human biases and sometimes increase human biases. For that matter, implications of technologies require continuous assessment, monitoring or evaluation. This is an important professional and social control mechanism.

7. Accounting professional bodies need to recognise the need for building audit data analytics capability not only for adoption in organisations but also for innovation and controlling technology for better impact. Technologies are not proxies for professional expertise, professional judgements, and professional communication. Technologies should be used in conjunction with professional judgement and effective communication between auditors, auditees, and users of audit reports.

8. In addition to the above recommendations, it is important to understand and formulate a set of ethical issues. This will help to develop a set of ethical principles/guidelines/frameworks for the development of ethical capability of auditors.

9. There is a need for raising awareness among accounting academics about the potential opportunity for undertaking research on audit data analytics technologies and practices. Then, the academics can inform their teaching and curriculum design based on the research findings to provide technological learning to accounting students. Accounting academics need to develop and support a strong and technologically enhanced audit curriculum for preparing graduates for future audit.

10. The results of this study should be widely disseminated using various traditional and online platforms so that Australian accounting professionals and community develops advanced understanding of the scope, trends, needs, challenges, and problems that audit profession is encountered with. Consequently, the accounting professionals will become more proactive in their efforts to be innovative and holistic to deliver on the promises of emerging technologies.

6. Future research directions

Whilst it is too early to fully comprehend the innovation, adoption and implications, the range of audit data analytics technologies that are implemented in audit firms is a relevant topic of interest among practitioners, accounting professional bodies and academic researchers. Drawing on the findings from this study, it can be argued that the audit technology related concerns of accounting professionals have far reaching implications not only for audit firms and their clients but also for the accounting professional bodies, accounting education in business schools, the regulators, the audit standards, and Australian businesses and society in general. Given the difficulty of audits in a big data environment, audit data analytics in Australia is a relatively under-researched issue that requires considerably more scholarly study. Thus, it is imperative that academic research in this area be continued with in-depth field studies or action research that would generate more comprehensive insights into the complexities of audit data analytics and the analytics capability needs of the accounting professionals in Australia and internationally. Future research can investigate the how technologies are used and what are the implications of these technologies on audit firm, auditee organisations and on wider society.

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Appendix A

Terms and Definitions in Table 2

Terms	Definitions	References
Text Mining (TM)	TM is an exploratory data analysis process applied to data in text format. TM emerged as a result of the need to use text-based unstructured data. TM is used to reveal the data and transform it into meaningful information to be used in the decision-making process. The main purpose of the TM method is to discover unknown information or to find answers to questions.TM helps to explore Term Patterns, Identify Text Clusters & Auto Classify Content	Appelbaum, Kogan, & Vasarhelyi, 2018; Brown-Liburd, Issa, and Lombardi, 2015; Yoon, Hoogduin, & Zhang, 2015; Cerchiello, 2009; Peji´c Bach, Krstic, Seljan, and Turulja, 2019;

Process Mining (PM)	PM is a technique to analyze and track processes. PM provides a new approach to gathering audit evidence by automatically analysing the entire population of event logs recorded in a company's IT system. In other words, the company's business processes, and the actions taken by its employees are chronologically captured in the event log for audit analysis. PM provides a quick and easy approach to taking any process and understanding how it operates at the technology layer. It enables unbiased and fact-based process compliance checking to verify that internal controls work as intended.	Chiu, 2018; Jans, 2011; Jans & Alles, 2014; Jans, Alles, & Vasarhelyi, 2013; Jans & Hosseinpour, 2019;
Support Vector Machines (SVM)	SVM is one of the statistical learning techniques that can achieve successful results in various classification tasks. SVM is a linear classifier that finds the hyperplane that separates by the largest possible margin, created after converting the data to a high dimension. The largest margin is expressed as the distance between the hyperplane and the nearest data point. SVM aims to correctly classify samples within a dataset.	Appelbaum, Kogan, & Vasarhelyi, 2018; Bhattacharyya et al. 2011; Yom-Tov, 2003;
Artificial Neural Networks (ANN)	Neural networks, also known as artificial neural networks, are designed to simulate the human brain. ANN is a method developed to have the ability to generate and discover new information through self-automatic learning, similar to the functioning of the human brain. ANN is an information processing system that simulates human brain functions such as thinking and learning. ANN are an important part of the future of AI and machine learning.	Appelbaum, Kogan, & Vasarhelyi, 2018; An, 2009);
Genetic Algorithm (GA)	GA is designed as a computer simulation. GA is one of the problem-solving and analytics techniques. GA contributes to the solution of problems where the number of input features is excessively large. GA is applied in data warehousing and mining. The parallelizable and flexible mechanism of GA enables the search and optimization of many important problems. The GA mechanism includes feature selection, partitioning, and extraction (especially through clustering). GA uses biologically derived techniques such as heredity, mutation, natural selection, and recombination in the medical world. These techniques are actually in a certain class of evolutionary algorithms.	Appelbaum, Kogan, & Vasarhelyi, 2018; Goldberg, 1989; Yom-Tov, 2003; Hsu, 2009;

Analytic Hierarchy Process (AHP)	AHP analytics is usually used for grading multi-criteria alternatives where a subjective (expert) comparison between alternatives is required. AHP is used to measure the effectiveness of auditing. This tool counts the number of deficiencies that were corrected during or after the auditing process. The correction of deficiencies is reported in the auditing report or the follow-up report, usually published one year after the original report. The significance of this tool is the idea that different categories of deficiencies should be weighted differently in the calculation.	Appelbaum, Kogan, & Vasarhelyi, 2018; Mizrahi & Ness-Weisman, 2007;
Pattern Recognition Technology (PRT)	A pattern recognition technique uses computer audit data of both normal activities and intrusive activities in the training data set to learn intrusion signatures. Each intrusion detection technique is tested using the entire set of the testing data. Developing this kind of auditing capability is based on a device we call an *audit daemon*, similar to the AI concept of a 'daemon'. Audit daemons consist of audit patterns and audit rules. Audit patterns are drawn graphically using the Petri net notation. However, they do not represent entire procedures, but only localized segments or patterns in the procedure. Numerous audit daemons are applied to the object procedure, each looking for a possible weakness or fault. When an audit daemons matches the procedure, the user is given a diagnostic message. The auditing of procedures is thus somewhat similar to syntax checking in programming language compilers. However, the fault's identified here are not simply syntactic, but focus on the semantic character of the procedure.	Yoon, Hoogduin, & Zhang, 2015; Ye, Li, Chen, Emran, & Xu, 2001; Lee, 1991.
Natural-language processing (NLP).	NLP is an area of computer science and artificial intelligence (AI) that aims to enable computers to process large amounts of natural (or human) language data. NLP significantly empower the audit, as it would enable auditors to analyse unstructured data.	KPMG, 2019; Yoon, Hoogduin, & Zhang, 2015;
Predictive Modelling (PMO).	The predictive audit is a forward-looking process that utilises predictive analytics to estimate possible outcomes of business activities and allow auditors to execute their work proactively.	Brown-Liburd, Issa, and Lombardi, 2015

Predictive Analytics (PAS)	PA uses past or historical data to predict future. For PA, machines learn from past examples of values or outcomes and then uses the learning to predict against unseen data.	Brown-Liburd, Issa, and Lombardi, 2015
External Audit Analytics (EAA)	EAA is derived from the idea of business analytics (BA), and it is used for analytical procedure in external auditing. EAA can be considered as a sub-field of BA. The EAA can be defined as the utilisation of various analytical procedures, methods, models to facilitate the transformation of audit data into external audit evidence and subsequently into audit judgements and decisions.	Appelbaum, Kogan, & Vasarhelyi, 2018
Market Information Data Analysis System (MIDAS).	MIDAS is a new system or technology that combines advanced technologies with empirical data to promote better understanding of markets.	Griffin & Wright, 2015
Accounting Quality Model (AQM)	AQM also known as RoboCop an automated system that uses data to detect fraud and accounting irregularities. This is also used a risk management tool.	Griffin & Wright, 2015; Pounder, 2012; Boyle, Boyle, & Carpenter, 2015; Lewis, 2013;
Business Analytics (BA)	BA can improve the efficiency of overall audit, including descriptive, diagnostic, predictive, and prescriptive analytics. BA can provide analysis on the entire population offering more larger and complete analysis (Early, 2015; Tang & Karim, 2017). The IAASB defines BA for audit as the science and art of discovering and analysing patterns, deviations and inconsistencies, and extracting other useful information in the data underlying or related to the subject matter of an audit through analysis, modelling and visualisation for the purpose of planning and performing the audit	Free text response from respondents
Statistical Analysis (Logistic Regression - LR)	Regression is a statistical method that detects whether there is a relationship between one or more independent variables and a dependent variable. LR is one of the traditional statistical methods and stands out among Data Mining (DM) applications used in real life	Free text response from respondents
Data Mining (DM)	DM refers to obtaining the desired information from a large data stack. DM can be expressed as a multidisciplinary approach using many different techniques. DM methods allow for the efficient processing of data with missing values, irrelevant data or highly correlated datasets automatically. DM techniques used in many fields are also preferred in audit planning activities in recent years. DM methods are used for financial distress forecasting and	Free text response from respondents. Amani and Fadlalla, 2017; González and Velásquez, 2013; Gepp et al. 2018; Gray and Debreceny, 2014; Ngai et al. 2011;

	financial fraud detection in the audit field. DM methods used in the audit field are mostly focused on prediction. DM methods are also used in risk management applications such as risk prevention, incident detection, incident mitigation. When DM is used to reveal hidden truths contained in huge amounts of data, it fills an important gap in financial fraud detection. DM methods are also frequently used for auditing financial statements	
Quantitative Analysis (QA)	QA is to examine high volumes of data and transaction in order to determine patterns and trends.	Free text response from respondents
Mathematical Models	Multidimensional analyses using a mathematical model to determine the audit risk. For example, Beaver model, two-factor model of Altman, five-factor model of Altman, Springate model.	Free text response from respondents
Computer-based Models	Computer-based Models or simulations are used create virtual environment in which auditors can test complicated transaction and processes. For example, balance sheet parallel simulation based on data mining.	Free text response from respondents
CaseWare IDEA Analytics	IDEA is a powerful and user-friendly data analytics tool designed to help auditors perform data analysis, audit sampling, and other audit procedures efficiently and effectively	Free text response from respondents
Decision Trees (DT)	DT are hierarchical or tree-structured forecasting models and are most used in classification and forecasting methods. DT have flowcharts that look like a tree structure. DT are created by many nodes and branches at different stages and under various conditions. Essentially, the purpose of the tree is to classify data according to the discrete values of a target variable using several predictive variables.	Free text response from respondents