FACTORS CONTRIBUTING TO THE IMPLEMENTATION OF DATA ANALYTICS IN EXTERNAL AUDITING

YEAMIN JACKY

FACULTY OF BUSINEES AND ACCOUNTANCY
UNIVERSITY OF MALAYA
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YEAMIN JACKY

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FACTORS CONTRIBUTING TO THE IMPLEMENTATION OF DATA ANALYTICS IN EXTERNAL AUDITING

ABSTRACT

The objective of the study is to explore the factors effecting the implementation of Data Analytics in Audit process and the impact of those factors on Audit Quality. Two stages of study were performed to achieve the objective of the study, First, this study analysed response letters on the use of Data Analytics (DA) in external auditing submitted by stakeholders of audit services to the International Auditing and Assurance Standards Board (IAASB)'s Data Analytics Working Group (DAWG). Using the Modified IT Audit Model as a framework, this study performs a directed content analysis on all 50 response letters sent to the DAWG. The analysis uncovered some contributing factors which were repeatedly discussed and commented by majority of the stakeholders. Some of the significant factors are namely, challenges in revising or developing new standards, whether DA will be used for substantive testing, test of controls or test of details. Moreover, the effect of DA on Audit quality and audit judgement, and Data reliability, Data security concerns while using DA. The second part of research conducted a survey among auditors based on Malaysia. The study performed an Exploratory Factor Analysis to confirm the validity of the measurements used for factors relating to Audit Profession, Standards (ISAs), Technology, Organizational, Client Factors, Limitation and Challenges and Other Relevant Factors in concern. Based on the initial results of Cronbach alpha, Bartlett test of sphericity (BTOS) and Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMOS) and the factor test, we retained all the attributes with appropriate factor loading. Further descriptive analysis of the findings revealed the current state of using and implementing DA by Malaysian Auditors and audit firms. The analysis suggests a high percentage of auditors and audit firms uses some sort of data analytics but is significantly limited to advance excel and in some areas of audit. The overall findings suggest that although Malaysian practitioners has started developing the use of DA in audit procedures but there are significant limitations and constraint. The findings of this study would be a very critical contributor for standard setters and regulators and as each and every factor has been discussed in different angles, making sure the adopters of DA are well aware of the concerning issues and the benefits in implementing DA in Audit.

Keywords: Data Analytics, Factors, External Auditing, Content Analysis, Factor Analysis

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ABSTRAK

Objektif kajian ini adalah untuk meneroka faktor-faktor yang mempengaruhi pelaksanaan data analitik (DA) dalam proses audit dan kesan faktor-faktor berkenaan kualiti audit. Dua peringkat pengajian dilakukan untuk mencapai matlamat kajian, Pertama, kajian ini menganalisis surat tindak balas mengenai penggunaan DA dalam audit luar yang dikemukakan oleh pihak berkepentingan perkhidmatan audit kepada Lembaga Piawaian Pengauditan dan Jaminan Antarabangsa (IAASB) Kumpulan Kerja Data Analytics (DAWG). Menggunakan 'Model Audit IT Modified 'sebagai rangka kerja, kajian ini melakukan analisis kandungan yang diarahkan ke atas semua 50 surat tindak balas yang dihantar ke DAWG. Analisis itu mendedahkan beberapa faktor penyumbang yang sering dibincangkan dan dikomentari oleh majoriti pemegang kepentingan. Beberapa faktor penting ialah, cabaran dalam menyemak atau membangunkan piawaian baru, sama ada DA akan digunakan untuk ujian substantif, ujian kawalan atau ujian butiran. Selain itu, kesan DA terhadap kualiti audit dan penghakiman audit, dan kebolehpercayaan data, kebimbangan keselamatan data semasa menggunakan DA. Bahagian kedua penyelidikan dijalankan tinjauan di kalangan juruaudit di Malaysia. Kajian ini menjalankan analisis faktor eksplorasi untuk mengesahkan kesahihan pengukuran yang digunakan untuk faktor-faktor yang berkaitan dengan profesion audit, piawaian (ISA), teknologi, organisasi, faktor pelanggan, had dan cabaran dan faktor-faktor lain yang berkaitan dengannya. Berdasarkan hasil awal alpha Cronbach, ujian Bartlett of sphericity (BTOS) dan Kaiser-Meyer-Olkin Measure of Complexity Sufficiency (KMOS) dan uji faktor, kajian mengekalkan semua sifat dengan memuat faktor yang sesuai. Analisis deskriptif lanjut mengenai penemuan menunjukkan status semasa menggunakan dan melaksanakan

DA oleh juruaudit Malaysia dan firma audit. Analisis menunjukkan peratusan tinggi juruaudit dan firma audit menggunakan beberapa jenis analisis data tetapi ketara terhad untuk memajukan kecemerlangan dan dalam beberapa bidang audit. Penemuan keseluruhan menunjukkan bahawa walaupun pengamal audit di Malaysia telah mula membangunkan penggunaan DA dalam prosedur audit tetapi terdapat batasan dan kekangan yang ketara. Penemuan kajian ini akan menjadi penyumbang yang sangat kritikal bagi penentu dan pengawal selia standard dan kerana setiap faktor telah dibincangkan di sudut yang berbeza, memastikan pemohon DA mengetahui tentang isu dan manfaat dalam melaksanakan DA dalam audit.

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In the name of Allah, Most Gracious, Most Merciful

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ABBREVIATIONS

BD- Big Data

DA- Data Analytics

ADA- Audit Data Analytics

IAASB- International Auditing and Assurance Standard Boards

IFAC- International Federation of Accountants

DAWG- Data Analytics Working Group

GAS- Generalised Audit Software

AP- Audit Profession Factors

FRS- Factors Relating to Standards

TF- Technological Factors

OF- Organizational Factors

CF- Client Factors

LC- Limitation and Challenges Factors

ORF- Other Relevant External Factors

CHAPTER 1 INTRODUCTION

1.1 BACKGROUND OF THE STUDY

‘Traditional audit methods served auditors for decades but as technology advances and stakeholders’ expectations evolve, so does the need for auditors to innovate and transform their approaches to keep pace with demand’ (The World Bank, 2017).

Since the dawn of industrial age, the advancement in technology has been unparalleled to its trend of innovation. As both are on the rise, we can see a massive leap within the industry. The advancement is influencing organizations to be more insightful and astute about their functions, opportunities, and environment. With the Origination of Industry 4.0 in Europe and spreading to the U.S., it emphasizes six major principles in its design and implementation: Interoperability, Virtualization, Decentralization, Real-Time Capability, Service Orientation, and Modularity (Dai & Vasarhelyi, 2016; Hermann, Pentek, & Otto, 2016). Among the many distinctive developments which the current world and Industry 4.0 is adhering to, the one which significantly contributes to the current industry is “Data Analytics” and “Big Data”.

“Big Data” is the concept that describes the huge data portfolio, which is exponentially growing (Beck, 2012). The related approaches to analyzing these data are often referred to as Data Analytics (hereafter, DA) or predictive analytics (Earley, 2015). The rapid increase in the volume of information extracted through the massive sources, starting from the Internet of things like multimedia, social media to organizational and enterprise log, and day to day advancement in directories. Client systems are now embedded with these external data sources, furthermore, they are integrating this Big Data with complex analytical procedures to initiate and finalize the decision-making process (Appelbaum, Kogan, Vasarhelyi, & Yan, 2017). The predicted view from all these is that data analytics will have a dramatic impact on enhancing productivity, profits, and risk management. And to enlighten the accountants, the "Audit Profession" is assured to encounter some rapid changes considering these conditions.

Technology hasn't been adopted to the extent it is supposed to be in the Audit profession for quite some time. Accounting Standard Setting bodies have lagged even further in terms of adoption (Dai & Vasarhelyi, 2016; H.-J. Kim, Mannino, & Nieschwietz, 2009; Curtis & Payne, 2008). Audit professionals, with their enduring knowledge and experience along with the application and smart usage of the latest technology, taking a much closer look at the financial aspects of a company and offering perspectives that would lead to better decision-making, higher quality audits and eventually value for its clients (KPMG, 2017).

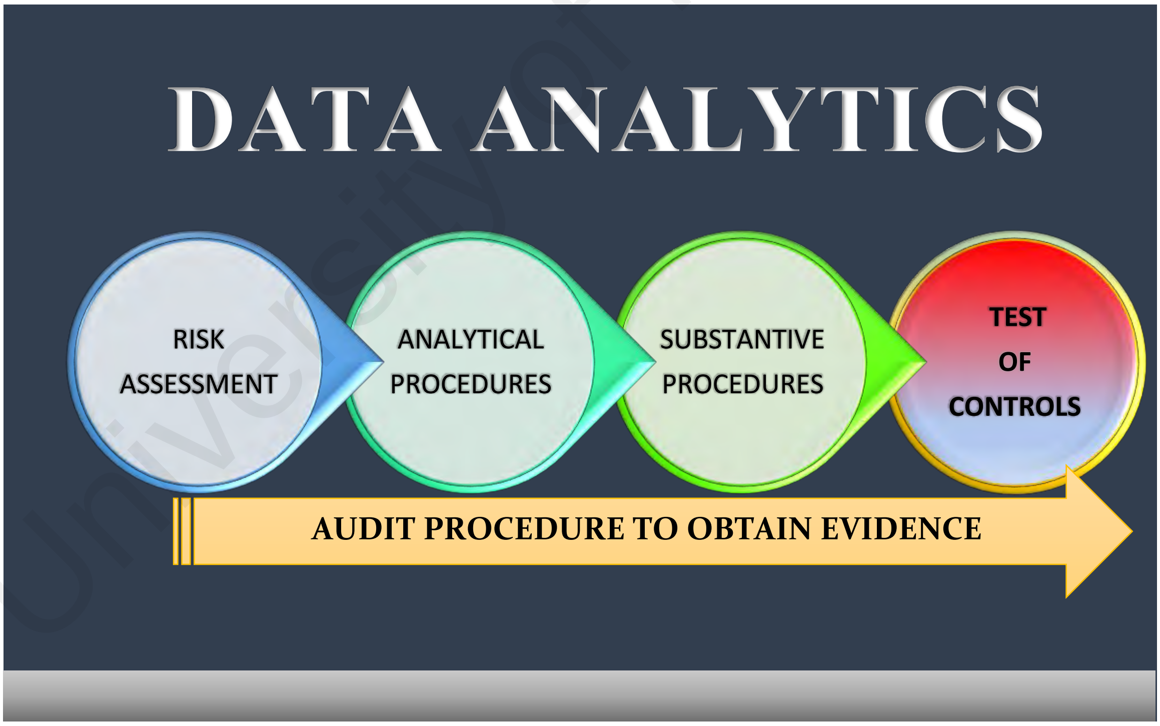


Figure:1.1 Data Analytics can have major impact on these Key Areas of Audit Procedures to Improve Audit Quality

As shown in Figure 1.1, Data Analytics can be used in several stages of an audit procedure to gather audit evidence. The audit profession has an opportunity to enlighten itself to a radical change and reinvent their typical arrangement and flourish itself to a new height of command. Regulatory changes need to proceed with caution at the same time an innovation in the audit process has become extremely important (ICAEW, 2016a). Without it, the growing demand in the market will create an expectation gap and the capacity of the industry to comply with these demands will be jeopardized, and the risk of scope and limitation of the external audit itself will be more vulnerable. Auditing data analytics is the perfect means of getting out of such a situation where the investors and stakeholders will be more enlightened with new opportunities and more informed data and the expectation gap will be much more minimized (ICAEW, 2016). Recent developments in the use of Data Analytics in other fields of accounting have heightened the need for its use in auditing.

1.2 PROBLEM STATEMENT

1.2.1 Shifts in Business & Audit Environment

The introduction of Industry 4.0 in a wide array of domains has set the tone for adopting technology (Piccarozzi, Aquilani, & Gatti, 2018). These changes in business environments lead to an expected change in the Audit environment. For business evolving into the next decade, auditing should also adapt to the new evolved environment. The use of technology adoption like data analytics hasn't advanced as swiftly as it expected to be in the field of auditing, where most of the firms in other industry use data-driven system and continuous monitoring of data to identify risks and irregularity of their internal control system (Appelbaum, Kogan, & Vasarhelyi, 2017). Due to the availability of Data Analytics and Big Data and its use in different sector of Accounting like distress modeling, financial fraud modeling, stock market prediction, etc. (Gepp, Linnenluecke, O'Neill, & Smith, 2018), there is an increasing pressure from the stakeholders to start implementing Data Analytics in auditing. External Auditors are expected to use the process and take advantage of such huge data sets available and to come up with a more rigorous and efficient way of auditing which will eventually provide more assurance and significantly less material misstatement in an audit report (Tang & Karim, 2017). This set back of DA implementation in the profession can be ascribed partially to the strictness of standard setters of the profession and also to the commitment to traditional values and ideas (Liu & Vasarhelyi, 2014). So, the Expectation Gap is increasing day by day, where the clients or stakeholders are expecting the use of such advancement as an integrated part of the whole system of auditing, whereas professional firms or standard setters are still lagging.

1.2.2 Knowledge Gap in the Field of Study

Researchers have been pondering about the fact that auditing is lagging in the use of valuable data analytics techniques (Gepp et al., 2018). The true scale of their use is still uncertain in practice (Acito & Khatri, 2014, Fay & Negangard, 2017). This is due to a gap been created between the practical application of Data Analytics in auditing and the theoretical assumption which rises from academic researches and other research areas in Audit. Past literature suggests the lack of using data analytics in auditing (Acito & Khatri, 2014; Brown-Liburd, Issa, & Lombardi, 2015; Griffin & Wright, 2015; J. Zhang, Yang, & Appelbaum, 2015). Although shreds of evidence from audit partners suggest that some leading firms have started to adopt the sophisticated use of DA and BD techniques in practice (Alles, 2015). So, it would be important to identify the factors which will impact and influence the implementation of DA in the audit process. There is a lack of evidence about these factors which can be associated when it comes to the implementation of DA. There is limited empirical evidence or perspective regarding this issue. So, this paper would like to contribute to narrowing the research gap by identifying those factors as empirical evidence from the perspective of different stakeholders and the perspective of Auditors. This will also help to understand the current scenario of using DA in auditing and how much implementation has taken place.The extent and the importance of data analytics incorporation into auditing can only be understood when the auditors and practitioners will start using them in a practical field and realize the scope, nature, and extent of the audit (Marr, 2017).

1.3 RESEARCH OBJECTIVES

Objective 1: To explore the perceptions of relevant Stakeholders on factors affecting the implementation of Data Analytics in the Audit process.

Although the literature of Data Analytics and Big Data in auditing is still in its infancy, past researches and responses show an increase in the implementation of these techniques. The International Accounting and Assurance Standard Board (IAASB) has an ongoing project "*Exploring the Growing Use of Technology in the Audit, with a Focus on Data Analytics*" which is conducted by Data Analytic Working Groups (DAWG). The DAWG has published a paper stating various opportunities, benefits, pros & cons in adopting Data Analytics compare to the current risk-based auditing. IAASB has collected several responses based on this paper. Stakeholders like accounting bodies, standard setters, professionals have shared their perspective regarding the implementation of Data Analytics through these responses. These responses have explored various themes and factors which are important to investigate. These factors give a basis for understanding the factors affecting the implementation of Data Analytics in auditing. The study aims to analyze all those responses to identify the important factors that would have a significant impact on implementing DA. The IAASB Framework of Audit Quality also points out the necessity of adopting information technology in audit methodology. The Financial Reporting Council also identified this as the key driver of audit quality (Financial Reporting Council, 2017). Based on this objective, the study sets to answer RQ1 through a directed content analysis of the 51 reports collected in response to the IAASB paper.

RQ1: What are the factors which will have a significant influence on implementing Data Analytics in the Audit process?

Objective 2: To explore the current usage of Data Analytics among auditors in Malaysia

It is also essential for the study to understand factors affecting the implementation of DA in practice perceived by the external auditors. Auditors are the ones who will be using and implementing these techniques in action, so it is important we cover their perspectives and also understand whether they agree to these factors. The second objective would obtain an overview of the auditors' usage of DA. This would address the current and overall state of DA usage and implementation among Malaysian auditors, by posing several questions through the survey questionnaire. The questions would reveal, what type of DA software's have auditors used and to what extent and for how long has DA been used by auditors and how satisfied are Auditors with the current level of DA usage? The questions would further include to what extent and in what stages of audit has DA been used together with what sort of DA techniques that have been used in the audit process and finally what are the perception of Auditors on the benefits of using DA in the audit process?The study would address this part of the research through a Survey Questionnaire. The facts and conclusions which will emerge from the analysis of the responses will give a clear indication of the current state of DA implementation and usage among auditors of Malaysia. Based on these objectives the Research Questions which we pose is:

RQ2: What is the current state of DA usage and its perception among auditors in Malaysia?

Objective 3: To further examine the contributing factors identified for the implementation of DA.

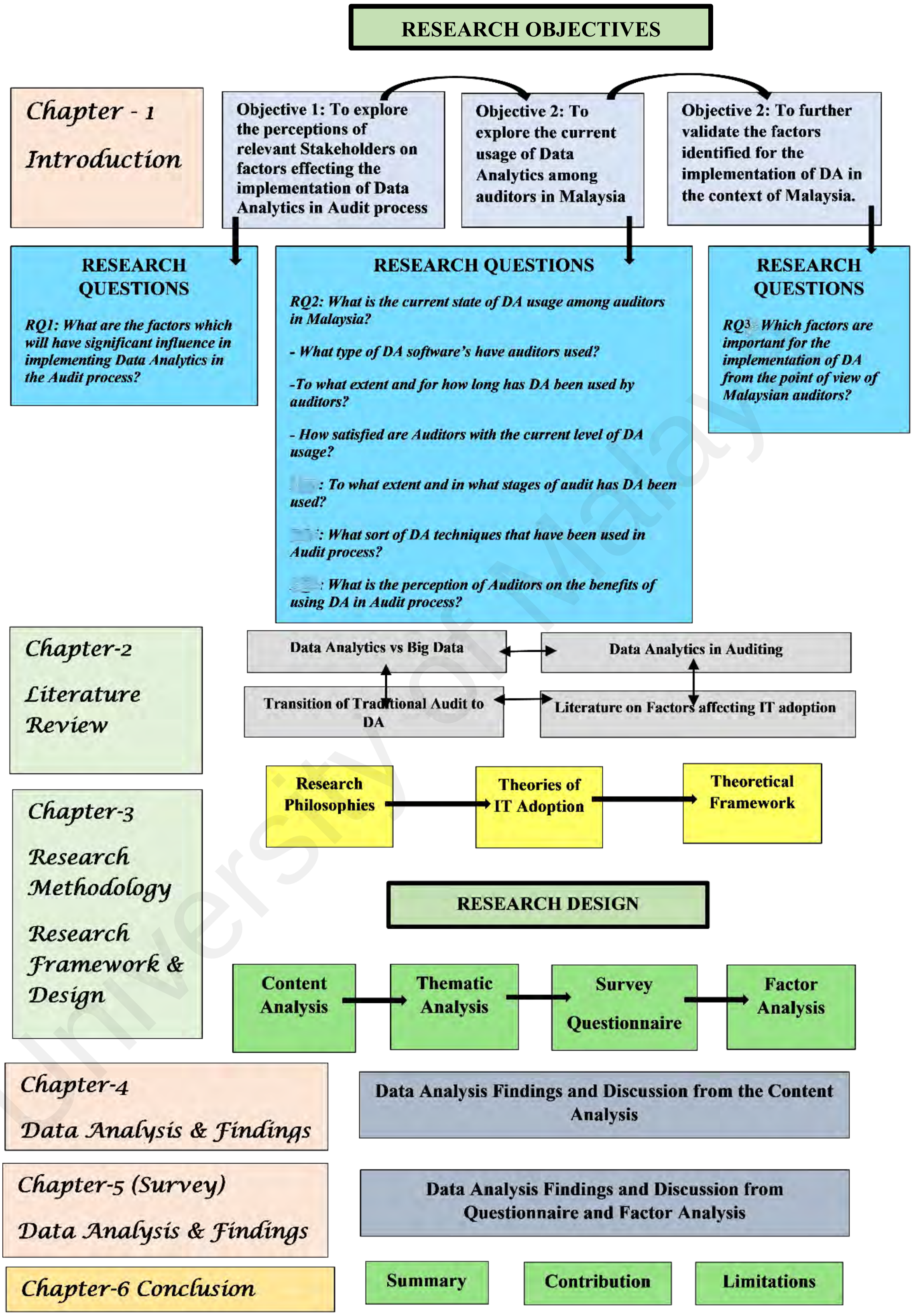
The content analysis of the stakeholder responses would give a fair idea about the state and the issues regarding the use of data analytics. So, for this study, we would like to converge these issues and focus them in respect to Malaysian external auditors. As for objective 2, the study explores the current usage of DA concerning Malaysia. For the third objective, we take it a step further and try to analyze these contributing factors to a better extent. Initially, the study would take perceptions of Malaysian auditors, on the factors and attributes which have emerged from the content analysis. This would indicate how far they would agree to these factors. Based on the responses we would like to further validate these factors and attributes with some statistical analysis, to show the importance of these factors in the implementation of DA in external auditing. So, the question we pose for this objective is:

RQ3: Which contributing factors are deemed to be important for the implementation of DA in external auditing?

1.4 RESEARCH CONTRIBUTION

The multi-stage method of this study has been developed to allow for a better understanding of the status of DA implementation in the audit profession. In general, this study contributes by offering insights, as well as obtaining a better understanding of the issues of the implementation of DA as a whole and also precisely in the context of Malaysia. The results of this study would be a very critical contributor to the accounting profession, standard setters, regulators, and as well as academicians. Currently, there is a lack of skills relating to Data analytics among professional accountants (Fay & Negangard, 2017). However, the potential skills of Data Analytics to improve decision making within a company or increase the effectiveness and efficiency of an audit cannot be ignored further.

1.4 STRUCTURE OF THE RESEARCH



1.5 Summary of Chapter

This chapter lays out and initiated the focus of the thesis, the background, and nature of the analysis, and the research scope and purpose, objectives, and the research questions. It has also addressed the study's main contributions regarding the existing literature in the area of auditing and Data Analytics. As the extent of implementation of Data Analytics is unknown and it is time that auditors start using DA in the audit process, this study aims to investigate the present condition of its use among auditors. Factors that influence the implementation of DA needs to be investigated. The initial investigation would rely on the response paper which has been collected in response to a paper published by the IAASB's Data Analytics Working Group (DAWG).

CHAPTER 2 LITERATURE REVIEW

2.1 OVERVIEW OF DATA ANALYTICS

Recently, researchers have shown an increased interest in this sector of auditing, but due to the lack of practical evidence in the field, previous studies have primarily concentrated on the theoretical aspect and the scope of implementation of such ideas.

2.1.1 Data Analytics vs Big Data

“Data analytics” (DA) is the method of analyzing raw information to come to conclusions and facilitate decision-making (WorldBankGroup, 2017). Many firms use data analytics to make smarter strategic decisions, foresee future performance, and manage risks. It is the practice of analyzing data sets to reach conclusions about the information contained therein, particularly with the help of advanced systems and software. According to Shamoo & Resnik, (2009) various analytic procedures “provide a way of drawing inductive inferences from data and distinguishing the sign from the vast amount of statistical fluctuations present in the data”. Data analytics as a concept, primarily refers to a variety of functions and applications, from basic business intelligence (BI), reporting, and online analytical processing (OLAP) to multiple modes of advanced analytics. Audit data analytics is much wider and complex than conventional analytical procedures. This requires the use of sophisticated software tools and advanced statistical procedures. These can include cluster analysis; predictive models; data layering; visualizations; and “what if” scenarios that discover news strategies for evaluating huge sets of audit relevant information, which are from internal and external sources to produce evidence for audit evidence during analytical procedures, control testing, risk assessment and substantive procedures (Tschakert, Kokina, Kozlowski, & Vasarhelyi, 2016). Data analytics are used by both internal and external auditors to allow for practices such as continuous monitoring, continuous auditing, and examination of complete data sets in circumstances where samples were audited only (Tschakert et al., 2016)

Big data can be defined beyond the volume of information. For example, Juan Zhang described big data with four “Vs”: massive volume, high velocity, large variety, and uncertain veracity (Zhang et al., 2015). Whereas other researches have explained Big Data as seven V's and the characteristics resemble the previous and are extended to namely Velocity, Volume, Variety, Veracity, Valence, Variability, and Value (Saggi & Jain, 2018). Strawn, (2012), described Big Data as the “fourth paradigm of science”, whereas Hagstrom, (2012) defined it as “a new paradigm of knowledge assets” or “the next frontier for innovation, competition, and productivity” (Manyika et al., 2011).DA Is used to extract knowledge, interest, success evaluation, economic and competitive advantages (Fosso Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015). The paper by De Mauro, Greco, & Grimaldi, (2016) states that “Big Data is the information asset characterized by such a high volume, velocity, and variety to require specific technology and analytical methods for its transformation into value”. The term “Big” falls in ambiguity as it is quite relative. An information system is considered to be big if the capacity doesn’t allow it function properly unless a more sophisticated system has been adopted or developed (Vasarhelyi, Kogan, & Tuttle, 2015). Big data is also referred to unstructured data which can be extracted from various sources of phone calls, videos, cctv footage, text etc. Starting from phone call details of customer support, to employees tapping in for attendance to acknowledging a shipment which can be viewed through security camera are all a part of Big Data evolution. The product of "datafication" has been the emergence of "Big Data" (BD). An example of such an innovation is RFID tags, which are incorporated in goods to monitor their product codes, the geographical information collected could also be used to analyze the quantities of inventories (Krahel & Titera, 2015).

2.1.2 Transition of Traditional Audit to DA

Recently, the audit profession has increasingly recognized the emergence and the growing use of data analytics (Vasarhelyi et al., 2015). The use of Data analytics in different business processes has set a new standard. The emergence of these sophisticated approaches using data analytics and Big Data has raised many issues among auditors, audit firms, standard setters, regulators, and academicians. Auditing has come across several phases during its lifetime and is now in a critical junction. There is a significant change in trends on how to audit has been performed over time. However, embarking on the use of analytics in audit is not a straightforward task. Before considering the presence of more sophisticated analytics and big data in engagement, it is important to understand the present scope and limits of the audit profession (Appelbaum, Kogan, & Vasarhelyi, 2017).

The traditional Risk-based approach was implemented, due to the high transaction rate which increased the complexity of testing all the underlying transactions and the limitations in technology (IAASB, 2016). The current auditing procedure is largely based on collecting evidence and applying analytical procedures that are guided by a parameter of regulation and standard. In the risk-based auditing, the auditors need to test basic assertions to make sure the objectives are met. These fundamental procedures have been carried on since the inception and will not be changed or altered, but the way these procedures are performed, or the evidence is collected might be subject to change when it comes to adopting data analytics. The development and widespread availability of technologies, such as personal computers, led to more widespread electronic data processing within organisations (Davis 1968). The increasing demand and need for micro-based computer-assisted audit tools (CAATS) designed to help automate the audit process came along with this extensive distribution of computing power and a security risk (P. E. Byrnes et al., 2018). Over time, the enhancement in audit technology has been upheld by auditors as technological improvements in auditing practices (Power, 2003). As a matter of fact, due to these developments, the audit process has been constantly objectified, formalized, and streamlined (Fischer, 1996). Previous studies showed that the incorporation of innovations such as statistical sampling, the Audit Risk Model, and the Business Risk Audit, followed a pattern of portraying auditing as the compilation of objective and almost ' factual ' evidence (Salijeni, Samsonova-Taddei, & Turley, 2018).

Big companies have invested large sums in programs intended to advance technology (Brown-Liburd & Vasarhelyi, 2015, Cao, Chychyla, & Stewart, 2015). The use of statistics in the process of collecting and evaluating audit evidence was intended to increase confidence in sample size (Higson, 2003), as well as shielding auditors from potential challenges to their judgments (Sully, 1974). Likewise, more technical advances in the audit resulting in the emergence of the Audit Risk Model and subsequently the Business Risk Audit were also interpreted as improving the credibility of the audit process (Curtis & Turley, 2007, Hansen & Messier, 1986). Therefore, the traditional view of audit-proof may no longer suffice, and the effect must be taken into account by the audit professionals and regulators. They need to be mindful of the fact that some traditional forms of audit evidence are likely to replace by a more advanced technological environment (Brown-Liburd & Vasarhelyi, 2015). Although the rise of DA is not the only example of systematic auditing studies over the years, it is an interesting case in particular because it raises concerns on whether Data-driven audit environments place considerable technical requirements on auditing and increase its remoteness. In fact at some point of time, without any proper guidance this could blur or smear the audit function itself (Alles, 2015). Therefore, the probability could be that DA will potentially be seen as a disruptive technological innovation in auditing (Salijeni et al., 2018).

2.1.3 Data Analytics in Auditing

The traditional Risk-based approach was implemented, due to the high volume of transactions which increased the complexity of testing all the underlying transactions and the limitations in technology (IAASB DAWG, 2016). But with the current perspective of Data analytics, it would be possible to obtain audit evidence with much more effectiveness. Accessing a large volume of data compared to a risk-based selection would also eliminate the sampling bias (IAASB, 2016). One of the crucial Audit Standards specifies that auditors should directly obtain and examine all the physical evidence as part of the risk assessment process (PCAOB, 2010;P. Byrnes, Criste, Stewart, & Vasarhelyi, 2014). Using DA technology can accomplish this vision in a much more effective and proactive way, bearing in mind the quality and verifiability of these external data sources which is important in the risk assessment evaluation process (Appelbaum, Kogan, & Vasarhelyi, 2017). Although the processes seem to be practically still in its infancy level in the meantime professional firms like Deloitte, KPMG, EY are trying to increase their market capitalization by providing innovative solutions to their client. They presumably Implementing analytics into their audit strategy and services, storing large customer data sets in their setting and making companies feel confident with the audit future (Beck, 2012).There are several key areas that Auditors need to keep in considerations when moving into this paradigm. Since access to data is a key factor, firms need to be aware of the scope of data barriers, and a significant importance needs to be put to literate the Company's IT function. Competency development is another key instrument to keep in mind for the success of any investments in data analytics. At the end of the day, the human element is the key factor and focus should not be limited to technical competencies, rather than developing the whole mindset to finance, risk and compliance functions to consume the analytics produced effectively (Beck, 2012)

From the studies presented thus far by other researchers, it is quite evident that data analytics provides an immense opportunity for the auditing profession to grow. However, the opportunity has not yet been capitalized to the extent that has been done in other related areas of Accounting (Gepp et al., 2018). As mentioned earlier, auditing will benefit from modern data models to forecast financial distress and identify financial fraud, and updating on standards will allow them to overcome the reluctance of engaging them with big data techniques (Gepp et al., 2018). As stated by Gepp *et al.* in their research, that it would be invaluable for auditors to get access to big data sets that comprise of non-traditional information and would add value to future audits. However, as of 2018, there has been little work been implemented practically by professional firms. A report from the Financial Reporting Council suggested that although large UK firms have invested a lot of money in DA capabilities such as software and skills, in practice the responses were surprisingly very low. The companies were unable to provide any reliable data concerning their scope of use (Financial Reporting Council, 2017). Nonetheless, UK audit firms are the spearhead of Global firms who have taken the lead to use of Data Analytics in their Audit process.

2.1.4 Use of Data Analytics in Auditing

The use of technology has lagged in the audit profession for quite some time. Accounting Standard Setting bodies have lagged even further in terms of implementation (Dai & Vasarhelyi, 2016; H.-J. Kim, Mannino, & Nieschwietz, 2009; Curtis & Payne, 2008). Audit clients are increasingly reliant on knowledge derived from data analytics, including information used to predict external financial reports (Appelbaum, Kogan, & Vasarhelyi, 2017). The audit profession has an opportunity to enlighten itself to a radical change and reinvent their typical arrangement and flourish itself to a new height of command. Regulatory changes need to proceed with caution at the same time an innovation in the audit process has become extremely important (ICAEW, 2016). As mentioned before, the implementation of DA hasn’t progresses much in audit for the last decade, where most of the firms in other industry use data-driven system and continuous monitoring of data to identify risks and irregularity of their internal control system (Appelbaum et al., 2017). Due to the availability of Data Analytics and Big Data and its use in different sector of Accounting like distress modeling, financial fraud modeling, stock market prediction, etc. (Gepp, Linnenluecke, O'Neill, & Smith, 2018), there is an increasing pressure from the stakeholders to start implementing Data Analytics in auditing. The set back of DA implementation in the profession can be ascribed partially to the strictness of standard setters of the profession and also to the commitment to traditional values and ideas (Liu & Vasarhelyi, 2014). So, the Expectation Gap is increasing day by day, where the clients or stakeholders are expecting the use of such advancement as an integrated part of the whole system of auditing, whereas professional firms or standard setters are still lagging.

Data analytics as a concept, primarily refers to a variety of functions and applications, from basic business intelligence (BI), reporting, and online analytical processing (OLAP) to multiple modes of advanced analytics. Audit data analytics is much wider and complex than conventional analytical procedures. This requires the use of sophisticated software tools and advanced statistical procedures. These can include cluster analysis; predictive models; data layering; visualizations; and "what if" scenarios that discover news strategies for evaluating huge sets of audit relevant information, which are from internal and external sources to produce evidence for audit evidence during analytical procedures, control testing, risk assessment and substantive procedures (Tschakert, Kokina, Kozlowski, & Vasarhelyi, 2016). Data analytics are used by both internal and external auditors to allow for practices such as continuous monitoring, continuous auditing, and examination of complete data sets in circumstances where samples were audited only (Tschakert et al., 2016). with the current perspective of Data analytics, it would be possible to obtain audit evidence with much more effectiveness. Accessing a large volume of data compared to a risk-based selection would also eliminate the sampling bias (IAASB, 2016). One of the crucial Audit Standards specifies that auditors should directly obtain and examine all the physical evidence as part of the risk assessment process (PCAOB, 2010;P. Byrnes, Criste, Stewart, & Vasarhelyi, 2014). Using DA technology can accomplish this vision in a much more effective and proactive way, bearing in mind the quality and verifiability of these external data sources which is important in the risk assessment evaluation process (Appelbaum et al., 2017).

Although the study on the implementation of DA in audit is still scarce, from the studies presented thus far by other researchers, it is quite evident that data analytics provides an immense opportunity for the auditing profession to grow. However, the opportunity has not yet been capitalized to the extent that has been done in other related areas of Accounting (Gepp et al., 2018). The knowledge of both Data Analytics and auditing is important for the understanding of Implementation. According to Gepp et al., (2018) the use of Data analytics(DA) and Big data(BD) is still very minimal in the Audit profession compare to other fields. Similar views were proposed in the research of Zhang et al., (2015).

2.2 Literature on Factors affecting IT adoption

2.2.1 Audit Profession Factors

This category concerns issues within the audit profession. The first is the requirement by auditing standards. Currently, the standards don't have enough scope to implement DA within this standard. So, there is a definite need to revise the standard. It is still debatable whether the revised standard should be rules-based or principle-based (IAASB DAWG, 2016). If the standards don't change very soon, then it would be interesting to know how to implement audit data analytics (ADAs) within the conceptual principles of existing auditing standards.

According to Kim, Nicolaou, & Vasarhelyi, (2013) determining a sample size would solely depend on the level of assurance. The extent of measurement would also depend on the level. Also specified by Janvrin, Bierstaker, & Lowe, (2008), audit judgment may have an impact when tools like GAS and other software's will be used. In the case of using DA, the advancement presumed will be much bigger, where they will be able to analyze 100% of the population and can help to enhance their audit opinion and judgment.

The level of Audit risk will be a determining factor of whether to use CAATs or not as stated by ISACA, (2008). Deloitte Chairman and CEO Joe Ucuzoglu write: "At Deloitte, we're investing several hundred million dollars in data analytics and artificial intelligence with some cutting-edge applications that we believe differentiate us and our audit approach. When we use these tools, we're able to get greater coverage. We're able to identify risks more quickly. We're able to complete the audit with a higher level of quality and ultimately deliver a greater level of insight to our clients" (Alles, 2015)**.**

2.2.2 Factors Relating to Standards (ISAs)

In some cases, the global market is demanding increased use of technology and data in the audit. Although the auditing standards are not obsolete, they have to reflect the current trends and technologies to stay relevant and fulfill investor demands of using technology successfully to provide high-quality audits(IAASB DAWG, 2016). There is a danger related to the use of new and innovative practices that do not have a strong framework within the standards. The ISAs are very likely to be revised to address technological advances and data analytics. Audit authorities or oversight bodies are waiting for standard setters to act in this area, such as the IAASB. Auditing standards should improve the quality of audits (IAASB DAWG, 2016). At the very same time, audit standards should also be able to accommodate advances that occur in the future (such as technological advances). Without further details, radical change to the ISAs could have unexpected implications in the near term (such as inhibiting innovation), because of the rapid nature of the data analytics advancements in the audit of financial statements.

2.2.3 Technological Factors

Past researchers like Mahzan & Lymer, (2008) found that the use of CAATTs largely depends on the tools' compatibility with ?. If the software doesn't support inline with other departments then it could act as a barrier to implementation and also visualization is a key factor to implementation. This would be relevant in terms of DA as the clients' system and data should compatible with auditors' firms when it comes to analysis. The auditors firm also should have that amount of expertise that can overcome any obstacle or ambiguity when using the clients' system.

Another important factor that is very much timely related to DA is to clearly understand the terms and scope of DA in terms of auditing. Several types of analytics are been used currently in several fields like a neural network, decision tree, logistic regressions. It is important to identify which of these or which other analytics would be more suitable in the field of auditing. What sort of analytics will be applicable and compatible with the audit. Rezaee, Sharbatoghlie, Elam, & McMickle, (2018) pointed out that when adopting CA, the firm must have an infrastructure that could retrieve data from various sources and platforms Similar concerns were put forward by Abd Rahman, (2008) on the current ICT infrastructure.

Banker, Chang, & Kao, (2002) stated that tasks are more feasible when the documentation process is elaborate and maintains quality. With CA it is also a concern on how much audit documentation would be needed. The Adequate and Sufficient amount of Documentation to follow is still in ambiguity and the standard setters need to set accordingly.

2.2.4 Organizational Factors

The organizational factors would include aspects that are concerning the audit firms. One of the important factors which have been pointed out by Mahzan & Lymer, (2008) regarding the adoption of CAATTs implementation is the support from the firm's top management itself. This would draw a similar picture in terms of DA implementation where the top management should be in support of this adoption process.

Havelka & Merhout, (2007) also described the importance of IT support in the implementation of new technology. In terms of DA, the knowledge and the existence of Data would be much more crucial. If auditors are unable to efficiently and effectively capture company data, they will not be able to use analytics in the audit (Marr, 2017) and the availability of IT audit professionals will be very crucial. Janvrin, Bierstaker, & Lowe, (2009) acknowledges the fact that this might be one of the barriers which segregate the smaller firms to bigger ones. Apart from all these, several other factors will be considered under organizational factors.

2.2.5 Client Factors

According to ISA 300, when Auditors set the course of an audit, the fundamental requirement is to identify the strength of the client's internal control. In the case of Data analytics, the options of choosing to use DA in the clients' business will largely depend on the effectiveness of their internal control. The complexity of the client's IT environment or the suitability of clients' IT infrastructure is crucial. Janvrin & Weidenmier, (2017) suggested in his research that the Big 4 firms do not use IT, specialists when they examine clients with low IT infrastructure.

The complexity and data availability of the client's business environment will be of major importance as well. Client factors would also comprise of the complexity of clients' business and IT structure. Flowerday & Von Solms, (2005) suggested, that due to the current complexity involved in the modern business setting, auditors are required to adopt continuous auditing and develop new methods and processes.

Debreceny, Lee, Neo, & Toh (2005) spoke about the compromise of clients' data to be a concern when it comes to limitations of using and this is going to be a valid concern in terms of implementing DA.

2.2.6 Limitation and Challenges Factors

There are several issues that need to be considered under inhibiting factors. These are the factors that restrict the implementation of DA. These factors could act as the barrier to DA implementation in the audit process. Lawrence, (2010) has talked about several inhibiting factors in his research. Factors like security, lack of knowledge, cost of investment, limitation to infrastructure are few of them.

It can be presumed that the implementation of DA will face several challenges from Audit Regulators. The process of using DA **may** be questioned by audit regulators, especially if the auditor has a different interpretation of how ADAs can be used to meet the standards. These are several inhibiting factors that need to be dealt carefully when we start to deal with large sets of data meaning to say Big Data.

2.2.7 Other Relevant External Factors

Due to the availability of Big Data, and its use in different sectors of Accounting like distress modeling, financial fraud modeling, stock market prediction, etc. (Gepp et al., 2018), there is an increasing pressure from the stakeholders to start implementing Big Data in auditing. Auditors are expected to use the process and take advantage of such huge data sets available and to come up with a more rigorous and efficient way of auditing which will eventually provide more assurance and significantly less material misstatement in an audit report. So, the Expectation Gap is increasing day by day, where the clients or stakeholders are expecting the use of such advancement as an integrated part of the whole system of auditing, whereas professional firms or standard setters are still lagging. According to Mahzan & Lymer, (2010) auditors' motivation can be impacted through the adoption of new technology and ts existing support from its developers which in case of analytics could be a data scientist. According to Wehner & Jessup, (2005) it is also essential to understand the external push for an audit firm would be the usability of new technology by its competitors or other audit firms. In the case of Data Analytics, it is quite probable that the Big 4 firms are already using them while the others are lagging, and it would also seem appropriate for other companies to follow more and adopt Big Data Analytics if it is being used by others in the auditing profession.

2.3 Research Contribution

Although the use of Data Analytics in auditing is not compulsory at any stage, however with the advancement of technology being used by client's businesses, auditors are expected to obtain the knowledge of data analytics and start implementing in their course of action. The knowledge of both Data Analytics and auditing is important for the understanding of Implementation. According to Gepp et al., (2018) the use of Data analytics(DA) and Big data(BD) is still very minimal in the Audit profession compare to other fields. Similar views were proposed in the research of Zhang et al., (2015). In that way, this study aims to contribute to this growing area of research. The study would contribute to the existing body of knowledge by addressing some key factors with respect to the implementation of Data Analytics in the Audit process. The study would provide more empirical insight on factors that would influence the implementation of Data Analytics. More empirical evidence would be gathered through perceptions of Auditors. Since the literature is still very scarce, a lot of research is needed to understand the process. At this point of time, there are hardly any studies which has given empirical perceptions on the implementation of Data Analytics. The uniqueness of this study would be able to highlight and identify those important factors which needs to be look at during implementation process. This will also be able to pose more practical insight on the current state of usage and implementation of Big Data from firm's perspective.

2.4 Summary of Chapter

With the current shift in Audit environment and the advancement of IR 4.0, Auditors are lagging invaluable use of data analysis techniques. Currently, businesses are more dependent on technology and the clients are becoming more demanding in terms of using sophisticated techniques. So, auditors instead of falling behind should embrace the analytics and techniques which might give them better judgment and evidence. However, due to lack of references to standard and various other issues, implementation of DA hasn't taken place in auditing as much as it is supposed to be. So, from building on from the factors affecting IT adoption in Audit, the study would try to find out the factors which will have a significant impact on the implementation of DA in Audit. The above literature discusses the importance of DA and big data and the development which has taken place in the field of auditing.

CHAPTER 3 RESEARCH METHODOLOGY

3.1 Research Methodology

This chapter deals with the methodologies available for this research and which options would be more suited in the context of this research. This study attempts to understand the factors that would influence the implementation

of Data Analytics in audit procedures. The chapter would focus on explaining the methods which have been applied to meet the objectives that were set earlier in chapter 1. It will clarify the methods employed in gathering and analyzing the data required to meet the research contributions. Nonetheless, it is necessary to address the fundamental research concepts within the study before continuing with the methods chosen method and research methodology such as research philosophies, research approaches, research strategy, research choices.

According to Saunders, Lewis, & Thornhill, (2013) the term research methodology relates to the concept of how to do analysis, including the assumptions taken for theoretical and philosophical premises which the study is based on and the significance of these approaches which are implemented. Research method can also be explained As the tools and methods used to collect and interpret research data (Saunders et al., 2013). In other words, research methods explain how research questions will be answered using available tools and techniques to gather and compile empirical evidence.

3.1.1 Research Philosophies

There are 10 different types of philosophical concepts. The first six concepts are the subsets of three main branches of research philosophy: epistemology, ontology, and axiology while the last four are the concepts within research paradigms. According to

Myers, (1997), all research focuses on certain fundamental assumptions as to what constitutes ' valid ' research, and which methods of study are acceptable. Thus, in conducting research, it is essential to understand the underlying principles before continuing with the next research strategy. Such theories concern the fundamental epistemology which will direct the study.

3.1.2 Positivism

Saunders, Lewis, & Thornhill, (2007) define positivism as the epistemological position that promotes dealing with socially observable reality. Myers, (1997) describes positivists are those who typically believe that truth is factual and can be defined by empirical properties that are independent of the researcher and his techniques. Research can be classified as positivist where there is proof of formal proposals, quantifiable measurements of variables, testing of hypotheses, and drawing conclusions from a sample to a defined population (Orlikowski & Baroudi, 1991). Positivist methods usually include the assumption that valid answers exist, and the researcher's responsibility is, to begin with the hypothesis about the nature of the world and then seek the data that will either verify or conclusively disprove, or the researcher exhibits several hypotheses and looks for data that will enable the correct one to be selected (Easterby-Smith, Lyles, & Tsang, 2008).

3.1.3 Research Approaches

There are various research approaches also referred to as "research method" or "methodologies" that have been used in the field of social science. However, one of the most prominent variations is between qualitative and quantitative research methods (Myers, 1997). Deductive is more positivist, and inductive is more interpretative.

According to Myers, (1997), quantitative research methods were originally developed in the natural sciences to study natural phenomena. Boudreau, Ariyachandra, Gefen, &

Straub, (2004) defined quantitative (positivist) research, as a technique that allows researchers to answer research questions about the interaction of humans and computers. The quantitative studies emphasis on testing hypotheses and generalizing the results to a wider population (Saunders et al., 2007). Examples of quantitative methods include surveys, laboratory experiments, formal methods (e.g. econometric) and numerical methods such as mathematical modelling.

Qualitative Research Myers, (1997) also indicates that qualitative research methods were developed in the social sciences to enable researchers to study social and cultural phenomena. Examples of qualitative methods are action research, case study research, ethnography, and grounded theory. Qualitative data sources include observation and participant observation (fieldwork), interviews and questionnaires, documents and texts, and the researcher's impressions and reactions

3.1.4 Research Choices

There are three research types to choose from: mono method, multi-method and mixed-method. Mono method uses a standard technique for data collection and subsequent inspections for analysis. More than one approach of data collection is used for Multi-method, but it does not blend either qualitative or quantitative analysis. The mixed-method uses both quantitative and qualitative data collection techniques and analysis procedures.

3.1.5 Selection of Research Strategies

The diversity of research approaches poses dynamic challenges in choosing relevant research strategies. This study did however choose the approaches to positivism. Using the five Likert scale responses for the quantitative data questions and from the answerers ' argument in the open-ended questions, a positivist view was established.

Initially, one of the approaches used in this study was to analyze the contents provided by stakeholders of the audit profession. The content analysis provided factors that affect the implementation of data analytics and then the study re-validate those findings from the content analysis by taking perceptions of auditors from Malaysia. Thus, by adopting the positivist view as the guiding principle, the study evaluates these variables further to determine the current state of the art in using DA in the audit profession. earlier.

In addition to those opinions, this study also obtained some knowledge of the plausible reasons behind the respondent's behavior in responding to the closed-ended Likert questions. For instance, the participants were asked to respond freely and openly for any other factors that might influence the implementation of DA or any other areas of audit that can be affected by DA implementation. This strategy is called positivism as the outcomes of these parts will be clustered and correctly thematized.

This analysis seems to have used both quantitative (deductive) and qualitative (inductive) approaches, based on the philosophies chosen above. Initially the use of responses of stakeholders on Data analytics implementation, had to be explored through to get the proper themes out of it. Then the survey method is considered to be the most appropriate research technique since the main goal is to examine the current usage of DA among different categories of audit firms in Malaysia. Different types of surveys are used routinely for information gathering including questionnaires, interviews, observations, and content analysis. According to De Vaus,(1986), the questionnaire is the most widely used in survey research. Consequently, this research has followed the approach of collecting data from the questionnaire. Data collection and analysis are rendered using mixed methods. Initially the content analysis and then the survey. Both closed-ended and open-ended questions have been asked in the questionnaire through an online survey and a hard-copy survey. The data were analyzed using both quantitative and qualitative analyses.

3.2 Research Design

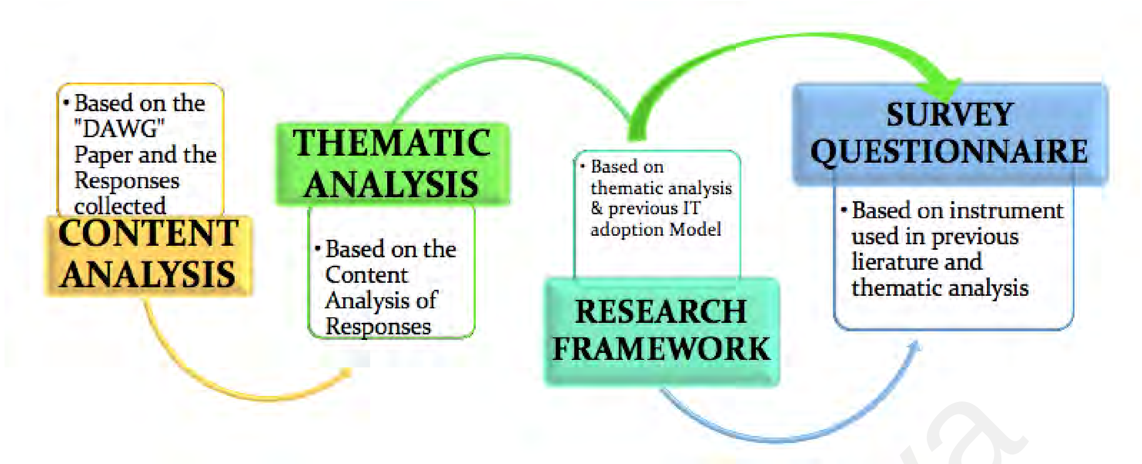


Figure:3.1 Research Design

3.3 Theoretical Framework

Previous researchers have found many factors that affect the adoption of technology in auditing. Several factors have been identified in the course of these implementations.

It was indicated in the research of (Ahmi & Kent, 2012) that implementation of GAS (Generalised Audit software) in auditing was influenced by many individual factors like behavioral and IT acceptance, which was focused in the works of (Mahzan & Lymer, 2008) and (Janvrin et al., 2009).

Researchers have implemented several theoretical frameworks to recognize the approval and implementation of technology among the auditors (Janvrin et al., 2009; Curtis & Payne, 2014). Mahzan & Lymer, (2008) and (M. B. Curtis & Payne, 2008) used the unified theory of acceptance and use of technology (UTAUT). Venkatesh, Morris, Davis, & Davis,(2003); used the decomposed theory of planned behavior (TPB) (Ajzen, 1991) and technology acceptance model (TAM) (F. Davis & Davis, 1989; Banker et al., 2002) have applied task-technology fit (TTF). Goodhue & Thompson, (1995) and Lovata, (1988) developed her Audit Adaptation Model based on Davis & Davis, (1989), Model of Stress and the Systems Hierarchy. These adoption theories UTAUT, TPB, and TAM are mostly focused on the behavioural aspect which leads to adoption. These frameworks do not capture the understanding of the process which leads to the actual use of these technologies.

Implementing Data Analytics in the full Audit process is not just about the intention but rather to understand the process and factors which would lead to its implementation in the future of Audit. The practical perspectives from the audit professional about the current stage of adoption and the pros and cons of implementation and their point of view regarding all these are also very limited (Gepp et al., 2018).

To understand the implementation process and the factors which will act and affect behind the implementation of DA we have considered adopting the framework of A Model of Information Technology Audit Quality by Havelka & Merhout, (2007) and also the Modified IT Audit Model which has been proposed in the research of (Ahmi, 2013).

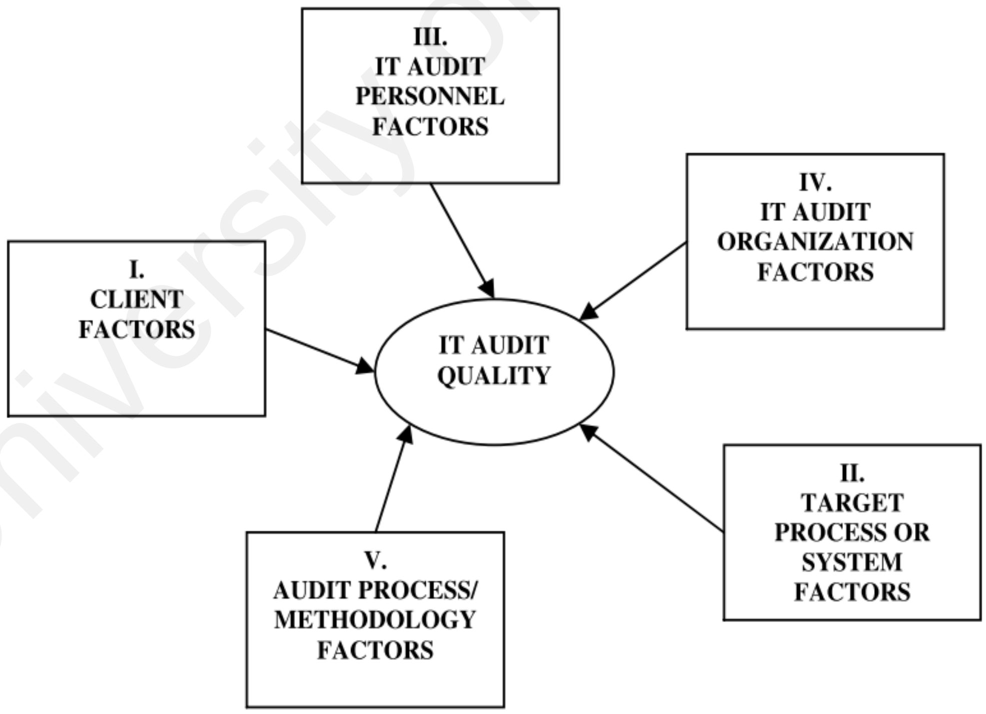


Figure 3.2. A Model of Information Technology Audit Quality

These theoretical frameworks have been chosen as the basis for this research since the factors which are identified under these models are quite comprehensive and cover a very wide array of variables, which are predominantly salient across IT audits or technology adoption. Furthermore, most of the variables within the model are suitable and relevant and also complements the study. These existing models have been further modified and few other factors were materialized from the content analysis and added to fit the objectives of this study. A new framework was proposed based on the identified factors for this study.

3.3.1 The Innovation Diffusion Theory (IDT) & Theory of Planned Behaviour (TPB)

When it comes to research based on IT adoption in Audit, several technology adoption research was conducted to understand how users come to use new technologies and embrace them (Ahmi & Kent, 2012). Most of these studies suggest the use of theoretical frameworks and models rather than any specific theories of IT adoption. Nguyen, (2009), Ghobakhloo, Hong, Sabouri, & Zulkifli, (2012) has used the reconceptualized framework of IT adoption process as the theoretical framework. Unified Theory of Acceptance and Use of Technology (UTAUT) is one of the most prominent and earliest theoretical frameworks which has been used in the study by Venkatesh et al., (2003). These frameworks were developed using the basis of a few theories. The Innovation Diffusion Theory (IDT) & Theory of Planned Behaviour (TPB) are among those theories. The basis of all the theoretical frameworks and models of IT adoption and new technology adoption is based on the components of these theories. They are very much interrelated, as they focused a lot on the behavioral aspect of organizations and individuals. Different Authors has focussed on different aspect and has amalgamated these theories to achieve their objective through further implementation of new models and frameworks.

Innovation Diffusion Theory (IDT) was developed by E.M. Rogers in 1962 and is one of the oldest social science theories. Innovation diffusion can be defined as "the process by which an innovation is communicated through certain channels over time among the members of a social system" (Rogers & Williams, 1983). It originated in communication to explain how, over time, an idea or product gains momentum and diffuses (or spreads) through a specific population or social system. It can be conceptualized at multiple levels of analysis (Ofondu, 2018). At the organizational level, the unit of adoption is the organization, while the social system is the organization's external environment (LaMorte, 2018a). At the individual level, the unit of adoption is the end-user, while the primary social system is the reference organization's internal social environment (LaMorte, 2018a). The result of this diffusion is that people, as part of a social system, adopt a new idea, behavior, or product (Rogers & Williams, 1983). The key to adoption is that it does not happen instantly in a social system; rather it is a process whereby some people are more apt to adopt the innovation than others. the person must perceive the idea, behaviour, or product as new or innovative. It is through this that diffusion is possible (LaMorte, 2018a).

The Theory of Planned Behaviour (TPB) is a theory based on psychology that links one's beliefs and behaviour. The Theory of Reasoned Action in 1980 was the basis of this theory (Ajzen, 1991). It dictates the intention of a person to commit to action at a particular time and place. The theory had the aim of describing all those people's behavior which can be self -controlled (Ajzen, 1991). The key component to this model is behavioural intent; behavioural intentions are influenced by the attitude about the likelihood that the behaviour will have the expected outcome and the subjective evaluation of the risks and benefits of that outcome (Ajzen, 1991).

The TPB states that behavioural achievement depends on both motivation (intention) and ability (behavioural control). It distinguishes between three types of beliefs - behavioural, normative, and control (LaMorte, 2018b). The TPB is comprised of six constructs that collectively represent a person's actual control over the behaviour (LaMorte, 2018b).

They are categorized as Subjective norms, Perceived behavioural control,Attitudes, Social norms, Behavioural intention, Perceived power (LaMorte, 2018b).

The theoretical model which has been used for the purpose of this study is the Modified IT Audit Model by Ahmi & Kent, (2012) and A Model of Information Technology Audit Quality by Havelka & Merhout, (2007). The study amalgamated both theoretical models and has chosen the factors which are best fitted to our research objectives to form the basis of initial themes. These theoretical models have stemmed out from the basis of innovation diffusion theory and theory of planned behaviour. The attributes which are used to define these theories also further explains the theoretical model which helps to adopt new technologies over time.

3.4 Research Method

3.4.1 Content Analysis

Auditing has gone through many faces of technology adoption. Starting from adopting computer-based auditing to using CAATs (Computer Assisted Audit Techniques) and GAS (Generalised Audit Software) and now to the era of Data Analytics. A vast amount of research has been carried out in adopting and implementing those technologies into the audit process. However, there are very few studies that have researched the implementation of Big Data and Data Analytics in the Audit process. This research has been carried out with the intention to find out the factors which will influence this evolutionary implementation process of Data Analytics and Big Data into auditing. The study intents to employ Content Analysis as one of the methods to identify and assess the empirical evidence and factors which will impact this process. The researcher believes analysing these relevant contents would bring out the factors which will effectively impact the implementation process of Data Analytics and Big Data in Audit. As the content is analysed in this study, comes from various stakeholders of auditing service, the Researcher believes these contents will provide a very crucial and intriguing perspective in developing a new era for Audit service. These factors would essentially guide the standard setters and the Audit firms to understand the link between Data analytics and Audit

3.4.1.1 What is Content Analysis?

In the early 1940s, the Content analysis started to appear in various literature and research as a methodological tool (Franzosi, 2004; Krippendorf, 2004). The method was initially developed to analyze and interpret verbal communications, however, later on, it was vastly used to study visual information (Zajko, 2012). It was also focused on identifying manifest content in its early days. Holsti, (1969) defined content analysis as a technique for making inferences by objectively and systematically identifying specified characteristics of messages. Later on, as content analysis gained much appreciation it was expanded to a new scope of qualitative methods, focusing on latent content as well (Drisko and Maschi, 2015; Franzosi, 2004; Krippendorf, 2004).

Content analysis has been used quite extensively in social accounting research (Gray *et al.*, 1995; Guthrie, J., Petty, R., Ferrier, F. and Wells, 1990; Adler and Milne, 1999; Parker, 2005). Content analysis allows the researcher to generate ideas and conclusions from a set of analyzed contents which can be further interpreted and generalized to other situations (Neuendorf, 2001). This means the method allows researchers to study social behavior without influencing it (Neuendorf, 2001). The method illustrates a technique by accumulating, assembling, and harmonizing diversified data through a systematic coding reference into various categories and themes (Guthrie, Petty, Yongvanich, & Ricceri, 2004). The purpose of content analysis is to study the written communication of humans unobtrusively. The method helps to identify and evaluate the current literature and the extent of its boundaries and evolvement of a particular topic or area (Yoo & Weber, 2005). Content Analysis helps to examine the past researches of a field and can project different perspectives, in-depth analysis, and insights of a particular phenomenon. Content analysis helps the researcher to answer the questions regarding what and why something is being discussed or communicated and to what extent it is affecting that particular issue (Babbie, 2015) Ordinarily in content analysis studies researchers represent their findings in the format of tables or charts. Various statistical analysis tools are utilized to illustrate specific trends and patterns.

3.4.1.2 Qualitative vs Quantitative

Content analysis can be carried out quantitatively but also qualitatively. According to Neuendorf, (2001) content analysis can be described as the systematic, objective, quantitative analysis of the characteristics of a message. However, (Klaus Krippendorf, 1980) in his discussion contends that all content analysis is qualitative in nature stating, ―all reading of the text is qualitative even when certain characteristics are later converted into numbers(p. 16).

Qualitative approaches to content analysis have their genesis in literary theory, the social sciences, and critical theory (Creswell, 2003). Quantitative content analysis refers to counting words. texts, phrases, paragraphs, or sometimes pages in a particular content. The analysis shows how many times a particular phrase or text has appeared in that content. Whereas Qualitative content analysis goes beyond merely counting words to examining the intent behind a particular phrase and classify those phrases into an efficient number of categories that represent similar meanings (Weber, 1990). The objective is to provide knowledge and understanding of the phenomenon under study (Downe-Wamboldt, 1992).

There are five distinct forms of qualitative content analysis: discourse analysis, social constructivist analysis, rhetorical analysis, ethnographic content analysis, and conversation analysis (Klaus Krippendorf, 1980).Besides, qualitative approaches have several characteristics in common: (a) they require a thorough reading of small amounts of textual material, (b) they require the interpretation of texts into new narratives, and (c) analysts acknowledge they are working within hermeneutic contexts that parallel their socially and culturally understanding of texts (Klaus Krippendorf, 1980).

This study uses Qualitative Content analysis to find and investigate the factors which will impact the implementation of DA and BD in Audit. The study will use the analysis to further explain the themes and the attributes behind each factor to give a clear perspective of all the stakeholders in concern.

3.4.1.3 Directed Content Analysis

Sometimes, Qualitative researchers can choose to use a directed approach for content analysis by using some existing theory. The existing theory or prior research could be about a particular phenomenon but hasn't been used the way the researcher wants to use it to explore his field of study. The existing theory could be incomplete or would benefit from further description (Hsieh & Shannon, 2005). The goal of a directed approach to content analysis is to validate or extend conceptually a theoretical framework or theory (Hsieh & Shannon, 2005). Potter and Levine-Donnerstein, (1999) categorize this as a deductive use of theory as it can provide initial predictability and guidance about the variables in concern and an overall idea about the factors which should be included at an initial stage. It helps to determine the initial coding scheme or relationships among variables and between codes (Potter & Levine-Donnerstein, 1999). This has been referred to as the deductive category application (Mayring, 2000). Directed approach for Content analysis is a much more steered process than the conventional process and also seen as a more reliable and structured process (Hickey & Kipping, 1996). The main strength of a directed approach is that the theory used will act as guidance and will provide a good basis for further discussions by supporting it or by extending it. Any new factors or categories will offer an insightful view that will enhance the existing theory (Hsieh & Shannon, 2005). Directed Content Analysis has been used for the study as this would provide more reliability and guidance.

Theoretical Framework for Directed Content Analysis

Past researches have shown the use of several theoretical frameworks in adopting new technologies in auditing. These frameworks have been constantly reconceptualized and adopted according to the needs of each study. These frameworks gave a foundational body for implementing new technologies. For example, Nguyen, (2009) proposed a reconceptualized IT adoption framework that was integrated from the drivers of the IT adoption model. The nearly similar model has also been proposed by Ghobakhloo *et al.*, (2012) in his research. Lawrence, (2010) has proposed a theoretical model that he claims provided a far richer understanding of the factors that influence SMEs' decision to adopt and use the Internet in business. One of the prominent theoretical frameworks which have been widely used in researches for adopting the latest technology is the Unified Theory of Acceptance and Use of Technology (UTAUT) and was proposed by Venkatesh *et al.*, (2003).Since then several other researchers has applied this framework namely Mahzan and Lymer, (2008); Curtis and Payne, (2008). Havelka and Merhout, (2007) in their research accumulated the factors which influence the IT audit process's efficiency, effectiveness, and quality. Wehner & Jessup, (2005) also Reviewed individual factors which influence the use of GAS by an auditor using similar frameworks. Several other types of research followed the same route, and which brings us to the conclusion that adopting new technology in the audit should be based on a theoretical framework to enhance the applicability and understanding of its stakeholders.

The study analyses all the contents through the theoretical lens of Modified IT Audit Model by Ahmi & Kent, (2012) and A Model of Information Technology Audit Quality by Havelka & Merhout, (2007). The study amalgamated both theoretical models and has chosen the factors which are best fitted to our research objectives to form the basis of initial themes.

3.4.1.4 Stages of Content Analysis

Content analysis has been explained over eight stages by Weber, (1990). 1) define the recording unit 2) define the categories; 3) test coding of a sample of text; 4) assess the accuracy or reliability; 5) revise coding rules; 6) return to step 3 if necessary; 7) code the entire text; and finally, 8) assess achieved reliability or accuracy. This can be simplified into four steps of data collection, coding, analysis, and interpretation of coded content (Duriau, Reger and Pfarrer, 2007; Holsti, 1969). Researcher adheres to all the steps necessary to create strong reliability for the study.

3.4.1.5 Advantages and Limitations

Content analysis is a useful tool that supports a researcher to portray their findings through a different paradigm. It helps to identify trends and realize how similar factors can be presented from a different perspective and can be treated in a different genre or means (Berelson,1952). However, the method has its fair share of limitations. Content analysis has been criticized for its methodological objectivity (Cleary, Quinn, & Moreno, 2018). Rose, (2016) regarded CA as a quantitative analysis which makes it a non-biased research method. But Content analysis inherently contains a certain level of subjectivity and certain criteria and analysis are deemed to be irrelevant for the study (A. Hansen, Cottle, Negrine, & Newbold, 1998). The researcher has to make some subjective decisions which may result in biasness and this is also one of the reasons why researchers prefer to use an existing theoretical framework in designing initial themes (Bauer, 2000). This would avoid biasness to a certain level.

Some scholars criticize content analysis for its over-reliance on a simplistic quantification of text into word counts, proponents of the method insist on the scientific utility of such quantification (Krippendorf, 2004). Fraenkel & Wallen, (2006) identify five advantages to using content analysis. First, content analysis is an unobtrusive research method. Second, it is useful in analyzing the interview and observational data. Third, the researcher can interpret the social life of an earlier time by delving into records and documents. Fourth, content analysis can be relatively economical in terms of time spent and resources. This is particularly true if the information is readily available in the form of books, periodicals, newspapers, and so forth. Finally, because data is readily available it is possible to replicate the conditions of a content analysis study.

On the other hand, Fraenkel & Wallen, (2006) also identify key disadvantages to content analysis methodology. First, analysis is usually limited to recorded information. Second, internal validity is predicated on assumptions that other researchers would similarly categorize the available data. Third, because researchers only have access to records that have been deemed important enough to preserve it may not be possible to construct a full picture of past trends. Finally, there may be a tendency of researchers to attribute a causal relationship between the variables of a phenomenon as opposed to emphasizing how their interpretations merely reflect patterns. Despite the limitations of content analysis, the nature of the methodology to be used to examine human communication makes it useful for this study.

3.4.1.6 Sample

The analysis was carried out on a paper, published by IAASB (International Accounting Standard Board) and its Data Analytics Working Group "DAWG". The paper was published in 2015 and was named as "Request for Input: Exploring the Growing Use of Technology in the Audit, with a Focus on Data Analytics (RFI)". There were 50 responses which were received around the world in response to this paper. The responses were from various stakeholders including Professional Audit Firms, Standard Setters, Professional Bodies, Individual Auditors, Research Institutes, etc. The study analyses all the 50 responses and the IAASB paper itself. This constitutes a total of 51 contents, which was analysed by using the directed content analysis method.

3.4.1.7 Unit of Analysis

The categories or the factors which a researcher uses for the content analysis should not be prepossessed or determined prematurely Researchers avoid using preconceived categories (Kondracki, N.L., Wellman, N.S. and Amundson, 2002) unless it is developed from an existing theory or framework. Researchers instead try to depict the themes or the categories to flow from the data itself (Hsieh & Shannon, 2005). The result is to engage with the emerged data from the analysis and depict some new and variable insights (Kondracki, N.L., Wellman, N.S. and Amundson, 2002). Many qualitative methods share this initial approach to study design and analysis**.**

Defining the Unit of Analysis

In the literature of Social Science and Accounting, there has been a lot of discussions on the 'unit of analysis' and has been debated at length. Holsti, (1969) describes a recording unit as "the specific segment of content that is characterized by placing it into a given category". Gray *et al.*, (1995) reported and discussed the issue of using words, sentences, paragraphs, or portions of pages as the basis for analysis or counting the amount of disclosure. Although many researchers are quite specific about how disclosure is counted or determined, many are far less clear about what unit of analysis forms the basis for their coding decisions.

In this study, the unit of analysis has been determined as the individual attributes that are given to each Factor or Themes. Under each Factor, several attributes characterize the broader theme. The research analyses to see whether each of these individual attributes is mentioned or discussed by the respondents in their responses or the sample contents. In the end, the analysis will be able to determine which of the attributes are more important than others. If an attribute has been discussed or mentioned by a higher number of respondents, which means, that particular attributes pose significant importance concerning the implementation of DA and BD in Audit. The individual attribute would have been discussed by different respondents or Stakeholders from different perspectives and viewpoints. This will also allow us to discuss further on that issue.

3.4.1.8 Developing Theme and Coding Scheme

The first step to the coding scheme is to convert data into text, that is if the data is in any other form, such as video or audio clips (Gaur & Kumar, 2018). Typically, textual data are coded into different categories, such as word, phrase, sentence, paragraph, or theme. The coding categories, which are represented by different attributes or characteristics of Themes or Factors are known collectively as the coding scheme or rules (Gaur & Kumar, 2018). In qualitative content analysis, they develop coding schemes inductively through an analysis of the collected data (Drisko & Maschi, 2015)

Using sentences as the basis of coding decisions has been widely used in content analysis. However, it's not also the most consistent basis of coding. Other studies have used words, topics, paragraphs, or whole documents (Cormier, Magnan, and Van Velthoven, 2005;Noble, Sinha, and Kumar, 2002;Wallace, 1992). There are several software packages that researchers use when the basis of coding is a word (Frazier, Ingram, and Tennyson, 1984; Davis, Piger and Sedor, 2012). These computer-aided techniques do not require researchers to specify coding categories. One such technique is known as topic modeling. These techniques improve the speed and reliability of the coding process through automation and reduce the biases created through subjectivity during the manual coding process (Krippendorf, 2004; Weber, 1990). A wide range of software is available to conduct computer-aided text analysis (CATA), including NVivo, Altas. ti, QDA Miner.

However, manual coding is more preferred and is more observant when the analysis is based on topics, paragraphs, sentences, or whole documents (Moreno & Cámara, 2014).

3.4.1.9 The study's Approach to Content Analysis

Coding

The study proposes a hand labeled coding approach for content analysis. As mentioned earlier the initial themes were formed based on the framework and the analysis of the DAWG paper published by IAASB. Since these frameworks were predominantly based on intention or behaviour of using software or computer-assisted techniques in auditing, the study had to mould them to fit our objective of adopting Big Data into auditing. This was perceived by going through the current literature of Big Data and Data Analytics in auditing and also by going through several responses before starting the initial analysis.

The primary factors for the analysis were classified as **Audit Profession Factors, Factors Relating to Standards (ISAs), Technological Factors, Organizational Factors, Client Factors, Limitations and Challenges, Other Relevant Factors**. These were further subdivided into several categories by providing them with attributes that describe the primary factors appropriately. These attributes can be termed as sub-themes which will help to get a better picture of the broad category, which is the primary factor.

3.4.1.10 Pilot Study

Researchers prefer to perform a pilot study to get familiar with the use of methods, codes, and the content itself. This also helps to clear out any confusion or ambiguity that may arise at the initial stage of analyzing the content. The pilot study also helps researchers to establish both content validity of the instrument and to improve research questions, format, and the scales (Dixon, 2008).

Once the initial coding was formed for the study, the study proceeds along with a pilot study for our content analysis. The researcher randomly selected 9 responses(content) among the 50 responses(contents) and also the IAASB paper itself to perform an initial pilot study before starting the main analysis. The Pilot Study helped us to determine more crucial attributes for all the factors identified through the theoretical framework. It has been reassured whether the attributes given to each Factor closely describes their phenomenon and also tags back with the responses from the contents. Several reshuffles took place and a final coding scheme was formed. To increase the validity and reduce the biases created due to a single coder, the researcher took the opinion of an Audit Lecturer who has vast knowledge on the field and is also aware of the present changes in technology adoption in Audit. This helps to reduce the subjectivity that was created when categorizing the attributes under each theme. This process helped the researcher to make sure, the attributes closely describe and tag back to the primary factors. During the pilot study, it was realized that some of the ideas generated from the content do not closely tag back to the Factors identified through the Theoretical Framework. So, a separate category of factors was introduced as "**Other Relevant Factors**" which also requires attention to successfully implement DA in Audit. Any overlapping or duplicate themes or attributes have been combined. To capture a broader detail of the responses, some of the attributes haven't been amalgamated together intentionally.

3.4.1.11 Study's Approach to Content Analysis

The 50 responses collected, mostly were in the Pdf version. Some of them were scanned pdf, so they had to be converted to other file formats to make it readable and copiable. Lincoln, Y. S., & Guba, (1985) outlined some strategies, which were followed in the study to ensure credibility and transferability of this study Initially, two folders were formed, one with all the Pdf versions another with 50-word files with the code names to be used for each response. Each Pdf version was read, and all the relevant information was picked out. Code words like Data Analytics, audit quality, audit judgment, data quality, data security, data acquisition, substantive testing, 100% sampling, estimates, etc. were used to identify the responses and the opinion related to that attributes. The paragraph containing the mentioned attributes has been highlighted and the viewpoint of the respondents and copied it to the word file of that respective respondent. This has been repeated and coded through the entire response and to all the contents. This helps us to separate the important ideas and perspectives of Stakeholders from the main body of the text and put it all in one place. After the first stage of highlighting and separation was done, the researcher went back and focused on the un-highlighted portions to find out whether those portions contain any other relevant information or not. A few more information was extracted which was instantly incorporated in the word file. This also increased the validity of the data extracted from the responses. Once all the relevant information was transferred to their respective word file, the responses were analyzed using the code word from the attributes. A separate excel file was used for this purpose, which contains the factors and its attributes as well as all the code names for the respondents. The presence of attributes was marked with 1 and the missing attributes were marked as 0. The information was all analyzed and tagged back appropriately under each factor and to its dedicated attributes.

The result of the analysis gave us an initial indication of how each attribute would affect the implementation of Data analytics. The result shows what percentage of the respondents have discussed each attribute in their responses. Each factor in the analysis will have a significant impact on the implementation of DA in auditing over time. Different perspectives and viewpoints were raised for each attribute from each stakeholder in concern. These will be presented and discussed further in our results and discussion segment.

3.4.1.12 Reliability and Validity of Content Analysis

When conducting content analysis, it is important to demonstrate the reliability of their instruments and/or the reliability of the data collected using those instruments, to permit replicable and valid inferences to be drawn from findings (Adler & Milne, 1999).

According to (Adler & Milne, 1999), reliability in the content analysis involves two separate issues. First, it is necessary to attest that the coded data set produced from the analysis is reliable. This is usually achieved by the use of multiple coders and by reporting that the discrepancies between coders are minimal. Another factor to consider is the reliability associated with the coding instrument. But if the study does not attend to multiple coders, the reliability of particular coding tools can be demonstrated through ensuring well-specified decision categories with well-specified decision rules, which will eventually reduce the need for multiple coders. This process of a single coder can be particularly enhanced by demonstrating that the particular coder has passed an adequate amount of training period. The reliability of the coding decisions can be implied in a pilot test to show that an acceptable level of judgment and procedures has been maintained (Dixon, 2008).

Krippendorf (1980) also identified three types of reliability for content analysis: stability, reproducibility, and accuracy. Stability refers to the ability of a judge to code data the same way over time. The aim of reproducibility is to measure the extent to which coding is the same when multiple coders are involved (Weber, 1990). Guthrie, J., Petty, R., Ferrier, F., and Wells, (2004) detailed three methods to increase reliability in recording and analysing data: first, selecting disclosure categories from well-grounded relevant literature or theory, and clearly defining them; second, establishing a reliable coding instrument with well-specified decision categories and decision rules. Very well-specified decision categories can generate very few inconsistencies, along with well-specified decision rules, when used by a single coder will decrease the need for expensive multiple coders.

The researcher performs a very close reading of the responses, keeping in mind to every minute details of the factors in concern and, to make sure all the seven factors that have been identified can capture all the opinions presented by all the stakeholders. As mentioned above a pilot test was performed before starting the actual analysis, which increases the reliability of the content analysis. Since the study uses a single coder, the reliability of the analysis was established through multiple assessments of the contents. The study also has chosen the factors through some established theoretical framework which also supposedly increased the validity of the analysis.

3.4.1.13 Second Round Testing

Lastly, the study follows the second round of testing, following the same procedure to make sure the coding in the first instances matches the second testing. This was done to ensure the validity and reliability of the method used. This would also reduce any biasness being created by the researcher during the first analysis. Once the second round of analysis was completed the results were compared with the first analysis and 95% similarity was observed. The 95% similarity was observed by comparing the previous coding results, which was based on the words, to the second analysis. In most of the cases, the attributes gave similar output. A small number of new responses were introduced after the second-round testing since these were missed out in the first attempt.

3.4.2 Surveys

In business research, Survey questionnaires are often used to gather participant information to test the research hypotheses or answer the research questions and objectives of the study (Brace, 2008). This technique is fairly common in business and management research, and generally used to get the replies to questions like who, what, where, how much and how many (Saunders et al., 2007). This is also the most widely used form that has been used in audit and technology adoption research (Wehner & Jessup, 2005; Mahzan & Lymer, 2010; Janvrin, Bierstaker, & Lowe, 2008). The process usually involves an economical way of collecting a large amount of data from a considerable population (Saunders et al., 2007). In a survey, the researcher seeks answers to questions or statements verbally or in writing (Straub, Gefen, & Boudreau, 2004). Straub et al., (2004) also emphasized that surveys could be very efficient in collecting data on individual preferences and expectations.

Easterby-Smith, Thorpe, & Jackson (2012) suggested three distinct types of survey: factual, inferential, and exploratory. Factual research is mainly linked to opinion polls and market research involves gathering and assembling factual data from various groups of people. Inferential surveys are aimed at establishing relationships between variables and concepts, whether there are prior assumptions and hypotheses regarding the nature of these relationships. Exploratory surveys attempt to develop a universal set of principles against which any culture can be measured – in the hope that this would provide a basis for predicting the behavior of individuals and organizations in almost any country.

3.4.2.1 Questionnaire Design

The development and the creation of the questionnaire were to capture the overall objective of the study and to effectively address all the research question which has been posted earlier. It has also been administered in a friendly and efficient manner keeping in mind the busy schedule of Auditors. A questionnaire can be classified into three main types which are: Web-Based Questionnaire, Self-Administered Questionnaire, and Face-To-Face Questionnaire (Dillman, 2011; Marsden & Wright, 2010;Denscombe, 2007;Rubin & Babbie, 2009).

The main sources of ideas for designing the questions for this particular study were adopted from established research which is mainly derived from an extensive review and analysis of the existing literature. These questions have been used repeatedly and shown to possess high reliability and validity. Other questions have been developed based on the content analysis of the IAASB paper and its responses. These have been designed to fulfill the objectives and needs of the research. The design of the questionnaire was introduced from the research questions outlined in Chapter 1. Therefore, every research question was transformed into specific relevant questions and put in the survey in order to collect the data needed to be evaluated later. Particular attention was paid to the format, during the development of the questionnaire and the wording of the questions. Questions were written in simple and easy words without any complications. It comprises both open-ended and close-ended questions to enable the participants to provide the researcher with additional information that they felt would help the study and to identify any missing subject topics which should be considered when implementing DA in auditing practices. No double-barrelled questions were present which could have led to some ambiguity. Finally, the validity and reliability of the survey instrument were also taken into consideration. Table 3.1 illustrates how the research questions tag back with the question within the survey.

Table 3.1: Survey Questions according to Research Question

Research Questions		Questions' No. in the Survey
RQ2	*What is the current state of DA usage among auditors in Malaysia?*	***Q5,Q6,Q7,Q8,Q9, Q10,Q11,Q20***
RQ3	*Which contributing factors are deemed to be important for the implementation of DA in external auditing?*	***Q12-Q18***

3.4.2.2 The Rationale for Each Section of the Questionnaire

This study followed the four basic principles of ordering and sequencing a questionnaire as proposed by D A Dillman, (1978). The four principles applied are suggested to increase the inspiration and strength of the respondents to complete the questionnaire. The four principles are:

1 Questions are ordered in descending order of importance and usefulness.

2 Group the questions that are similar in content together, and within areas, by type of question.

3 Take advantage of the cognitive ties that respondents are likely to make among the groups of questions in deciding the order of the questions involved.

4 Position the questions that are most likely to be objectionable to respondents after the less objectionable ones.

Based on these four principles, the final version of the questionnaire is divided into four main sections, each encompassing a different theme:

Section 1: The first section includes Questions intended to collect background information on the audit firm. This question group is geared towards the location, year, category, number of employees, year of establishment and the number of auditors.

Section 2: The second section is designed to understand and explore the current usage of Data Analytics by Auditors in Malaysia. To achieve Objective 2 of this study, this section consists of questions like what sort of DA software they are currently using, how often they use data analytics, and for how long their organization has been using DA and how satisfied they are?

Section 3: This section investigates factors that relate and influence the implementation of DA in audit procedure. Each of the factors has several attributes to define the factors and is measured using a five-point Likert scale. A 5-point Likert- type scale was designed to measure the extent to which the respondents perceive that each statement was undermined or enhanced concerning the implementation of DA (J. V. Remenyi, 2002). Moreover, the neutral choice was provided in the middle. Saunders, Lewis, & Thornhill, (2013) recommends that by using a Likert-type neutral option, the researcher attempts to reduce any bias that may result from their statement as the participant may not have any cognitive response to the statement. There is also one open-ended question asking about other factors that the respondent thinks might influence their decision in implementing DA. The section ends with a vital question on the perceptions of Auditors on the benefits of using DA in several Audit areas.

Section 4: The final section focuses on the background of the auditors. These questions ask about individual auditors' demographic profile.

3.4.2.3 Rules on Ethics and Confidentiality

It is a prerequisite of the University of Malaya that all research involving human subjects should be open to ethical review and approval before the study begins. Therefore, the clearance before conducting the survey was applied for and obtained from the University of Malaya Research Ethics Committee (UMREC). A declaration attached to the questionnaire cover page was prepared to discuss the intent of the study and the ethical regulations. In the survey, a privacy notice was also added explaining that the survey is anonymous, data will be kept confidential and will be used for research purposes only.

3.4.2.4 Validity and Reliability Measurement

The questionnaire was pre-tested and pilot tested before proceeding with the actual data collection phase. Pre-testing or a pilot study of the questionnaire needs to be undertaken before final administration (D. Remenyi, Williams, Money, & Swartz, 1998). The primary objective of pre-testing is to identify possible weaknesses and flaws in the design of the questionnaire (Zakari, 2011; Ary, Jacobs, Irvine, & Walker, 2018). Pre-testing can be informal where one consults friends, colleagues, experts, and people of diverse opinions, or it could be formal, involving a pilot study which is a replication, on a small scale of the main study (D. Remenyi et al., 1998). The pilot study is a recommended process by Saunders et al., (2013) as a method to establish, that the questionnaire suggested is comprehensible and understandable to the sample population.

3.4.2.5 Pre-Test

The pre-testing was utilized in this study to provide the opportunity to assess the clarity of the questionnaire instructions and questions, the quality of the information and the ability to perform meaningful analysis of the information obtained, the time taken to complete the questionnaire, which questions are irrelevant, and which are relevant (Sekaran & Bougie, 2003;Zakari, 2011). The pre-test was run on a few identified auditors and academicians with prior research knowledge on survey questionnaires and audits. A cover letter addressing each respondent was included in the pre-test questionnaire. The cover letter stated the main objectives of the study and the basis of the formation of the questionnaire. It also includes an assurance of anonymity and confidentiality regarding the responses being collected.

To ensure comprehensiveness in the questionnaire, it was pre-tested with 15 participants – 10 academicians with prior knowledge in survey questionnaires and auditing and 5 audit practitioners. Upon receipt of the observations and comments from the participants, these were gathered and analyzed further to improve the contents of the questionnaire. their comments, the questionnaire was revised and further refined. The objective was to make the questions more understandable and make sure the questionnaire doesn't take too long to answer. When questions are too long it makes the respondent bored and fewer people are likely to answer them all (Oppenheim, 1966). The questionnaire was laid out and given a professional view as much as possible. Based on their feedback, the items were further refined, and a revised version of the questionnaire was developed.

3.4.2.6 Pilot Test

To confirm the reliability and validity of the questionnaire, a pilot test was conducted. A total of 50 questionnaires was forwarded to auditors through online google form and physical hard copy. They were invited to be involved in the pilot test. A total of 38 questionnaires was able to be retrieved after a period of one month. But some of them had to be disregarded as they were half-filled, and some were empty. In the end, 30 responses were selected which were 100% completed. To evaluate the reliability of a multi-item measurement scale, the most regularly used and widely accepted method is Cronbach's alpha (Hair, Black, Babin, Anderson, & Tatham, 1998).

For testing reliability, only the factor that influences the implementation of Data Analytics in auditing has been considered and tested. All other items and demographic variables were excluded. Table 3.2 below shows the result of Cronbach's alpha for all the constructs. It indicates an overall 0.9455 for a scale of 50 attributes. The highest was 0.9410 for client factors with 8 attributes and the lowest was 0.8295 for factors relating to ISAs with 6 attributes. According to Pallant, (2005) and Hair et al., (1998), as a standard measure of reliability, 0.7 should be used as a cut-off point. All the variables in the study are showing a value above 0.7, at this stage of the study. However, there is a need to further confirm these results and validate the scale further. This would be done using the final main survey questionnaire in the full-scale research. So, all the factors are retained at this stage to perform a full study and to proceed with further factor analysis to validate the scale of the survey. This pilot study with 30 responses disclosed higher internal consistency for all scales.

Table 3.2: Overall Cronbach Alpha

Test scale = mean (unstandardized items)	
Average interitem covariance:	0.1185437
Number of items in the scale:	50
Scale reliability coefficient:	0.9455

Table 3.2: Cronbach Alpha for each Factor

	Cronbach Alpha	Number of Items
Audit Profession Factor	0.8678	11
Factors Relating to International Standards of Auditing	0.8295	6
Technological Factors	0.9243	5
Organizational Factors	0.9139	7
Client Factors	0.9410	8
Limitation and Challenges	0.8683	7
Other Relevant External Factors	0.7499	6

DATA COLLECTION

The feedback from the pre-test helps the researcher to improve and finalize the questionnaire for distribution. Several procedures of questionnaire distribution were undertaken to increase the response rate. Initially, a google-form link containing the survey questionnaire was distributed over the internet to a list of auditors. The email address of the auditors was collected from training and seminars attended before. A total of 47 emails was sent out initially. A very slow response rate was observed. After a month and a half only 5 responses were recorded. So, to increase the efficiency of the responses, the researcher took permission to attend training conducted by the Malaysian Institute of Accountants (MIA) and organized specifically for Auditors in Malaysia. Once the permission was granted a total of 10 training seminar was attended. A total of 200 questionnaires were distributed among the auditors who were present, over these 10 pieces of training, In the end, a total of 126 questionnaires were recollected with a response rate of 63%. Normally an online survey would give a response rate of 12% (Ahmi, 2013) but in this case, the response rate is quite high since the researcher collected the response by being physically present during the session.

3.4.2.7 Study Population and Sample

The term `population' refers to the entire group of people, events, or things of interest under investigation, and the population frame is a listing of all the elements in the population from which the sample is drawn (Sekaran & Bougie, 2016). In this study, the population is defined as Auditors of Malaysia. A total of 200 surveys were printed out and a total of 47 emails was sent out to auditors. After defining the population, it was necessary to identify an appropriate sample and a suitable sampling frame. Selecting a sample is a fundamental element of a positivistic study (Collis & Hussey, 2013). The reasons for sampling are the lower cost, greater speed of data collection, and the availability of population elements (Cooper, Schindler, & Sun, 2006). Sampling is important because it is usually not possible to collect information from all members of the population being studied (Black, 1999). The sample of the study was external auditors who worked in an Audit firm of any size and situated in Malaysia. The sample frame of the study was 5 online survey and a total of 126 hands filled hard copy surveys.

Table 3.3: Details of Survey Sample

Survey form	Target Population	Sample received	Usable Amount
Online	**47**	**5**	**5**
Physical	**200**	**126**	**113**
Total Survey	**247**	**131**	**118**

3.5 Summary of Chapter

Firstly, the chapter discusses the methodological approaches and procedures involved in the collection of relevant data capable of producing meaningful results and useful findings capable of advancing information frontiers in the field of auditing and the use of DA. This work is focusing on positivism. The findings of the qualitative analysis shall be backed by the statistical analysis input from the open questionnaires. Next, this chapter reviews theoretical frameworks that have been used in earlier studies that relate to IT adoption in Audit. A relevant theoretical framework and theory have been adopted, and its implications were discussed for selected studies. Next, the chapter details the two methods which have been used in this study. The first one was content analysis and the second survey questionnaire. A detailed explanation of how to conduct a directed content analysis using a suitable framework has been discussed and the initial factors which have been determined from the analysis of the content. Next, the chapter discusses the survey questionnaire as a method. The chapter has also shown how the online and hard copy survey and questionnaire technique could be used to collect useful sets of research data.

The formation and rationale behind the questionnaire have been discussed along with the pre-study and the pilot study which has been conducted using 30 respondents.

CHAPTER 4 DATA ANALYSIS & FINDINGS

CONTENT ANALYSIS

4.1 Data Analysis and Discussion on Findings

The result of the analysis gave us an initial indication of perceptions of respondents on the effect of each attribute affecting the use of DA. According to the framework, the primary factors for the analysis are classified as Audit Profession Factors, Factors Relating to Standards (ISAs), Technological Factors, Organizational Factors, Client Factors, Limitations and Challenges, Other Relevant Factors, which are labeled in Table 4.1, along with all the attributes and the percentage of the respondents. The percentage of the responses were derived from the coding analysis. This represents, among the total of 50 respondents, what percentage of the respondents responded to a particular attribute or commented on a particular attribute or posed their view on that particular attribute or factor. For example, the first attribute represents 54%, which means out of 50 respondents, 27 (54%) of the respondents have posed their view on these particular attributes. If an attribute has a higher percentage this means, it has been discussed by more stakeholders and is deemed to be more important. Each of these factors would be considered for the analysis. Each of these factors is described broadly through different attributes. Respondents' viewpoints were analyzed for each of these attributes in concern. These are presented and discussed further in the results and discussion segment. Table 4.2 details the segregation of all the stakeholders who responded to the DAWG paper.

Table 4.1: All the Factors and their respective attributes with a percentage of responses achieved for each attribute from an overall 50 respondents

	Audit Profession Factors (AP)	Code	%
1	DA as substantive testing, Test of control or Test of details	**AP5**	54%
2	Audit Quality/ Audit Judgement	**AP6**	52%
3	Audit Documentation	**AP9**	48%
4	Testing 100% of the population (Sampling)	**AP3**	42%
5	Sufficiency of Audit Evidence	**AP7**	42%
6	Risk Assessment/ Measurement/Audit Risk/Risk of Assertion using DA/ROMM	**AP10**	40%
7	Outliers and Exceptions in Sampling/population	**AP8**	34%
8	Application of Professional Scepticism & Professional Judgement (ISA-315)	**AP2**	26%
9	Audit Opinion (Reasonable Assurance or more)	**AP11**	26%
10	Risk-Based Audit compared to DA audit	**AP1**	24%
11	Accounting Estimates and Disclosures (ISA 540)	**AP4**	12%
	Factors Relating to Standards (FRS)	**Code**	
1	Revising /Challenges in developing new Std /Current ISAs not suitable for DA	**FRS3**	72%
2	Developing a Principle-based standard	**FRS4**	32%
3	Collaborative work from Auditors, Std setters & Oversight Authorities on ISAs	**FRS1**	26%
4	Analytical Procedures using DA (ISA 520)	**FRS5**	14%
5	CAATs vs DA in respect to ISAs	**FRS2**	12%
	Technological Factors (TF)	**Code**	
1	Data Reliability / Data Quality/Data Validation	**TF1**	52%
2	Data Acquisition/Data Security	**TF2**	48%
3	Data Accessibility/Store and Retention for Audit Trail	**TF3**	26%
4	IT specialist's role in Audit for using DA	**TF4**	18%
5	Conceptual Challenges (Data related)	**TF5**	10%
	Organizational Factors (OF)	**Code**	
1	Skills of Auditors as Data Analyst/ Need for Data Analyst	**OF1**	30%
2	Re- training & Re- Skilling Auditors	**OF2**	30%
3	DA for SMEs and SMPs, Public Accounting and Group Audits	**OF3**	28%
	Client Factors (CF)	**Code**	
1	Understanding Entities Environment, Internal Control using DA (ISA 315)	**CF1**	30%
2	General IT controls	**CF3**	26%
3	Understanding the data in use (Clients Data)	**CF4**	18%
4	Clients Infrastructure or internal control	**CF2**	12%
	Limitation and Challenges (LC)	**Code**	
1	Impact on time and cost in using and implementing DA	**LC1**	26%
2	Reliance on External/Third party/ Internal Audit Data	**LC2**	22%
3	Legal/Regulatory Challenges	**LC5**	12%
4	Appropriate controls for using DA/Quality Controls	**LC3**	10%
5	Ethics and Professionalism in using DA	**LC4**	10%
	Other Relevant External Factors (ORF)	**Code**	

1	Issuance of Non- Authoritative Guidance on ISAs for using DA	**ORF5**	42%
2	Future of Audit using Predictive Algorithms/text Mining/Data Mining/blockchain/Continuous Auditing	**ORF7**	42%
3	SK Expectation/ Expectation Gap/Knowledge Gap/	**ORF3**	36%
4	Over reliance on technology	**ORF8**	36%
5	Shifts in Audit Environment/Technology	**ORF2**	34%
6	Fraud Detection Using DA	**ORF9**	28%
7	Role of Academicians, Universities	**ORF4**	22%
8	Defining Data Analytics	**ORF1**	16%
9	DA as a tool or Audit method	**ORF6**	12%

Table 4.2: Segregation of all the Stakeholders

Stakeholder Group of Respondents	Number of Respondents from each Stakeholder Group
Member Bodies and Other Professional Organizations	15
Accounting Firms	10
National Auditing Standard Setters	9
Individuals and Others	5
Regulators and Oversight Authorities	4
Public Sector Organizations	3
Investors and Analysts	2
Academics	2
Total	**50 respondents**

Stage 1: Directed Content Analysis

The study analyses all the contents through the theoretical lens of **Modified IT Audit Model by Ahmi & Kent (2012)** as the basis of directed content analysis

Stage 2: Sample

IAASB (International Accounting Standard Board) and its Data Analytics Working Group "DAWG" published a paper in 2015 which was named as "**Request for Input: Exploring the Growing Use of Technology in the Audit, with a Focus on Data Analytics (RFI)**". The analysis was carried out on 50 responses which were collected as a feedback to this paper from different stakeholders in audit profession.

Stage 3: Defining the Unit of Analysis

The unit of analysis has been determined as the individual attributes that are given to each Factors. Each of these Factors have several attributes which characterizes and interprets the broader theme. The research analyses to see whether each of these individual attributes are discussed by the respondents in their responses or the sample contents.

Stage 3: Defining the Unit of Analysis

The analysis will be able to determine which of the attributes are more important than others. If an attribute has been discussed or mentioned by a higher number of respondents, which means, that particular attributes poses a significant importance in relation to implementation of DA in Audit. The individual attribute would have been discussed by different Stakeholders from different perspectives. This raises the opportunity to discuss further on that issue.

Stage 4: Developing Theme and Coding Scheme

The content analysis uses key words as the basis of coding decisions which has been widely used in content analysis. It's also the most consistent basis of coding. Manual coding is more preferred and is more observant when the analysis is based on topics, paragraphs, sentences or whole documents (Moreno & Cámara, 2014)

Stage 5: Pilot Study

Researchers prefer to perform a pilot study to get familiar with the use of methods, codes and the content itself. 9 responses(content) were randomly selected among the 50 responses and also the IAASB paper itself to perform an initial pilot study before starting the main analysis. The Pilot Study helped us to determine crucial attributes for all the factors identified through the theoretical framework. It reassured whether the attributes given to each Factor closely represents their phenomenon and also tags back with the responses from the contents.

Stage 6: Reliability and Validity of Content Analysis

Since the study uses a single coder, the reliability of the analysis was established through multiple assessment of the contents. The pilot study also helps researchers to establish both content validity of the instrument and to improve research questions, format, and the scales(Dixon, 2008). The study also has chosen the factors through some established theoretical framework which also supposedly increased the validity of the analysis

Stage 7: Second Round Testing

Lastly, the study follows a second round of testing, following the same procedure to make sure the coding at the first instances matches the second testing. This was done to ensure the validity and the reliability of the method used. This would also reduce any biasness being created by the researcher during the first analysis. Once the second round of analysis was completed the results were compared with the first analysis and 95% similarity was observed

Figure:4.1 Steps followed for the directed content analysis

4.2 Findings and Discussion

4.2.1 Audit Profession Factor

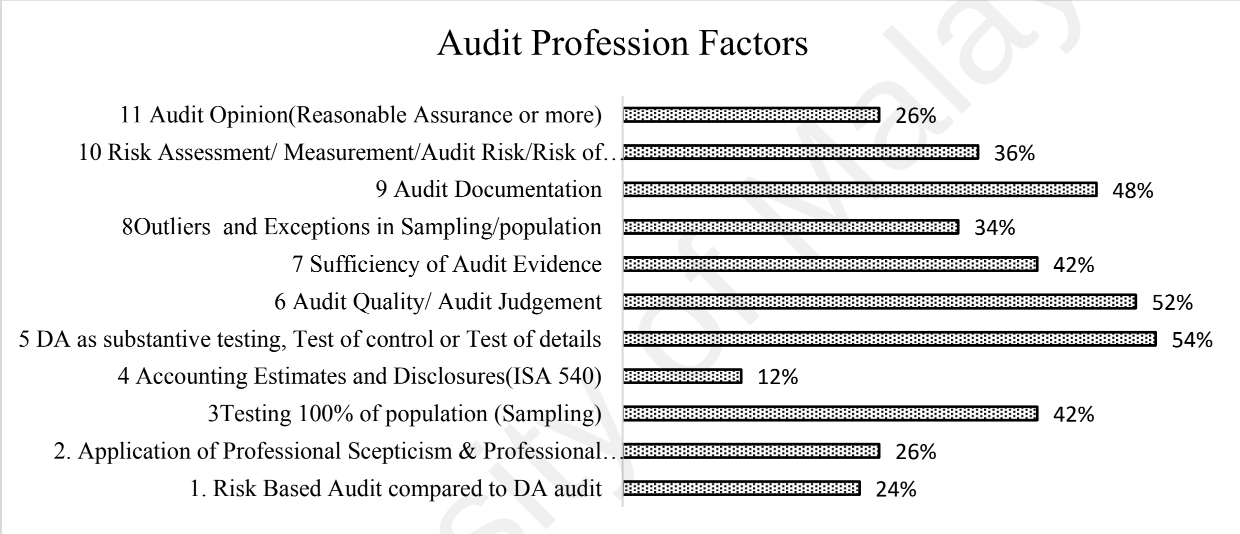


Figure:4.2 A Graphic representation of Audit Profession Factors

Table 4.3: A percentage breakdown of the total responses by each stakeholder group on each attribute under Audit profession factors

Audit Profession Factors	Member Bodies and Other Professional Org. (15)	Accounting Firms (10)	National Auditing Standard Setters (9)	Individuals & Others (5)	Regulators & Oversight Authorities (4)	Public Sector Organizations (3)	Investors & Analysts (2)	Academics (2)
DA as substantive testing, Test of control or Test of details	16%	8%	14%	4%	6%	4%	0%	2%
Audit Quality/ Audit Judgement	18%	10%	6%	4%	6%	4%	2%	2%
Audit Documentation	14%	14%	8%	2%	6%	2%	0%	2%
Testing 100% of population (Sampling)	10%	14%	8%	4%	0%	2%	2%	2%
Sufficiency of Audit Evidence	12%	6%	8%	4%	4%	4%	2%	2%
Risk Assessment/ Measurement/Audit Risk/Risk of Assertion using DA/ROMM	14%	8%	8%	2%	2%	2%	2%	2%
Outliers and Exceptions in Sampling/population	12%	8%	8%	0%	2%	2%	0%	2%
Application of Professional Scepticism & Professional Judgement (ISA-315)	12%	4%	4%	2%	2%	0%	2%	0%
Audit Opinion (Reasonable Assurance or more)	10%	8%	0%	2%	2%	2%	0%	2%
Risk Based Audit compared to DA audit	8%	4%	4%	2%	4%	0%	2%	0%
Accounting Estimates and Disclosures (ISA 540)	8%	2%	0%	0%	0%	2%	0%	0%

DA as substantive testing, Test of control or Test of details

The nature of data analytics is such that multi-purposes may be achieved with single test design. This has been one of the most sought out attributes under audit profession factors with overall 54% of respondents posing their perspective on the beneficial use of DA in external auditing. Among them, 16% of responses came from professional and member bodies (see Table 4.3). A mix of opinions has been posted by respondents. As quoted by the ***Australian Auditing and Assurance Standards Board***:

"The dilemma arises whether the current distinction in the auditing standards between risk assessment, controls testing, and substantive procedures are still relevant when using DA…."

Whereas another viewpoint was referred by the ***Institute of Public Auditors***, an incorporated organization of private and public firms in Germany:

"The multi-purpose nature of data analytics would also have to be extended to the testing of classes of transactions, accounts balance, and related disclosures. Moreover, the more data is generated electronically, the more important controls over completeness, reliability, and validity of the data become because these are the matters that may not be susceptible to audit via data analytics……"

It can be difficult to determine whether DA is a risk assessment procedure or a further audit procedure, deemed to be substantive analytical procedures or a test of details, since DA-routines, frequently analyze data at the transaction level(KPMG, 2017). As the ***International Association of Insurance Supervisors (IAIS)*** has focused on their feedback, that consideration should be given to the fact, that even though data analytics can provide some pervasive audit evidence, they are not a substitute for all audit evidence. In particular, audit evidence that has to be obtained through controls testing, specific understanding of the entity and its environment, and use of professional judgments to gain reasonable assurance over the financial statements. In the end, audit practitioners need further clarity on which audit procedures data analytics may be used. Whether they will be used as an exploratory tool or a confirmatory tool only?

Audit Quality/ Audit Judgement

According to several interviews conducted by Kostić and Tang, (2017) for their research, majority respondents suggests that audit quality can be improved in the future through automation. Cao, Chychyla, and Stewart,(2015) pointed out that the increased use of Big Data and DA can lead to an improvement in the efficiency and effectiveness of financial statement audits. This has been one of the most discussed audit topics, with 52% of respondents presenting their opinion on it. Overall there was a common consensus between the respondents, that the use of data analytics in the financial statement audit has the potential to enhance audit quality. As illustrated by ***New Zealand Auditing and Assurance Standards Board*** in their feedback:

"data analytics provide potentially the biggest opportunity and the most exciting development influencing the audit profession is a long-time and given its potential, DA can fundamentally reshape the audit model and should allow procedures to evolve leading to a more efficient, high-quality audit that affords investors greater transparency………"

However, the ***European Federation of Accountants and Auditors*** mentioned that data analytics will not automatically lead to a better audit and auditors need to gain a strong awareness of data analytics issues. The use of those tools can also represent a risk for the quality of the audit, depending on how those tools are developed, implemented, and applied in the audits as recognized by the ***International Forum of Independent Audit Regulators***. While many agree that data analytics can enhance audit quality, there does not appear to be a consensus as to the use of data analytics as an alternative to traditional audit techniques. Auditors need to be clear about the relative value of DA in enhancing audit quality. Specifically, on the issue of how DA enhance audit quality in practice. For instance, as stated by the ***Association of chartered certified accountants (ACCA)***:

"Ultimately, it is important to understand where the value in data analytics really lies. Data analytics may contribute to better audit quality either by increasing efficiency or by permitting a greater depth of auditor enquiry……."

Audit Documentation

As auditors begin to place more reliance on IT-related controls in data-driven audits, potentially vast amounts of data will be analysed and tested as part of the audit. The emphasis on documentation requirements will increase, and as represented by the analysis in Figure 4.2, 48 % of the respondents has shared their view on this topic. The ISAs currently do not require the auditor to retain all of the information used in selecting items for testing. It is important to understand whether the same principle continues to apply when data analytics are used. Whether Data that was used in the performance of data analytics but that is not directly audit evidence should be retained or not?

Standards should consider expanding upon the documentation requirements when it comes to using data analytics (e.g. electronic documents vs. original documents, system information, etc.). It is important that detailed information regarding the methods used, including the scripts used to extract data, should be retained on the archived audit file. The same observations also apply to the significant judgments made in the audit - data analytics provides good information to support high-quality risk assessment procedures which in turn supports the judgments the auditor makes when identifying and assessing risks and evidence of this should be retained on the audit file. Document and store/archive not only the nature, timing, and extent of the use of the tools and the results thereof, but also the support for the conclusions about the reliability of the results, for instance, the verification of the routines used, the data extraction procedures, the procedures used to evaluate the quality of the data. In relation to professional scepticism, the relevant considerations as to how technology tools may impact auditor behaviours and biases can also be aligned with the identified challenges of what the appropriate level of work effort is and expectations for auditor documentation The auditor should be provided with additional guidance on how and what constitutes in the audit file and for what length of time, including snapshots of 'real-time data', should be retained, as well as who should retain the data file used in audit procedures .the auditor is required to include the logarithm to enable the experienced IT expert or auditor to rerun the actual data analytics or is it sufficient for the auditor to document the process followed. Inspectors should have identifiers that would allow the audit procedure to be re-performed.

Auditors may need clarity on how the system's algorithms need to be documented, and how much work of the data analytics specialist would need to be documented. They need further clarity on what constitutes sufficient appropriate evidence when using a data analytics tool that was used to perform the audit procedures. How would the use of the tool be recorded? Finally, the standards should provide guidance over clients' data retention after the completion of a financial statement audit and meeting reperformance standards when data retrieval and recoverability may be challenged.

Testing 100% of the population (Sampling)

One of the most significant changes that DA is expected to bring in, is on the aspect of audit sampling (ISA 530). Table 4.3 illustrates that an overall 42% of the respondents discussed this issue and within that 14% of the respondents were from Accounting Firms, who believed that the use of DA in testing all the population will affect audit efficiency. Auditors have traditionally used the application of audit procedures to less than 100% of items within a population of audit relevance such that all sampling units have a chance of selection in order to provide the auditor with a reasonable basis on which to draw conclusions about the entire population (IFAC, 2009). However, DA will be able to test 100% of the population and is presumably expected to provide a higher level of assurance, which may lead to higher quality audit evidence that is free from bias and sampling risk (EY, 2017). But this brings to a lot of inquisitive considerations in limelight. First of all, the statement 'testing 100% of the population could be misinterpreted by stakeholders. As mentioned by the ***International Auditing and Assurance Standards Board*** (***IAASB)*** in their paper as well as the respondents:

"*Being able to test 100% of a population does not imply that the auditor is able to obtain more than reasonable assurance or that the meaning of "reasonable assurance" changes…….*"

The ***Swiss Expert Association for Audit, Tax, and Fiduciary*** opinionated that what is meant in this context is that 100% of the transactions are subject to analysis', but it doesn't mean that the auditor identifies and reports every single outlier. Although some respondents do agree to it, there is some further clarification to ponder about. A level of assurance reached through analyzing 100% population should not be as same as dealing with half the population. It will not reflect the true essence. This can also bring in the question of whether sampling is still needed when an auditor has electronic access to the entire population?

Sufficiency of Audit Evidence

Data analytics can provide sufficient and appropriate audit evidence and reduce the amount of effort and the time spent compared to manual analysis that motivates the use of DA in external auditing (CarLab, 2017). As illustrated by ***Deloitte Touche Tohmatsu Limited***, a member of Big Four Firms:

"It is currently unclear whether the use of data analytics to test the operating effectiveness of controls can provide the auditor with sufficient audit evidence………"

Thus, one question to consider is whether the use of DA automatically addresses the sufficiency and appropriateness of audit evidence. 42% of the stakeholder shared a view of ambiguity regarding this issue, within that almost 20% of them were from the professional organization and standard setters. Currently, there is a misconception amongst auditors that the performance of data analytics alone provides the auditor with sufficient, appropriate audit evidence and therefore negates the need for the auditor to perform additional testing. DA cannot be seen as an alternative, rather they must complement than replace each other. This has also been acknowledged by ***Independent Regulatory Board for Auditors*** in their responses, that there should be further clarity on what is regarded as sufficient appropriate audit evidence when using data analytics tools and how would the use of the tool be recorded and what sort of factors to consider when assessing the sufficiency of audit evidence.

Risk Measurement/Audit Risk/Risk of Assertion using DA/Risk of Fraud

As DA provides an opportunity to analyze larger populations of data, it allows auditors to focus their attention on riskier transactions. DA can have a material impact on ISA 500, Audit Evidence. DA techniques can start as a risk assessment procedure and transform into an evidence gathering procedure. ***The Rutgers Continuous Auditing & Reporting Lab*** narrated in their Responses:

"DA techniques can effectively assist the auditor in verifying management assertions such as completeness, accuracy, and cut-off. In an audit environment where data analytics can be performed on a continuous basis to gather audit evidence, it is possible that fraud may be mitigated, as continuous checks and controls are in place, or that it may be detected in a timely manner......"

Similarly, machine learning methodologies such as neural networks, logistic regressions, and support vector machines could be used to predict the likelihood of fraud in financial statements (Perols & Lougee, 2011). Audit evidence gained through applying DA in risk assessment has an opportunity to clearly and more precisely define risks of material misstatement in order to design a focused, risk-based response(EY, 2017). So, a guide on how auditors can be comfortable that all assertions have been met when using data analytics will also be helpful.

Application of Professional Scepticism & Professional Judgement (ISA-315)

The majority of the respondents opined in their responses that technology should not override the human factor or physical presence, as human interactions are still important to fully understand a client's business and its processes as well as to identify and resolve the issues. 26% of the respondents believe that the factors of professional skepticism and professional judgment should be considered even when we are using DA. For instance, ***European Federation of Accountants and Auditors*** believes that the advantages of using high specification data analytics tools can easily be undermined by poor judgments of inadequately trained auditors using the same predictable approach and methods, both traditional and data analytics, year after year may impair audit effectiveness and give rise to a higher risk of fraud. The ***Australian Auditing and Assurance Standards Board*** also referred in their responses:

"Importance of professional judgment, professional skepticism, and critical thinking should continue to be emphasized, as these are integral in determining the appropriate data to use, the procedures to perform, and evaluation of the results of data analytic procedures……."

However, to remain fully relevant, the profession should be careful not to head towards 'virtual-audits'.

Risk-Based Audit compared to Data analytics audit

Risk-based audit is probably the most exciting and significant development until now in the Audit profession's history(Griffiths, 2005). The simplest way to think about risk-based audit conceptually is to audit the things that matter to your organization and which poses the greatest risks. When Data analytics (DA) came into the picture it has been a continuing discussion on how DA would change or fit into this current risk-based approach model. From the study, several perspectives have come into the limelight. The content analysis of respondents depicted that most of them agree on the fact that DA should not alter the fundamental Risk-based audit assurance. For instance, as quoted in the responses of ***Deloitte Touche Tohmatsu Limited***, a member of Big Four Firms:

"Moreover, guidance and consideration should be given as to whether the auditing standards need to be clarified to more explicitly acknowledge the use of data analytics in the audit…………"

However, some believe strongly that data analytics does have a fundamental impact on the model and that IAASB should take the time now, to consider its impact on the thinking underlying concepts(ICAEW, 2016b). The use of data analytics will significantly impact many audit areas (risk assessments, controls testing, substantive and analytical procedures, and gathering of audit evidence) and will consequently affect the current structure and definition of several audit steps. Presumably, the ***Swiss Expert Association for Audit, Tax and Fiduciary*** indicated that there is a risk that an audit performed using data analytics could be regarded as being of a different quality than one that is based solely on the current audit evidence model. IAASB should develop criteria in identifying under which conditions it will be advisable to apply data analytics.

Audit Opinion (Reasonable Assurance or more)

The issue of DA and reasonable assurance of audit opinion is one of the topics highlighted in the response letters to the DAWG. As quoted by ***New Zealand Auditing and Assurance Standards Board:***

"Although there has been a growing effort to use data analytics in transaction variation analysis, significant effort is yet to be directed into understanding how the annual audit can be carried out more effectively or efficiently to give a better assurance…."

The question arises, whether the use of DA will increase the expectation to another level of assurance? Changes in audit techniques through the use of data analytics may create an unintended expectations gap. As mentioned by ***Rutgers Continuous Auditing & Reporting Lab*** that today, the audit opinion reflects a static assurance model, however, as audits become data-driven, the "point in time" audit opinion report may become obsolete since it is issued weeks, even months after the financial statements have been finalized. In the future, audit opinions will be presented quantitatively and/or qualitatively, and most importantly, in real-time. ***Accountancy Europe***, a professional organization stated in their responses that if DA would enhance the quality of audit compares to traditional audit, it would be unfair to express a similar opinion, so, even though the definition of reasonable assurance is unlikely to warrant a change, the perceptions of what it signifies, or its values should capture the relative developments which are brought about by DA.

Outliers and Exceptions in Sampling/population

When testing a broader population, considering the fact that DA tools usually analyse items in a more granular way, thereby producing significantly more outliers/exceptions than traditional audit techniques. There is a significant implication on controls when exceptions are identified through data analytics used. When outliers or exceptions are detected, the standards should be clear as to whether auditors are given the option to view them from the risk of material misstatement only or include the need to dispose of the risk of fraud. It would be rather impractical and ineffective for auditors to test all the outliers detected resulting from DA procedures. Furthermore, testing a random sample from the outlier population may not be adequate. In such cases, instead of automatically deciding to sample or test each case, it will be necessary to consider whether the subject of these procedures and the audit evidence required belong to an area with a relatively high probability of material misstatements when extracting specific items. The absence of any identified outliers in the remaining population does not necessarily mean that risk assessment procedures are not required, since, while not falling under any extraction standards for analysis the above procedures alone will not ensure that it is free of the risk of other material misstatements

As mentioned by ***Rutgers Continuous Auditing and Reporting Lab*** in one of the contents that:

"Applying risk-based filters in the processing of outliers can be beneficial. These filters will consist of qualitative or quantitative criteria that can facilitate the isolation of the data instances that are exceptions and represent riskier transactions or process flows. From a substantive analytical procedure's perspective, for example, non-traditional financial metrics such as square footage, may be used as a risk-filter to identify the accuracy of revenue for real estate inventory. It would be the auditors' responsibility however, to determine the appropriate risk filters to use in the analytic as these filters may vary by industry and audit client".

However, the results of the data analytic technique – conversely, the filtering and analysis of a population may result in no exceptions. Guidance would be required to determine what type of additional procedures. Also, the definition of an exception might need to be revisited, as it will be necessary to reconsider, as a profession, what is meant to be an exception under Data Analytics.

IAASB needs to provide guidance to clarify that outliers are not by default exceptions or misstatements and also provide further guidance on how to determine whether an exception exists through the use of data analytics. Training on biases such as confirmation bias and selection bias and how to handle outliers will be important for auditors and their clients when sourcing requests for data as well as when analyzing requests for data. IAASB should also explore how the identification of such exceptions might impact our conclusions concerning the configuration and effectiveness of controls in service.

-Accounting Estimates and Disclosures (ISA 540)

Guidance to address the appropriateness of the use of data analytics to obtain evidence over accounting estimates and disclosures is required. To properly assess the reasonableness of the accounting estimates and disclosures the application of professional skepticism and judgment are needed besides Data Analytics.

Application of Professional Scepticism & Professional Judgement (ISA-315)

Technology should not override the human factor or physical presence, as human interactions are still important to fully understand a client's business and its processes as well as to identify and resolve the issues. The advantages of using high specification data analytics tools can be easily undermined by poor judgments of inadequately trained auditors using the same predictable approach and methods, both traditional and data analytics, year after year may impair audit effectiveness and give rise to a higher risk of fraud.

Importance of professional judgment, professional skepticism, and critical thinking should be continuing to be emphasized, as these are integral in determining the appropriate data to use, the procedures to perform, the relevance to the audit, the nature of audit evidence, and evaluation of the results of data analytic procedures. Auditors can effectively apply professional skepticism when DA is used in the risk assessment phase. This would help auditors to make an educated judgment to identify areas that warrant further investigation. The current ISAs allow auditors to apply professional judgment when performing audit work. The standard-setters need to work further on this concept to extend the area of DA and their use within the framework in existence (ISA-315).

However, in order to remain fully relevant, the profession should be careful not to head towards 'virtual-audits'.

4.2.2 Factor Relating to International Standards of Auditing (ISAs)

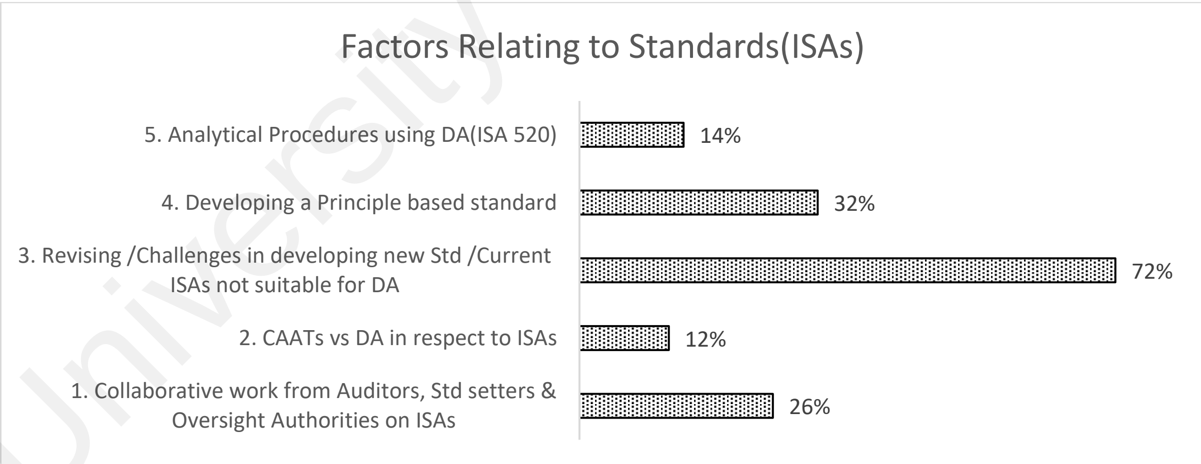


Figure:4.3 A Graphic representation of Factors relating to International Standards of Auditing (ISAs)

Table 4.4: A percentage breakdown of the total responses by each stakeholder group on each attribute under factors relating to standards (ISAs)

Factors Relating to Standards (ISAs)	Member Bodies and Other Professional Org. (15)	Accounting Firms (10)	National Auditing Standard Setters (9)	Individuals & Others (5)	Regulators & Oversight Authorities (4)	Public Sector Organizations (3)	Investors & Analysts (2)	Academics (2)
Revising /Challenges in developing new Std /Current ISAs not suitable for DA	22%	16%	16%	2%	4%	4%	4%	4%
Developing a Principle-based standard	12%	6%	8%	0%	4%	2%	0%	0%
Collaborative work from Auditors, Std setters & Oversight Authorities on ISAs	2%	6%	10%	2%	2%	0%	2%	2%
Analytical Procedures using DA (ISA 520)	4%	4%	2%	2%	0%	0%	0%	2%
CAATs vs DA in respect to ISAs	8%	2%	0%	0%	0%	2%	0%	0%

Revising /Challenges in developing new Standard /Current ISAs not suitable for DA

The International Standards on Auditing (ISA) need to be reconsidered and adapted in the context of the new technology environment. The Audit stakeholders have a massive concern about existing audit standards. The content analysis in Figure 4.3 shows a large number of responses (72%) sharing their viewpoint, making this the most discussed issue on DA use in external auditing. The ***Association of International Certified Professional Accountants (AICPA)*** has pointed out in their responses that while the current standards do not prohibit the use of data analytics, they do not encourage the use of innovative, technology-enabled procedures. It is important, that the auditing standards are relevant and responsive to the evolution in audit technology. Thus, the standards should incorporate, where needed, the provisions required to ensure the appropriate use of new tools and technologies in the audit, including DA (IFIAR, 2017). By preparing industry-wide standards and implementing them, all auditors can develop the skills necessary to perform audits effectively and efficiently. ***Hunter College*** has also indicated that the current audit standards are limited in its ability to incorporate technological advances that optimize audit results. Lack of reference to data analytics in the ISAs signifies the challenges that many auditors are facing in fitting the audit evidence derived from data analytics into the current existing ISA model (IAASB DAWG, 2016).

However, many stakeholders have also raised concerns about changing standards prematurely. ISAs should not completely be rewritten due to technological advancements and developments in data analytics. As quoted by the ***Institute of Chartered Accountants in England and Wales*** (***ICAEW)*** in their responses:

"We do not believe that it is appropriate for IAASB simply to shoehorn data analytics into the existing ISA approach. …………"

Which brings back the question, whether the regulators should attempt to deal with data analytics within the existing ISA approach without any consideration of whether a new or revised approach might enhance audit quality? While a lot of concerns have been shown, about an urgent need to revise the ISAs, premature standard-setting could be counterproductive and have unintended consequences such as restricting innovation(KPMG, 2017). Therefore, Regulators should evaluate whether current ISAs continue to meet stakeholder needs based on technological advances and the increasing use of data analytics in business decision-making, with the aim of ensuring standards and guidance for auditors facilitate high-quality audits. A consistent, international approach should be taken to revise the standards which will provide a better understanding of available and emerging data analysis techniques and how they are being used. The development of guidance should be the priority for the regulators rather than to have instant change or seek enhancement of the standards themselves.

Developing a Principle-based standard

When incorporating the use of data analytics into the auditing standards, care must be taken to ensure that any new requirements are principles-based, to ensure standards may appropriately accommodate future changes and to avoid becoming obsolete with future technological developments and also without needing to be in a continual state of change(CFA, 2016). ISAs need to allow innovation, by providing sufficient flexibility to accommodate techniques which may not be available yet. As suggested by ***BDO International Limited,*** a public accounting firm in their responses that ISAs designed to address DA techniques will need to consider fluidity and ensure that the appropriate framework is established to recognize this reality and also the need for auditing standards to remain principles-based and sufficiently flexible and adaptable so that, they are relevant in a changing business environment and do not lag behind technological developments. However, as pointed out by the ***European Federation of Accountants and Auditors:***

"*Professionals are not necessarily seeking new standards and requirements they welcome standards that offer the flexibility and ease of navigation that accommodate these new technologies………"*

Collaborative work from Auditors, Standard setters & Oversight Authorities on ISAs

The ***Rutgers Continuous Auditing & Reporting Lab*** believes that it is expected for not only auditors, but audit oversight authorities, and regulators to be well prepared to audit and inspect audit engagements that use data analytics and also the application of innovative technologies on an audit engagement may require a change in how these parties evaluate audit evidence in the new "data-driven" audit process. Currently, the views of regulators remain a key barrier to firms fully adopting Data Analytical techniques. Regulators have a key role to play by being closer to developments and able to provide input on the effectiveness of the standards and interpretations. If the ISAs are vague or non-existent regarding the use of ADAs, there is a risk that audit regulators may develop their own, perhaps inappropriate, interpretations regarding the use of ADAs(CPA, 2017a). As proposed by ***KPMG IFRG Limited*** that a resource group consisting of IAASB representatives (e.g. DA working group and staff, audit firms, regulators, other national standard setters & other interested parties) should be formed, to support this implementation. This would bring everyone on the same page and would establish a consistent change. The question is whether such involvement will be performed more prospectively rather than retrospectively.

CAATs vs DA in respect to ISAs

Current standards do contain references to the use of CAATs, but not specifically the use of data analytics. The current ISAs neither prohibit nor promote the use of data analytics. The reference to CAATs is insufficient given the developments that have taken place in data and technology. It is also important for standards to clarify the differences between the use of Computer Assisted Audit Techniques (CAATs) as a form of audit testing procedure in comparison with data analytics being used in audit planning and obtaining audit evidence and other stages of Audit.

4.2.3 Technological Factors

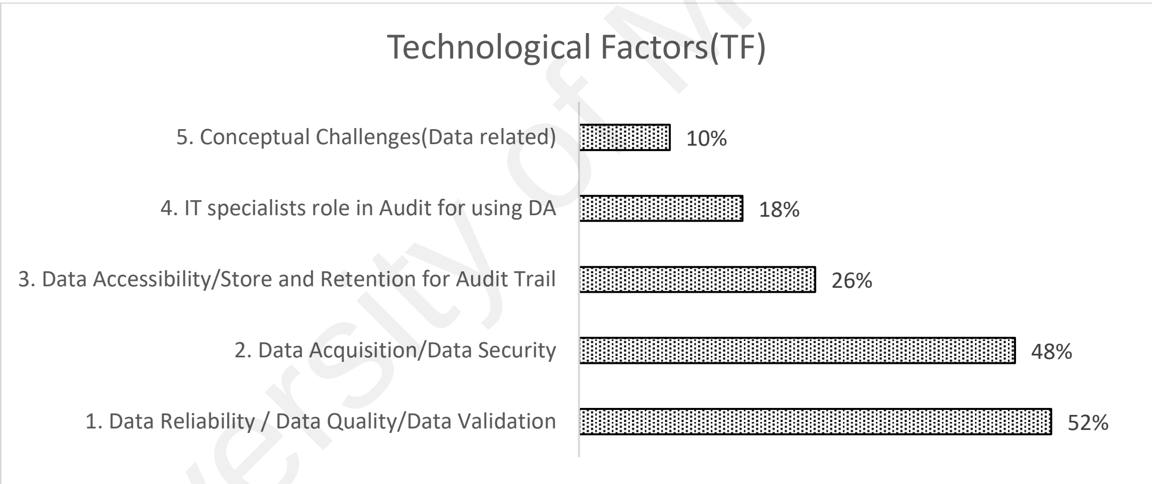


Figure:4.4 A Graphic representation of Technological Factors

Table 4.5: A percentage breakdown of the total responses by each stakeholder group on each attribute under Technological factors

Technological Factors	Member Bodies and Other Professional Org. (15)	Accounting Firms (10)	National Auditing Standard Setters (9)	Individuals & Others (5)	Regulators & Oversight Authorities (4)	Public Sector Organizations (3)	Investors & Analysts (2)	Academics (2)
Data Reliability / Data Quality/Data Validation	14%	10%	12%	4%	2%	4%	4%	2%
Data Acquisition/Data Security	12%	12%	10%	4%	4%	2%	0%	4%
Data Accessibility/Store and Retention for Audit Trail	10%	4%	10%	2%	0%	0%	0%	0%
IT specialist's role in Audit for using DA	4%	6%	6%	2%	0%	0%	0%	0%
Conceptual Challenges (Data related)	4%	2%	2%	0%	0%	0%	0%	2%

Data Reliability / Data Quality/Data Validation

Data reliability are significant issues to be addressed regarding both internal and external data used in performing DAs(CPA, 2017a). The ***Rutgers Continuous Auditing & Reporting Lab*** also notified in their responses that data requires validation of completeness, accuracy and reliability, independent irrespective of its origin. The greater the extent to which data is generated directly by electronic means, the more important controls are needs over the reliability, validity, and completeness of data. The quality of the underlying data used for data analytics needs to be assessed. It should not be assumed that data obtained from a third party, is suitable, accurate, and complete. ***Independent Regulatory Board for Auditors*** cited in their responses:

"Although data analytics have the potential to optimize efficiency and effectiveness and thus, improve audit quality, however, if the underlying data is of poor quality, the results from data analytics will be unsatisfactory….."

When it comes to big data the auditors can efficiently analyze more of the same data (volume), the ability to involve non-traditional data sources (variety), the ability to perform audit routines more in real-time (velocity), which is a combination of multiple developments. So, in addition to considering internally produced data, the standard setters should also consider providing guidance on how auditors may assess the level of completeness, accuracy, and reliability of exogenous Big Data (e.g. social media, RFIDs, GPS) and its provenance (Appelbaum, Kogan, & Vasarhelyi, 2017). As expressed by 52% of the respondents in figure 4.4, greater specificity and guidance is required to consider in various circumstances relating to audit procedure while using DA. Procedures, the auditor needs to perform when considering the relevance and reliability of information obtained from third parties will vary, depending on the nature and source of the information(Stephens, 2017). How to define data of appropriate quality in the context of a financial statement audit(Stephens, 2017)? What parameters should the auditor use to determine data quality?

Data Acquisition/Data Security

One of the significant issues discussed in the response letters is related to data acquisition and security in using DA in external auditing. From acquiring data to maintaining data security, dealing with large amounts of data can be a challenge. These and other related technology concerns would require expanded efforts from the auditors, resulting in higher audit fees(Li, No, & Boritz, 2016). Increasing the use of data analytics results in an increase in confidential client information that is at risk of being inappropriately accessed. Data acquisition is the number one challenge for auditors especially when data comes from multiple systems. ***Harvest Investment Ltd.***, an independent securities valuation specialist has recognized in their responses:

"*…………currently, there is a situation where a large amount of data is routinely used, but not necessarily well understood. This concludes the fact that more data does not necessarily mean better data nor can it substitute for rigor and expertise……..*"

In addition to the challenges relating to access to large data sets, data security, and privacy, as well as insufficient infrastructure to store data, is a significant challenge faced by the IT expert. The use of live systems that provide real-time data also can pose a challenge in acquiring the correct data. Cyber-attacks on enterprises are increasingly prevalent., including data breach events and these ask for particular attention, considering the essential nature of data validation and verification (CarLab, 2017). ***Inflo limited,*** an innovative auditing software maker mentioned in their statement that data confidentiality and privacy concerns must be addressed between the client and the accounting firm regarding cloud-based secure data storage and there should be some guidance over how the data should be safeguarded at the auditors' end and a prevalent standard is developed which could be globally applicable.

Data Accessibility/Store and Retention for Audit Trail

Along with data security and acquisition, issues around data ownership, transfer, privacy and retention are important for auditors to consider and manage. Data that are related to client governance, CSR and integrated reporting information, etc. does not emerge from traditional accounting. Which brings us to the point which has been raised by ***Independent Regulatory Board for Auditors***:

"With the significant volumes of data available, the challenge that IT experts will face is identifying and accessing the correct data to be used in the performance of data analytics that is meaningful to the auditor….."

The use of prior year data to identify and analyze trends is essential in performing certain data analytics. But there is often a lack of a clear or adequate audit trail about the data used. So, the concern which is posed by 26% of the respondents is that, if the auditor is to retain such data, the question is: What are the requirements and rules with respect to the retention of client data and the use of this in subsequent audits. This clearly will affect the motivation in adopting DA in an audit.

IT specialist's role in Audit for using DA & Conceptual Challenges (Data related)

IT specialists will have a much bigger role to play when performing DA in external auditing. ***Independent Regulatory Board for Auditors*** believes that it is important to consider an approach to liaise with IT and data science specialists on each of its standard-setting projects so as to continue to reflect the growing use of data analytics and addresses opportunities and threats presented by the current wave of innovation in data analytics. IT professionals from both the audit firm and client must strive to work together to overcome conceptual challenges and ensure that systems are producing reliable data. For instance, ***Chartered Professional Accountants of Canada*** quoted in their responses:

"*……..an auditor may use an insightful DA but the DA seem likely to be abandoned if they are perceived as adding more negatives than benefits…….*"

The use of data analytics may prove to be ineffective in some instances and the time spent to create them might not result in useful audit evidence. Moreover, the auditor needs to be considerate in the timing of any data related requests and should not underestimate the time that it can take for the client to source the required data.

IT specialist's role in Audit for using DA & Conceptual Challenges (Data related)

IT specialists will have a much bigger role to play when performing a future audit involving Data. It is important to consider an approach to liaise with IT and data science specialists on each of its standard-setting projects so as to continue to reflect the growing use of data analytics and addresses opportunities and threats presented by the current wave of innovation in data analytics. IT professionals from both the firm and client must strive to work together to overcome conceptual challenges and ensure that systems are producing reliable data. Several conceptual challenges might arise during audit procedures. As stated by ***Chartered Professional Accountants of Canada***:

"*For example, an auditor may use an insightful ADA, but may not take appropriate credit for its use due to the lack of clarity from audit regulators on how they view the use of ADAs in obtaining audit evidence. ADAs used solely as "add-ons" seem likely to be abandoned if they are perceived as adding more costs than benefits*"

The use of data analytics may prove to be ineffective in some instances and the time spent to create them might not result in audit evidence that is useful. Moreover, the auditor needs to be considerate in the timing of any data related requests and should not underestimate the time that it can take for the client to source the required data. The auditor needs to allow sufficient time for the client to source the required data, especially when the auditor is requesting data for the first time as a result of new procedures that may have been designed.

4.2.4 Organizational Factors

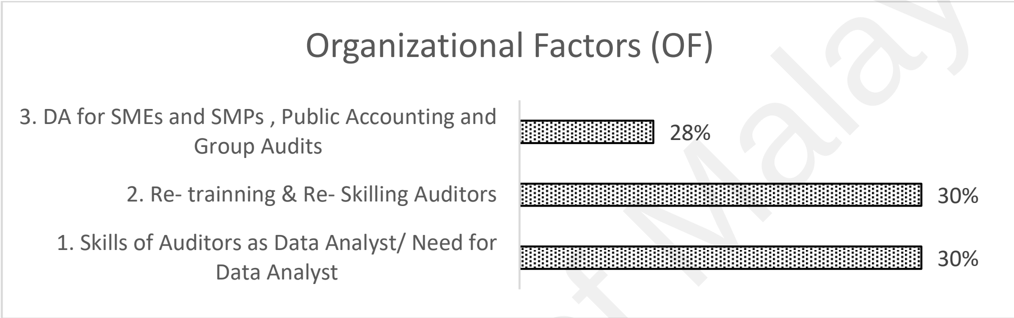


Figure:4.5 A Graphic representation of Organizational Factors

Table 4.6: A percentage breakdown of the total responses by each stakeholder group on each attribute under Organizational factors

Organizational Factors	Member Bodies and Other Professional Org. (15)	Accounting Firms (10)	National Auditing Standard Setters (9)	Individuals & Others (5)	Regulators & Oversight Authorities (4)	Public Sector Organizations (3)	Investors & Analysts (2)	Academics (2)
Skills of Auditors as Data Analyst/ Need for Data Analyst	10%	2%	6%	4%	2%	0%	2%	4%
Re- training & Re- Skilling Auditors	8%	6%	4%	4%	4%	0%	0%	4%
DA for SMEs and SMPs, Public Accounting and Group Audits	8%	4%	6%	0%	4%	2%	4%	0%

Skills of Auditors as Data Analyst/ Need for Data Analyst

The ***Association of International Certified Professional Accountants*** surmised in their response:

"as one individual may not possess all of the skills needed, audit teams will need to adapt to include individuals with the expanded skillsets and the accounting firms will need to consider hiring more data scientists ("specialists") to meet the demand……"

Essentially, the "new" audit engagement model will entail the continuous collaboration of audit staff and data specialists for auditors to harmoniously transition to the era of data analytics (CarLab, 2017). Auditors need to invest in developing their IT skills to enjoy the full benefits that can be gained from using data analytics. IT specialists would need to respond positively by a better understanding of the audit process. In the past, auditors were trained with little emphasis on information technology (IT), so currently a lot of auditors are not well versed in data analytics and cannot adequately understand the data analysis performed and how its results influence the audit (IRBA, 2017). The lack of knowledge results in a knowledge difference between the work carried out by the IT specialist and the auditor's understanding of the work performed, which can lead to inadequate or improper audit-proof being collected.

The ***Institute of Chartered Accountants of Scotland*** notified in their responses that audit teams of the future might also need to be composed of different types of individuals from more diverse backgrounds with a broader range of skills and experience which currently, the profession is not seeing sufficient technological skills in auditors. In addition, the standard setters could consider developing a competency framework to encourage auditors to acquire other relevant skill sets such as IT skills. This will help narrow the knowledge gap with data specialists.

Retraining & Re- Skilling Auditors

With such a requirement on auditors' skills, the question arises on how the existing auditors would enhance their existing knowledge and skillset. The ***Chartered Professional Accountants of Canada*** illustrated in their response:

"……firms will need to invest significant resources in making auditors aware of what analytical tools and techniques are available and training them to use those tools and techniques effectively......"

Re-training is required for audit professionals and regulators responsible for evaluating the work of auditors (e.g., PCAOB, IAASB) in a more technology-driven audit environment. ***Rutgers Continuous Auditing & Reporting Lab*** opined in their statement that a key challenge that arises relating to these professionals is whether they can be trained to adopt a different mindset when evaluating the evidence generated from the use of data analytics. However, accounting professors may not be prepared to teach analytics and students may not be receptive to learning innovative tools(Appelbaum, Kogan, Vasarhelyi, et al., 2017). Hence, it is expected that the re-training of audit professionals and regulators will happen in gradual stages.

International Association of Insurance Supervisors (IAIS) notified in their statement that this new wave of innovation in data analytics will likely affect all sizes of audit firms, but particularly the big audit firms that audit large entities and in addition to the investment in re-training and re-skilling auditors, it may also be necessary to consider a fundamental change to how many firms operate. These significant investments both in physical and human capital, to develop and drive future capabilities, will likely require some changes in the business model of audit firms.

DA for SMEs and SMPs, Public Accounting and Group Audits

The Institute of Chartered Accountants of Scotland referred to a very vital issue in their responses:

"....the largest audit firms have invested heavily in technology to enable them to incorporate the use of data analytics in the audit process for their largest clients. However, audit firms operating at the SME end of the audit market may not be able to invest in such technology, which might lead to a two-tier audit system……"

A similar tone has been raised by ***Canadian Auditing and Assurance Standards Board*** in their statement, that small and medium-sized firms may not have dedicated technical resources to consider the wider implications of deploying data analytic techniques and to respond accordingly. Also, it has been viewed from other responses that, the use of data analytics is not practical for all engagements, especially in group audits where it is challenging for the group auditor to control the competency level of its component auditors. ***New Zealand Auditing and Assurance Standards Board*** stated in their feedback that small to medium practices are likely to use or rely on the third party developed tools to perform data analytic procedures and retain their capacity to audit with the use of data analytics and remain competitive with larger firms. So, the possible solution or a way-in might be to cooperate in some form of a common venture by pooling the resources of small and medium firms and engaging with appropriate software providers for support.

4.2.5 Client Factors

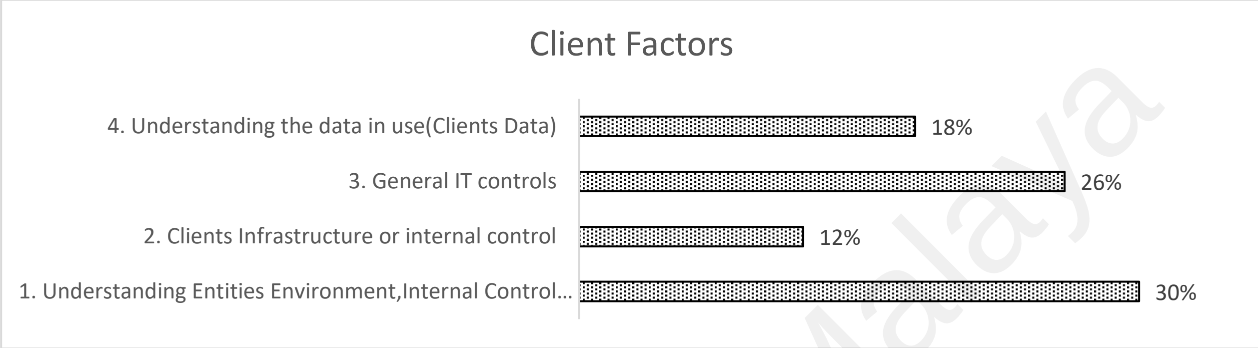


Figure:4.6 A Graphic representation of Client Factors

Table 4.7: A percentage breakdown of the total responses by each stakeholder group on each attribute under Client factors

Client Factors	Member Bodies and Other Professional Org. (15)	Accounting Firms (10)	National Auditing Standard Setters (9)	Individuals & Others (5)	Regulators & Oversight Authorities (4)	Public Sector Organizations (3)	Investors & Analysts (2)	Academics (2)
Understanding Entities Environment, Internal Control using DA (ISA 315)	12%	6%	4%	2%	4%	0%	2%	0%
General IT controls	8%	6%	6%	2%	0%	2%	0%	2%
Understanding the data in use (Clients Data)	4%	2%	8%	2%	0%	0%	0%	2%
Clients Infrastructure or internal control	8%	2%	2%	0%	0%	0%	0%	0%

Understanding Entities Environment, Internal Control using DA (ISA 315)

A common consensus among the respondents has been determined from the analysis of the importance of understanding the client's environment when using DA in the audit. As reflected in Figure 4.6, 30% of the respondents shared their views on it and the responses were very much similar. ***PKF International Limited***, a network of independent firms opined in their statement that Data analytics may improve the auditor's understanding of the organization, it's business and IT processes and during the initial phases of the audit, the use of data analytics enables to contribute to a better understanding of the entity and its environment and the identification of risks.

As represented by ***International Forum of Independent Audit Regulators*** in their feedback:

"*We understand that data analytics techniques or tools can potentially provide benefits in obtaining an understanding of the client, as well as in the performance of risk assessment procedures…………………*"

This increased understanding of the quality and the objectivity of the information and transactions increase the likelihood of identifying and testing audit areas associated with higher risk and to perform more effective and efficient audit work. In a highly automated client environment, there is still a need to consider the evaluation of the control environment, since, this is the foundation of the client's internal control system.

General IT controls & Clients Infrastructure or internal control

Rutgers Continuous Auditing & Reporting Lab acknowledged in their feedback statement: *"…….the robustness of General IT controls is critical when performing data-driven audits and on top of that general IT as well as IT Application Level controls are essential to financial statement audits that use data analytics…."*

A significant portion of the 26% of respondents believes that auditors need to place more reliance on the data produced by the accounting systems. The major risks associated with data analytics arise in the generation of data. General IT controls, including the entity's choice and implementation of its accounting and reporting system or package, contribute to an effective control environment(CPA, 2017b). Some audit clients are likely to perceive that they lack the ability and time required to present more varied data sets (CPA, 2017a). However, ***New Zealand Auditing and Assurance Standards Board*** notified that while an understanding of the IT process controls is important to understand the entity and its internal control environment, it may be more efficient for the auditor to validate data, depending on its nature and source. The extent of testing of the general IT controls would, therefore, differ depending on the client-specific circumstances. ISA 315 is not clear in guiding what is considered to be the minimum level of general IT control testing.

However, there is also a different perspective being put forward by the ***International Association of Insurance Supervisors (IAIS)***:

"*We are not completely convinced that the use of data analytics increases the need to focus more on IT general controls…………………………….*"

It is advisable for the standard setters to elaborate more on audit technique when deficiencies in IT general controls are identified and give the auditor practical guidance on the requirements. A specific ISA addressing General IT Controls, data security will be a better way to deal with it.

4.2.6 Limitation and Challenges

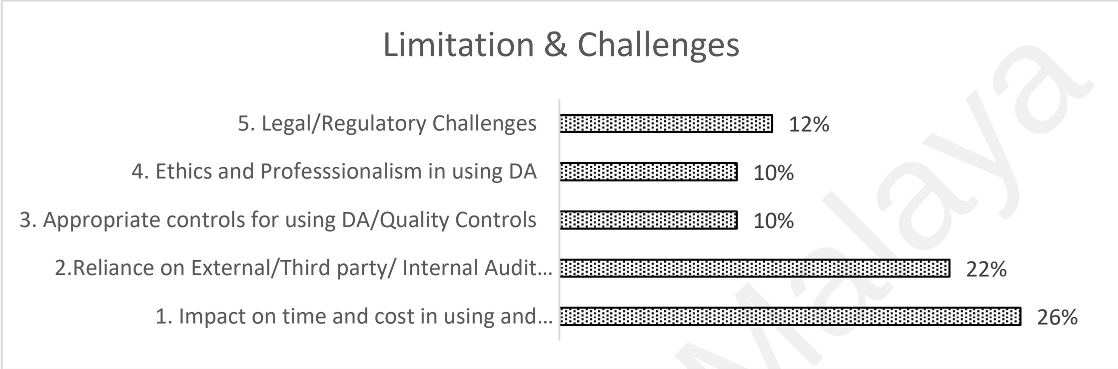


Figure:4.7 A Graphic representation of Limitation & Challenges Factors

Table 4.8: A percentage breakdown of the total responses by each stakeholder group on each attribute under Limitation and Challenges

Limitation and Challenges	Member Bodies and Other Professional Org. (15)	Accounting Firms (10)	National Auditing Standard Setters (9)	Individuals & Others (5)	Regulators & Oversight Authorities (4)	Public Sector Organizations (3)	Investors & Analysts (2)	Academics (2)
Impact on time and cost in using and implementing DA	12%	8%	2%	0%	0%	0%	4%	0%
Reliance on External/Third party/ Internal Audit Data	6%	8%	4%	2%	0%	0%	2%	0%
Legal/Regulatory Challenges	2%	4%	6%	0%	0%	0%	0%	0%
Appropriate controls for using DA/Quality Controls	0%	2%	2%	2%	4%	0%	0%	0%
Ethics and Professionalism in using DA	0%	4%	4%	0%	0%	0%	0%	2%

Impact on time and cost in using and implementing DA

It is important to understand the cost and benefits perceived by the responses on the use of DA in external auditing. As shown in figure 4.7, 26% of the respondents believe this factor would have an impactful notion when it comes to the adoption of DA. The professional bodies (12%) were more interested in this issue as represented in table 4.8. Due to the costs involved in setting up data analytics, these techniques are usually limited to larger clients. Increased costs and complexity could arise from a need for the auditor to maintain sufficient DA infrastructure for all versions of tools for the duration of the audit documentation retention period(KPMG, 2017). The use of data analytics could enhance audit quality but does not always mean a lower audit budget. Potentially significant investments are required to make effective use of data analytics(Chitty, 2017). Some SMPs, concerned about cost in gaining the necessary expertise and access to the tools, maybe deterred from using data analytics or else only afford to do so on a collective basis. The ***Institute of Chartered Accountants of Scotland*** cited in their feedback:

"……. automation of some of the more routine and repetitive audit tasks might free up at least some auditor time, but the question remains whether the audit will be more expensive, and will the audit reveal more insight that could extract enough value on investor contributions….."

Reliance on External/Third-party/ Internal Audit Data

The client system can have two main sources of data, namely structured data where the data is generated from the client's formal accounting system and unstructured data (which is all other data sourced from sources other than the client's formal accounting system). ***New Zealand Auditing and Assurance Standards Board*** have perceived in their response:

"………it is evident that a more sophisticated method than before will be required when assessing the reliability of these data….."

"These data" in this context meaning to say, unstructured data from different sources. In principle, the data obtained from independent sources outside of the entity employing data analytics or for purposes of applying data analytics is no different from other audit evidence so obtained(EY, 2017). The definition of information relating to audits produced by the entity should be clarified in ISA 500 Audit Evidence. ***BDO International Limited a public accounting firm*** has also mentioned in their feedback that it should be ensured that there are no factors that would unintentionally or unnecessarily inhibit the external auditor's ability to rely on the work of internal audit as it pertains to data analytics.

Reliance on External/Third-party/ Internal Audit Data

The client system can have two main sources of data, namely structured data (where the data is generated from the client's formal accounting system, whether maintained internally or outsourced externally and unstructured data (which is all other data sourced from sources other than the client's formal accounting system). A more sophisticated method than before will be required when assessing the reliability of these data. Evidence obtained from third parties both in digital and paper form needs to be considered to determine how to assess its reliability and how to preserve it as evidence.

In principle, the data obtained from independent sources outside of the entity using data analytics or for purposes of applying data analytics is no different from other audit evidence so obtained. Some additional considerations relating to relevance and reliability, as currently addressed in the application material of ISA 500, may serve to address the evolving nature of information and the impact of technology.

A further consideration is required with regards to information prepared by the entity vs the third party, to clarify the issues relating to risks and the reliability of evidence. The definition of information relating to audits produced by the entity should be clarified in ISA 500 Audit Evidence. It should be ensured that there are no factors that would unintentionally or unnecessarily inhibit the external auditor's ability to rely on the work of internal audit as it pertains to data analytics.

Appropriate controls for using DA/Quality Controls

One of the key challenges of DA use is related to It important for firms to apply quality control processes when developing tools, and to assess the reliability of the tools and technology utilized, to avoid a potential 'overconfidence in technology'. ***International Forum of Independent Audit Regulators*** has specified in their feedback that quality control procedures secure the integrity of the tools against unauthorized access, and the protection of entity's data privacy and confidentiality, data protection and cybersecurity risks mitigation. The audit firms' internal procedures drive the appropriate use of data analytics, including controls over the proper development and deployment of those tools. ***International Association of Insurance Supervisors*** shared their concern in the feedback statement:

"………the challenge encountered by firms which have to adapt their systems of quality control with the aim of obtaining assurance will be to ensure the tools used to analyze the data meet the audit objectives and there should be a strong quality control processes over the use of analytics by auditors in these procedures….."

The required competence and training should make sure appropriate controls are set by the engagement partner and is also known by the staff in order to use and interpret the results of Data Analytics.

Ethics and Professionalism in using DA

Interaction between standard setters and the International Ethics Standards Board (IESBA) is required in particular, to encourage the IESBA to address any ethics and independence issues that might be created through the increased use of data analytics in the financial reporting and auditing process.

-Legal/Regulatory Challenges

Regulatory risk has been identified as a key issue and this has the potential to be a major deterrent to the increased use of data analytics in the audit. This issue was particularly raised by small and medium-sized practitioners. Engagement with stakeholders, including particularly regulators, is important.

Advanced DA capabilities frequently require significant investment and specialist support. With many jurisdictions prohibiting the cross-border transfer of data and/or audit work papers, Legal or regulatory challenges may make it difficult if not impossible for smaller audit firms to deploy the more advanced DA tools in their markets. Moreover, the use of technology solutions in different jurisdictions may be restricted by legal and regulatory requirements, the sophistication of client IT systems, the nature of the audit firm's tool deployment (usually cascaded), the availability of skills in the local market to operate the tools, software licensing restrictions and other factors can have a massive impact.

Also, there could be further legal and regulatory challenges in relation to the access and storage of client data, especially when it comes to cross border audits. These approaches might be quite different from what the entities may face regularly. So, the standard setters should have a specific eye on these issues before moving into DA.

4.2.7 Other Relevant External Factors

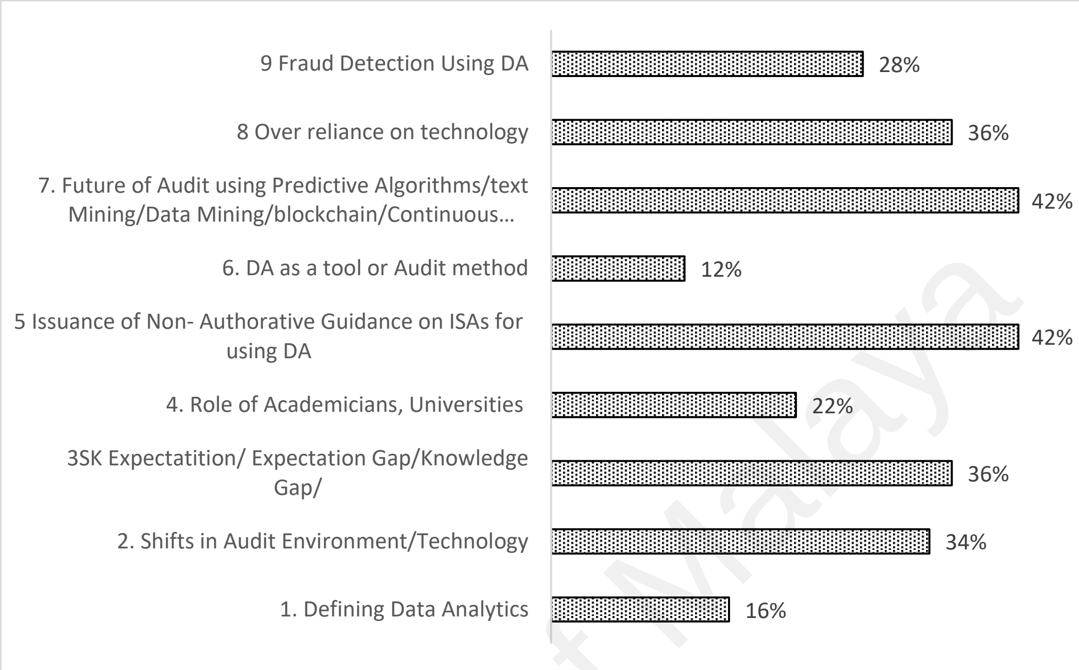


Figure:4.8 A Graphic representation of External Factors

Table 4.9: A percentage breakdown of the total responses by each stakeholder group on each attribute under Other Relevant Factors

Other Relevant External Factors	Member Bodies and Other Professional Org. (15)	Accounting Firms (10)	National Auditing Standard Setters (9)	Individuals & Others (5)	Regulators & Oversight Authorities (4)	Public Sector Organizations (3)	Investors & Analysts (2)	Academics (2)
Issuance of Non- Authoritative Guidance on ISAs for using DA	12%	6%	14%	4%	4%	2%	0%	0%
Future of Audit using Predictive Algorithms/ text Mining/Data Mining	10%	12%	8%	4%	2%	0%	2%	4%
SK Expectation/ Expectation Gap/ Knowledge Gap	12%	8%	8%	4%	2%	2%	0%	0%
Over-reliance on technology	12%	8%	8%	4%	2%	2%	0%	0%
Shifts in Audit Environment/Technology	12%	12%	2%	2%	4%	0%	0%	2%
Fraud Detection Using DA	12%	8%	2%	4%	0%	0%	0%	2%
Role of Academicians, Universities	12%	2%	6%	0%	0%	0%	0%	2%
Defining Data Analytics	2%	4%	4%	2%	2%	0%	2%	0%
DA as a tool or Audit method	6%	0%	4%	0%	2%	0%	0%	0%

Defining Data Analytics & DA as a tool or Audit method

One of the basic problems and ambiguity which has been discussed over and over by Stakeholders is the definition and the use of DA. Currently, no consistent definition of data analytical techniques exists in terms of auditing. What constitutes a data analysis technique and the uses of that technique may mean different things to different stakeholders and similar data analytical techniques may be used for different purposes at different stages of the audit. Is data analytics about audit automation or not? The term Data Analytics, and audit technology more generally, is much misunderstood and misinterpreted. It is not clear whether there is any difference between a CAAT and an ADA and if so, what the differences are. Similarly, some auditors perceive there to be significant overlaps between analytical procedures and ADAs. Moreover, the stakeholders are still confused about the fact, whether DA will be used as a tool or a complete audit method. The respondents representing 12% in figure 4.8, has a mixed view on whether data analytics is merely an audit tool to facilitate the audit process or is it a conceptual change to the fundamental audit framework which should be integrated as part of the auditing standards. Some believe that data analytics procedures are simply new tools that enhance the value of an audit, but it does not believe that the fundamental principles of the audit or the audit standards need to change to accommodate data analytics procedures. As the ***CFA Institute*** stated:

"Indeed, we believe data analytics should be integrated into the entire audit life cycle—risk assessment, scoping, fieldwork planning, execution, monitoring, and reporting. It would lead to improved coverage of transactions and enhanced risk focus and insight and support professional skepticism"

Challenges may exist in developing a consistent understanding and definition of what data analytics comprise, how these different techniques can be applied in different circumstances, and the evidence that they contribute. The standards setters and regulators should clarify whether data analytics is an entirely new auditing approach which impacts on the scope and objectives of the audit or whether data analytics is merely another tool that the auditor can use in achieving the stated overall objectives of an audit. Further clarification of the definition of data analytics and the scoping of the issues will strongly contribute to determining the most effective path forward and the pace thereof.

Judging from the literature, the study would like to suggest that data analytics should be – at least in the foreseeable future – considered to be just one possible concept to conduct an audit. Every Audi firm should engage in Data Analytics to reap the benefit of the data available in the era of Industry Revolution 4.0. Without data analytics, Auditors won't be able to submerge them into different forms of Big Data.

Shifts in Audit Environment/Technology & Over-reliance on technology

Rapid advancements in both the ability to access significant amounts of data and to apply unique technologies to such data require us to revisit the current auditing standards and interpretative literature**.** The environment in which audits are performed today continues to evolve and become increasingly complex. The increasing availability of data as well as analytical technology and tools have advanced very rapidly. Whilst the nature, timing, and extent of the impact that technology will have on the audit are difficult to predict, emerging technologies like automation, artificial intelligence, blockchain, and even drones have the potential to transform the way an audit is conducted whilst enhancing audit quality. In areas with rapid technological advancements, various definitions and environments, upon which assumptions are made, change significantly with time, and the technology, which had been the subject of discussion, become outdated in a short period. Therefore, prompt initiation and development of discussions are thought to be crucial.

A business risk that has been identified from an audit practice point of view is that practitioners who are not upskilling and incorporating technology into their auditing processes are at risk of losing business. Furthermore, the various range of techniques to analyze digital data might result in changing perceptions by stakeholders about audit quality and the level of assurance. Auditing in the current environment requires an auditor to have an awareness of the benefit of using data analytics, for both performing audit procedures and to obtain audit evidence. This need will likely escalate in the future

Auditors should be encouraged to expand their skills to include an understanding of data analytics. Conversely, data specialists should have an understanding of why the auditor requires the data and what the auditor will use it for. To ensure that the auditing profession remains relevant to stakeholders' needs, the technological advances that are impacting on the profession and in-line with the objectives of serving the public interest, recognize the need to explore the most effective and efficient way to respond to the evolving business environment and changing needs of stakeholders.

However, there are always concerns that an over-reliance on the use of data analytics might lead to less direct interaction and discussion with the client about the entity's operational activities thereby potentially inadvertently reducing the extent of the auditor's understanding of the entity. Auditors need to make sure they do not over-rely on a technique without making any professional judgment.

SK Expectation/ Expectation Gap/Knowledge Gap

There is an expectation from clients and other stakeholders that auditors use data analytics and have appropriate skills to effectively use technology in the financial statement audit. Stakeholders, in this technology-driven era, expect that auditors are using the possibilities of the current state of technology whenever needed. Pressure from clients who are increasingly using data analytics in their business, expect their external auditor to do the same.

An unintended expectations gap may be created as stakeholders (including users of audited information and regulators) come to assume that auditors are testing larger samples because of the possibilities offered by data analytics. When stating that "100% of the population is tested" it means only that the whole population of transactions was 'analyzed', but not to conclude that this corresponds to "100% tested" or "100% confirmed". This could lead to the overconfidence of technology and will increase the expectation gap. Also, with access to almost 100% of the client's data, clients may have the misconception that auditors carry out 100% testing, to the extent of expecting auditors to detect fraud. Hence, auditors may not be willing to use data analytics until their clients have a more realistic expectation of the amount and type of work being performed. Educating the stakeholders and providing information in order to bridge the gap between reality and expectations will also be required.

An expectation gap may also emerge between what the market and other stakeholders expect from DA in the audit and what is possible given the nature of the IT systems. As the use of technology in the audit increases, there may be an expectation in the market that the costs of delivery decrease and that this should be reflected in audit pricing. However, the costs of delivery are unlikely to decrease and may even increase, given the significant investment required to develop, maintain and upgrade DA capabilities and infrastructure the need for more training, increased involvement of specialists and more senior audit professionals, plus the increased effort to extract and validate data, analyze the output and potentially investigate a larger number of outliers/ exceptions. The information that auditors may derive through data analytics and other tools has the potential to add considerable value to the audit that may benefit management and those charged with governance. There are therefore growing expectations that such tools and techniques will become an integral part of the audit, particularly for larger entities

Finally, a different set of Knowledge gaps can exist between data specialists and auditors within an audit firm can create a different set of challenges. Data specialists and auditors need to communicate effectively with each other

Issuance of Non- Authoritative Guidance on ISAs for using DA

This was one of the important issues which have been talked about the most under several factors. As the analysis shows in figure 4.8, 42 % of the respondents did discuss this at length. Several guidance is required under each factor. At this moment there is a strong need for guidance from standard setters and also regulators. The guidance that explains their point of view regarding procedures to be followed and documentation criteria that have to be met(CPA, 2017b). ***Australian Auditing and Assurance Standards Board*** has notified in their feedback statement that there is a need for standard setters to provide practical guidance on how the use of data analytics can improve audit quality and efficiency. ***Deloitte Touche Tohmatsu Limited*** also referred in their responses:

"…….. issuance of non-authoritative guidance with practical examples of using data analytics in the audit will provide auditors with the most effective reference materials that would both help to further advance the application of data analytics……."

Swiss Expert Association for Audit, Tax, and Fiduciary also maintained the same tone when discussion about the issue that regulators should develop short-term guidance for the auditors in terms of recommendations, manuals or practice notes, before revising the relevant ISAs as this is a rather long-term project. Regulators and standard setters should consider developing an overarching framework for data analytics to guide auditors on the use of data analytics(INFLO, 2017). Such guidance will ultimately align the motivation of auditors and the concerned stakeholders to adopt DA in the auditing process.

Future of Audit using Predictive Algorithms /Text Mining / Data Mining /Blockchain /Continuous Auditing

The application of new technology brings new risks with it that need to be addressed. Techniques like process mining allow auditors to gain a deeper understanding of business processes and have the potential to provide insight into the operating effectiveness of internal controls(AICPA, 2017). The ***Australian Auditing and Assurance Standards Board*** has specified in their responses:

"....... additional consideration should be given for newly emerging technologies such as the use of audit procedures utilizing artificial intelligence (machine learning) and the use of automated self-learning controls providing a continuous audit. Examples of these could be identified at the level of data discovery and visualization, data-mining, process mining, open-source analytics, using algorithms, using artificial intelligence (machine learning, deep learning) ......"

Chiu, Liu, & Vasarhelyi, (2014) use process mining for segregation of duty analysis and timestamp examination. They provide evidence, that this methodology can be effective in detecting potential risks and inefficient internal processes. Moreover, predictive analytics can test the existence, completeness, and accuracy of the population. Therefore, it is essential to consider whether it would be appropriate to replace or reduce other analytical procedures when predictive analytics provides validation for management assertions(CarLab, 2017). The ***Swiss Expert Association for Audit, Tax, and Fiduciary*** has mentioned in their report that in the long run, there is a need for auditing standards that facilitate continuous auditing towards data level assurance instead of assurance at the level of documents and the potential implications of blockchain technology on businesses and the audit function is also on the rise. ***Rutgers Continuous Auditing & Reporting Lab*** has also surmised in their feedback:

"……..it would also be important as well to shed light on Process mining logs that can be used to perform analytical procedures to test internal controls to ensure compliance and SAP software to be used to perform log analysis….."

Independent Regulatory Board for Auditors has also raised their opinion stating that additional concerns will be regarding the analysis of unstructured data, which can be derived from social media trends and other non-financial data and also auditors would need to satisfy themselves as to the suitability and accuracy of algorithms used to produce and perform the data analytics. This means that audit firms and standard setters also need to keep this factor in contention before they start adopting DA in audit procedures. Continual development of those skills through the next generations of auditors will be critical in an increasing technology-enabled profession.

Role of Academicians, Universities

It is important for standard setters to work closely with academics, as accountants and auditors will need to develop different skills through increased education in technology and analytic methods. Greater research is required by both accounting firms and academics on how and which audit procedures and audit standards may be changed -- not just to improve the audit process but also to allow it to truly evolve. From an academic perspective, for example, studies examining the application of various forms of data analytics in an audit engagement may provide evidence of how data analytics impacts the performance (e.g., skepticism, critical thinking, etc.) and judgment of auditors. Further, research can identify factors/circumstances that may lead auditors/firms to resist the implementation of new methodologies.

It is critically important for accounting firms and academic institutions to maintain communications with the Standard Setters. In this manner, the Standard setters can be aware of the application of data analytics in the different phases of the audit (e.g.

planning, fieldwork, concluding phases), and the impact and potential challenges that arise from such an application.

The profession may also have to consider how to work with schools and universities to ensure that the next generation of recruits is receiving appropriate and relevant education. Education and Training to build the knowledge and skillsets of auditors. Technological implementation barriers are much more cultural than they are educational. So, the re-education of today's accountants and auditors will take place within the industry, but a wider perspective will be required for nurturing a new type of professional including coordination with institutions of higher learning and research institutes, joint research, recommendations for and cooperation with university curriculums as part of the education before hiring. To ensure that candidates entering the profession have the required competence, a suitable competency framework should be developed which drives the training and teaching that takes place during the academic program (academic period) and the contract period of training. There is no specific requirement for competence in terms of data analytics as regards the current competency framework. Teaching begins at the university level and tends to continue as part of the on-the-job practical training. This is therefore a collective responsibility between the universities and the audit firms supported by their professional accountancy organizations.

Stakeholder Expectation/ Expectation Gap/Knowledge Gap

There is an expectation from clients and other stakeholders that auditors use data analytics and have appropriate skills to effectively use technology in the financial statement audit. Stakeholders, in a technology-driven era, expect auditors to use technology whenever needed. ***Chartered Accountants Australia and New Zealand (CAANZ)*** mentioned in their feedback that there is pressure from clients who are increasingly using data analytics in their business, and they expect their external auditor to do the same and this would create .an unintended expectations gap as stakeholders come to assume that auditors are testing larger samples because of the possibilities offered by data analytics. ***Swiss Expert Association for Audit, Tax, and Fiduciary*** has also posed their view as:

"*When stating that "100% of the population is tested" means only that the whole population of transactions was 'analyzed', but not to conclude that this corresponds to "100% tested" or "100% confirmed ……..*"

Also, with access to almost 100% of the client's data, clients may have the misconception to the extent of expecting auditors to detect fraud. Hence, auditors may not be willing to use data analytics until their clients have a more realistic expectation. As the use of technology in the audit increases, there may be an expectation in the market that the costs of delivery decrease and that this should be reflected in audit pricing(KPMG, 2017).

Defining Data Analytics & DA as a tool or Audit method

One of the basic problems and ambiguity which has been discussed over and over by Stakeholders is the definition and the use of DA. Currently, no consistent definition of data analytical techniques exists in terms of auditing. ***Info limited*** *an innovative auditing software maker* has mentioned in their Responses that the term Data Analytics and audit technology is much misunderstood and misinterpreted and what constitutes a data analysis technique and the uses of that technique may mean different things to different stakeholders. Is data analytics about audit automation? ***CPA, Australia*** has also questioned in their feedback that it is not clear whether there is any difference between a CAAT and DA, and if so, what are the differences? Moreover, the respondents representing 12% in figure 4.9 have a mixed view on whether data analytics is merely an audit tool to facilitate the audit process or is it a conceptual change to the fundamental audit framework which should be integrated as part of the auditing standards. *The* ***Pennsylvania Institute of Certified Public Accountants*** believes:

"………data analytics procedures are simply new tools that enhance the value of an audit and there will be challenges in developing a consistent understanding and definition of what data analytics comprises of……"

The standards setters and regulators should clarify whether data analytics is an entirely new auditing approach which impacts on the scope and objectives of the auditor whether data analytics is merely another tool that the auditor can use in achieving the stated overall objectives of an audit. Judging from the literature, this study would like to suggest that data analytics should be – at least in the foreseeable future – considered to be just one possible concept to conduct an audit. Every Audit firm should engage in Data Analytics to reap the benefit of the data available in the era of Industry Revolution 4.0. Without data analytics, auditors won't be able to submerge them into different forms of Big Data.

4.3 Summary of Chapter

This chapter details the analysis and the discussion of the findings from the content analysis. Each of the factors was explained through several attributes. These attributes were broken down and represented according to different stakeholders. A percentage representation was given for each factor and each attribute. These attributes were discussed at length from a different perspective. The different perspective of stakeholders was quoted and referred back to find the detail of the issue. Factors like revising/challenges in developing a new standard had been discussed the most. 72% of the stakeholders have discussed this issue while 54% of the stakeholder discussed whether DA will be used as substantive testing, a test of controls, or a test of details. 52% of the stakeholder discussed Audit quality and audit judgment whereas data reliability, data quality, and data security have been discussed by 52% of the stakeholders.

CHAPTER 5 DATA ANALYSIS & FINDINGS

SURVEY QUESTIONNAIRE

This chapter presents the data analysis for all the responses from the questionnaire. Data analysis has been divided into several parts. The first part is about the sample profile. The profiles of the responding auditors as well as the characteristics of their firms are described. The second part is about the descriptive findings related to the usage of DA in audit procedures.

5.1 Survey Analysis

All the statistical analysis for the survey was carried out using Stata 14.2. Initially, all the responses were tabulated in Excel and coded accordingly. Then they were all exported to Stata for analysis. Two types of data analysis were conducted in this study relating to the survey. The first one involved the descriptive analysis in the form of frequency tables and cross-tabulated based on the issues that will be investigated. The Demographic profiles along with the usage of Data Analytics will be used for this purpose. The detailed findings and discussion on descriptive findings are provided in this chapter.

The second type of analysis involves Factor Analysis. Since the survey was formed based on multiple sources, an exploratory factor analysis (EFA) was performed to validate the scale and see which factors can be retained and will have a major influence on DA implementation.

5.2 Demographic Profile

As explained above a total of 118 completed survey responses were collected and used in the analysis. This section provides background information of the firms and the respondents who participated in the survey. The characteristics of the audit firm category, size of the audit department, size of the audit firm, audit firm age, how adept they are with DA. The characteristics of the respondents include their experience with the current firm and position and their knowledge of IT skills and with computerized auditing etc.

5.3 Organizational Profile

5.3.1 Category of Audit Firm

The profile from Table 5.1 audit firms suggests that most of the auditors were from smaller and mid-tier audit firms. Just a few firms from Big four have participated in the survey. Gaining the participation from the large audit firms was difficult due to the time constraint of their auditors. Initially, they were targeted through an online survey, but most of the auditors failed to reply since either they were too busy with their profession or their position to participate in any of the surveys is limited unless they have gained preliminary permission from the organization. As a result, the study prominently had to rely on respondents from the mid-tier practices and smaller practices to capture the current scenario of DA usage in Malaysia.

Table 5.1 Category of Audit Firm

Tabulation of Audit Firm

Q2	Frequency	Percent	Cum.
Big Four Firm	2	1.69	1.69
Mid-Tier Firm	32	27.12	28.81
Smaller Firm	84	71.19	100.00

5.3.2 Size of Audit Department

Table 5.2 below shows the size of the audit department based on the number of auditors within the audit firms. 33 out of 118 audit firms have less than 5 auditors which represent 28% of the total respondents and 25% of the total respondents have 5 to 9 auditors. From the table below, it may also be seen that 3% of firms have more than 50 auditors.

Table 5.2 Size of Audit Department

Q3	Tabulation of Size of Audit Department			
	Big Four Firm	Mid-Tier Firm	Smaller Firm	Total
Less than 5 Auditors	0	4	29	33
5 to 9 Auditors	0	7	23	30
10 to 19 Auditors	0	10	19	29
20 to 50 Auditors	0	9	13	22
More than 50 Auditors	2	2	0	4
Total	2	32	84	118

5.3.3 Size of Audit Firm

The number of employees is used to indicate the size of a firm. Table 5.3 below shows the size of the audit firm based on the number of employees in the firm. Most of the mid-tier practices have employees ranging between 10-999. While most of the smaller practices have employees ranging between 10-99 employees.

Table 5.3 Size of Audit Firm

Q4	Tabulation of No. of Employees			
	Big Four Firm	Mid-Tier Firm	Smaller Firm	Total
Less than 10 Employees	0	3	23	26
10 to 49 Employees	0	12	51	63
50 to 99 Employees	0	8	10	18
100 to 499 Employees	0	6	0	6
500 to 999 Employees	0	2	0	2
More than 1000 Employees	2	1	0	3
Total	2	32	84	118

5.4 Personal Profile

This section will tabulate the result on the profile of respondents.

5.4.1 Respondents' Gender

Table 5.4 shows the breakdown of respondents by gender. While 67% of the respondents were male 51% were female respondents. This shows that both males and females have quite similar participation as auditors in Malaysia unlike what can be seen in the UK with male dominance in the field of audit profession (Ahmi, 2013).

Table 5.4 Gender Profile

Tabulation of Gender Profile							
Q21	Big Four Firm	Mid-Tier Firm	Smaller Firm	Total	Freq.	Percent	Cum.
Male	1	13	53	67	67	56.78	56.78
Female	1	19	31	51	51	43.22	100.00
Total	2	32	84	118			

5.4.2 Respondents' Age

Table 5.5 below presents the collected responses by age of the respondents. When asked for their age range, about 45% of the total respondents stated that they were in the category of 45-54 years old.

Table 5.5 Age of Respondent

Q22	Tabulation of Age of Respondent						
	Big Four Firm	Mid-Tier Firm	Smaller Firm	Total	Freq.	Percent	Cum.
18 to 24 years	0	0	3	3	3	2.54	2.54
25 to 34 years	0	19	29	48	48	40.68	43.22
35 to 44 years	2	6	19	27	27	22.88	66.10
45 years & above	0	7	33	40	40	33.90	100.00
Total	2	32	84	118			

5.4.3 Respondents' Position

Table 5.6 below shows the breakdown of respondents' position in the Audit Firm. As shown in table 5.6, 35% of the respondent are partners, being the highest number of respondents. Quite a high number of responses came from senior associate and director, which is about 32% of the overall responses, which also means we go some valuable insight regarding the current state and adoption of DA in the Malaysian Audit Industry.

Table 5.6 Age of Auditor's current position in Firm

Q23	Tabulation of Respondent's Current Position in Firm						
	Big Four Firm	Mid-Tier Firm	Smaller Firm	Total	Freq.	Percent	Cum.
Director	0	2	7	9	9	7.63	7.63
Partner	1	5	35	41	41	34.75	42.37
Manager	0	6	15	21	21	17.80	60.17
Assistant Manager	0	3	8	11	11	9.32	69.49
Senior Associate	1	13	14	28	28	23.73	93.22
Associate	0	0	3	3	3	2.54	95.76
Others	0	3	2	5	5	4.24	100.00
Total	2	32	84	118			

5.4.4 Number of Years in Position

The respondents were also asked to indicate the audit experience. Results show that 60 % of respondents had at least 6 years of auditing experience, and around 40 % of them have an experience of fewer than 5 years in the field. This suggests that most of the respondents are quite experienced in this field and would be able to give very meaningful insights about the transition of the audit process in Malaysia. Table 5.7 below summarises the results.

Table 5.7 Auditor's working in current position (no of years)

Q24	Tabulation of Respondent's years in current position						
	Big Four Firm	Mid-Tier Firm	Smaller Firm	Total	Freq.	Percent	Cum.
0 to 5 years	1	14	31	46	46	38.98	38.98
6 to 10 years	0	8	10	18	18	15.25	54.24
11 to 15 years	1	6	18	25	25	21.19	75.42
16 to 20 years	0	1	8	9	9	7.63	83.05
21 years & above	0	3	17	20	20	16.95	100.00
Total	2	32	84	118			

5.4.5 Number of Years with Firm

The number of years employed reflects the length of time the respondent has been associated with the current audit firm, and hence it shows the level of familiarity with the goals and operations of this particular organization and is well aware of the company's transition. If we have a look at table 5.8 there is an interesting suggestion we can depict, which is, almost 60% of the respondents are with their current firm for more than 6 years and above which suggests, auditors tend to stay with their practicing firms longer and grow along with them. Table 5.8 shows the details for the respondent's length of employment for the sample.

Table 5.8 Auditor's working in the current firm (no of years)

Q25	Tabulation of Respondent working in current Firm (in years)						
	Big Four Firm	Mid-Tier Firm	Smaller Firm	Total	Freq.	Percent	Cum.
0 to 5 years	1	15	28	44	44	37.29	37.29
6 to 10 years	0	7	15	22	22	18.64	55.93
11 to 15 years	1	6	15	22	22	18.64	74.58
16 to 20 years	0	1	11	12	12	10.17	84.75
21 years & above	0	3	15	18	18	15.25	100.00
Total	2	32	84	118			

5.4.6 Number of Years' Experience in Auditing

Table 5.9 shows the number of years of experience by auditors in auditing. It shows that more than 56% of auditors have more than 10 years of experience. Thus, demographic data indicates that responding auditors are quite experienced in their careers.

Table 5.9 Auditor's Experience

Q26	Tabulation of Respondent's experience in Auditing						
	Big Four Firm	Mid-Tier Firm	Smaller Firm	Total	Freq.	Percent	Cum.
0 to 5 years	0	13	15	28	28	23.73	23.73
6 to 10 years	1	9	16	26	26	22.03	45.76
11 to 15 years	1	3	16	20	20	16.95	62.71
16 to 20 years	0	1	12	13	13	11.02	73.73
21 years & above	0	6	25	31	31	26.27	100.00
Total	2	32	84	118			

5.4.7 Number of Years' Experience in Computerised Auditing

Table 5.10 shows the number of years of experience of auditors in computerized auditing. Surprisingly 10% of the respondents do not have any experience with computerized auditing which suggests they might still not be adept at computers or audit partners who still have a traditional view on IT. As expected over 50% of the respondents have experience with a minimum of 6 years.

Table 5.10 Auditor's Experience with computerized auditing

Q27	Tabulation of Respondent's experience with computerized auditing						
	Big Four Firm	Mid-Tier Firm	Smaller Firm	Total	Freq.	Percent	Cum.
None	0	1	9	10	10	8.47	8.47
0 to 5 years	0	16	31	47	47	39.83	48.31
6 to 10 years	2	11	27	40	40	33.90	82.20
11 to 15 years	0	4	8	12	12	10.17	92.37
16 to 20 years	0	0	7	7	7	5.93	98.31
21 years & above	0	0	2	2	2	1.69	100.0
Total	2	32	84	118			

5.4.8 Respondents' IT Skill

Respondents were asked about their general IT skills. Nearly 27 % of the respondents indicated that they have very basic IT skills, whereas the majority of the respondents (48 %) pointed out they have an adequate amount of skills required to carry out the Audit processes. Table 5.11 shows the frequency and percentage of skills of the respondents in the sample.

Table 5.11 Auditor's IT Skills

Q28	Tabulation of Respondent's Information Technology Skills						
	Big Four Firm	Mid-Tier Firm	Smaller Firm	Total	Freq.	Percent	Cum.
Very Good	0	0	2	2	2	1.69	1.69
Good	2	4	20	26	26	22.03	23.73
Adequate	0	19	38	57	57	48.31	72.03
Basic	0	7	21	28	28	23.73	95.76

Very Basic	0	2	3	5	5	4.24	100.00
Total	2	32	84	118			

5.5 Current State of Art in using Data Analytics among Auditors of Malaysia

5.5.1 Use of Data Analytics

To gather information about the usage of DA by auditors, the respondents were asked. To what extent DA has been used in their company's audit operations. Interestingly only 7% of the respondents have indicated that they haven't come across any sort of DA in performing their audit operations. However, the major chunk of 94% of respondents has used some sort of analytics which spreads from rarely to always.

Table 5.12 DA Usage

Q6	Tabulation of Estimates of DA usage in Respondent's Company						
	Big Four Firm	Mid-Tier Firm	Smaller Firm	Total	Freq.	Percent	Cum.
Never	0	2	7	9	9	7.63	7.63
Rarely	0	4	15	19	19	16.10	23.73
Sometimes	1	10	34	45	45	38.14	61.86
Often	0	14	19	33	33	27.97	89.83
Always	1	2	9	12	12	10.17	100.00
Total	2	32	84	118			

5.5.2 Number of Years of Implementing DA in Respondent's Firm

The respondents were asked to indicate for how long their firm has implemented Data Analytics software in Audit processes. As shown in Table 5.13, 40 % of the responses suggested that their firm has been using DA for more than 3 years and a further 25 % has been using it for more than 1 year. 31% of the smaller firms have very minimal exposure to DA software. The result implies that not all firms are well versed and experienced with DA software at present, in the context of Malaysia, but have started using them which will lead to further improvement in the future.

Table 5.13 Implementation of DA (no of years)

Q7	Tabulation of how many years Respondent's Firm has been using DA						
	Big Four Firm	Mid-Tier Firm	Smaller Firm	Total	Freq.	Percent	Cum.
Don't Know	0	8	26	34	34	28.81	28.81
Less than 1 year	0	4	10	14	14	11.86	40.68
1 to 2 years	1	2	13	16	16	13.56	54.24
2 to 3 years	0	5	9	14	14	11.86	66.10
More than 3 years	1	13	26	40	40	33.90	100.00
Total	2	32	84	118			

5.5.2 Type of Audit Software Used

Excel Advanced is still the most popular type of software that is used by auditors in Malaysia as represented by 55 % of the respondents in Table 5.14. Excel advanced has been used for techniques like Macros, VBA, Miner, Solver. auditing. 12 % of the mid-tier and smaller firms have developed their in-house application to cater to computerized auditing and 24% of the firms use different Data Management Systems and Visualization software like Tableau, SAS Visual Analytics, Power BI, etc. along with Excel. Table 5.14 indicates the type of software that has been used for auditing.

Table 5.14 Types of DA used

Q5	Tabulation of Usage of Data Analytics Software						
	Big Four Firm	Mid-Tier Firm	Smaller Firm	Total	Freq.	Percent	Cum.
Excel Advanced	0	16	45	61	61	54.46	54.46
Business Intelligence Analytics	0	0	1	1	1	0.89	55.36
Database management Systems	0	1	3	4	4	3.57	58.93
Visualization	0	1	5	6	6	5.36	64.29
In House Application	0	5	8	13	13	11.61	75.89
Excel & a combination of above software*	2	6	19	27	27	24.11	100.00
Total	2	29	81	112			

5.5.3 Level of satisfaction in using DA

The Respondents were asked about their level of satisfaction in using DA, in their Audit procedures. As expected, Table 5.15 42 % of the responses indicated that they would require further support whereas 40 % of them are reasonably satisfied with their current software. As the usage of different analytics software is at a minimal stage, it would take a while for Malaysian auditors to get used to the software they are using currently.

Table 5.15 Satisfaction of DA usage

Q8	**Tabulation of Respondent's satisfaction in using DA**						
	Big Four Firm	Mid-Tier Firm	Smaller Firm	Total	Freq.	Percent	Cum.
Very Satisfied	0	3	4	7	7	6.03	6.03
Reasonably Satisfied	0	11	35	46	46	39.66	45.69
Need Further Support	2	13	34	49	49	42.24	87.93
Dissatisfied	0	4	5	9	9	7.76	95.69
Very Dissatisfied	0	0	5	5	5	4.31	100.00
Total	2	31	83	116			

5.5.4 Use of DA at different stages of Audit

As derived previously from the content analysis, auditors are still unsure in which stages of audit can DA be most effective. Respondents were asked in which stages of Audit they have used some sort of analytics and how often they have used it in those separate stages. The different stages of audit that have been determined for this particular question were Audit planning, Evidence gathering, and Completion and review. Table 5.16 shows that respondents tend to use DA sometimes to more often (mean = 3.314 to 3.407) in these stages of Audit. More respondents tend to utilize DA in the evidence-gathering phase.

Table 5.16 Level of DA usage

	Never (1)	Rarely (2)	Sometimes (3)	Often (4)	Always (5)	Total	Mean
Audit Planning	11	13	35	35	24	118	3.407
Completion & Review	10	14	38	34	22	118	3.373
Evidence Gathering	12	17	24	52	13	118	3.314

5.5.5 Use of DA at different areas of the Audit process

To further explore the usage of Data Analytics in Audit procedures, the respondents were asked to highlight how often they have used DA in different areas of audit procedures. Although the use of data analytics is increasing, more rapidly at some firms than others, the pace of change is not as fast as thought by audit committees and investors (Financial Reporting Council, 2017). A list of audit procedures has been segregated for the purpose of this question, which included evaluating the risk of fraud, testing journal entry, understanding the client's operational environment, assessing the risk of material misstatement, etc. The results seem consistent with what we had for DA usage in different stages of Audit. Most of the responses in Table 5.17 show a mean above 3.000 which suggests that auditors tend to use DA software sometimes too often for these audit areas. The highest mean was 3.475 which is for performing substantive procedures. This was one of the findings from the content analysis where the stakeholders around the world were unsure about whether DA will enhance the substantive procedure or not. Judging from the responses of the survey, it can be predicted that this ambiguity can be much clearer as more auditors in Malaysia are using DA to perform substantive procedures. The lowest mean was 2.432 for reviewing board and audit committee meetings and minutes. Apart from these, a higher mean can be seen for conducting analytical procedures (3.331), to perform audit planning (3.424) and to determine the level of materiality (3.373).

Surprisingly, testing 100 percent of the population instead of the sample has a lower mean of 2.754. However, the content analysis of the responses around the world sees this as one of the major benefits of using DA. Appelbaum, Kogan, & Vasarhelyi, (2017) also suggested the variability of advantages that can be achieved through testing 100 % of the population using DA. However, concerning Malaysia, these could be still new and as our sample respondents are from small to medium firms, this could still not be adopted in a wider way.

Table 5.17 Extent of DA usage

	Tabulation of the extent of DA usage at different areas of Audit						
	Never (1)	Rarely (2)	Sometime (3)	Often (4)	Always (5)	Total	Mean
To perform substantive procedures	12	14	25	40	27	118	3.475
To Perform Audit planning	13	13	29	37	26	118	3.424
To determine the level of materiality	16	11	30	35	26	118	3.373
To conduct analytical procedures	16	13	30	34	25	118	3.331
To perform test of controls	17	14	26	43	18	118	3.263
To identify and assess risks of material misstatement	14	17	33	36	18	118	3.229
To examine financial statements disclosures and notes	20	14	28	37	19	118	3.178
To Test journal entry	14	22	36	33	13	118	3.076
To determine key audit matters (KAM)	24	13	30	33	18	118	3.068
To Evaluate Risk of Fraud	14	21	39	32	12	118	3.059
To understand our client's operations, performance & environment	18	24	25	40	11	118	3.017
To evaluate client's internal controls over financial reporting	20	19	31	39	9	118	2.983
To test 100% population instead of sample	28	24	25	31	10	118	2.754

To resolve disagreement with management on accounting issues	27	26	42	18	5	118	2.559
To review board and/or audit committee meeting minutes	34	32	24	23	5	118	2.432

5.5.6 Techniques Used by Respondents in DA

This study has also examined the different sorts of techniques that can be used by auditors in different areas of the audit. A description of the techniques has been provided to help the respondents understand the techniques much better. Descriptive statistics include the mean, min, max, variance, frequency, distribution, etc. Data visualization presents descriptive statistics in a pictorial or graphical format to assist in identifying relationships and patterns. The tools that can be used for this purpose are Tableau, SAS Visual Analytics, Excel, Python, Idea, etc. Advanced Statistical Analysis techniques could use such as linear and/or logistic regression and cluster analysis. The software that is used for these purposes is SAS Enterprise Miner, SPSS Advanced Statistics, SPSS modeler, R, Python, etc. Optimization uses statistical and mathematical techniques to make predictions and then suggest decision options to leverage these predictions and can be generated using Excel Solver, MATLAB, Gourbi, etc. Text Mining derives information from the analysis of text-based data. Examples of tools used for this purpose include SAS, Word Stat, IBM/SPSS, Textalytics. Table 5.18 shows that Visualization and descriptive analysis is the most used techniques for these audit procedures. Although it has been observed that a significant number of respondents has chosen the not applicable option as they were unsure of what sort of technique they have used and also as seen from the demographic analysis of the previous table 5.17, a lot of firms still haven’t used much of DA in these areas of audits.

Table 5.18 DA software used in different stages of Audit

Q11	Tabulation of usage of different DA software at different areas of Audit						
	Visualization & Descriptive Statistics	Advanced Statistical Analysis	Optimization	Text Mining	N/A	Combination of Techniques*	Obs
To Evaluate Risk of Fraud	50	4	12	2	46	4	118
To Perform Audit planning	53	5	10	6	39	5	118
To Test journal entry	52	2	12	5	44	3	118
To understand our client's operations, performance & environment	46	4	7	57	52	2	118
To review board and/or audit committee meeting minutes	34	3	4	5	70	2	118
To identify and assess risks of material misstatement	45	11	8	5	46	3	118
To evaluate client's internal controls over financial reporting	48	4	9	3	49	4	117
To determine the level of materiality	59	3	12	5	35	4	118
To determine key audit matters (KAM)	46	7	10	5	48	2	118
To perform substantive procedures	53	11	10	5	37	2	118
To perform test of controls	54	8	11	5	37	3	118
To examine financial statements disclosures and notes	43	3	9	7	54	2	118
To conduct analytical procedures	49	13	16	3	33	4	118
To test 100% population instead of sample	41	10	7	3	52	5	118
To resolve disagreement with management on accounting issues	34	3	6	3	69	3	118
Total							

5.5.7 Perception on Benefits of using DA

From the content analysis of the responses which was done in the earlier part of the research, it couldn't be predicted whether DA will have many benefits if used in the audit procedure. However, the study decided to take the perceptions of Malaysian auditors through this survey to have a perceived opinion on whether DA would improve audit quality. Previous literature suggests the use of different factors of audit procedures to measure audit quality (Feroz, Park, & Pastena, 1991). Academic researchers have conceptualized different ways to measure audit quality. A combination of measures has been used linking the size of the audit firm and audit fees to audit outcomes such as financial reporting quality and accurate audit opinion (Sulaiman, Yasin, & Muhamad, 2018; Feroz et al., 1991; Becker, DeFond, Jiambalvo, & Subramanyam, 1998; Gul, Sun, & Tsui, 2003). The ability to enhance the detection of material misstatement will supposedly affect audit quality. As suggested by previous studies, auditors in larger audit firms are better able to detect material misstatements and so an effect on audit quality can be observed (Elitzur & Falk, 1996); Caramanis & Lennox, 2008)). Long tenure is said to improve audit quality, as the practitioner has greater knowledge in client's business and it improves the ability to detect material misstatement (Johnson, Khurana, & Reynolds, 2002; Ghosh & Moon, 2005; Stanley & DeZoort, 2007; Manry, Mock, & Turner, 2008;Bryan & Reynolds, 2016). The efficiency and effectiveness of audits seem to affect the audit quality as well. Eining, Jones, & Loebbecke, (1997); Wilks & Zimbelman, (2004); Agoglia, Brazel, Hatfield, & Jackson, (2010) have documented that the contextual factors may shape or impact the efficiency of the audit process, such as corporate governance, legislative and regulatory requirements, are considered important to achieve high audit quality.

Table 5.19 Perceptions on benefits of using DA

Q20	Tabulation of Respondent's perception on Benefits of using DA							
	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Obs	Mean	Std. Dev.
Using DA improves audit efficiency		4	21	79	14	118	3.873	.648
Using DA improves audit effectiveness		4	24	74	15	118	3.856	.67
Using DA improve ability to detect material misstatements		4	24	77	13	118	3.839	.653
Using DA improve ability to report misstatements		7	28	68	15	118	3.771	.744
Using DA improves accuracy of audit opinion		5	33	71	9	118	3.712	.668
Using DA ensure audit has been conducted in accordance with prescribed standards and regulatory requirement	3	8	30	71	6	118	3.585	.799
Using DA reduce earnings management		10	35	69	4	118	3.568	.698
Using DA reduce financial restatements	1	8	43	59	7	118	3.534	.747
Using DA improve audit client's satisfaction	2	7	49	49	11	118	3.508	.814
Total								

This study has used some of these measures to observe the perceived benefits of using DA in these procedures. The Table 5.19 shows a maximum mean of 3.839 for "using DA improve the ability to detect material misstatements" and a minimum mean of 3.508 for "using DA improve audit client's satisfaction", A higher mean has also been achieved for improving audit efficiency and audit effectiveness, which shows the auditors believe that DA can enhance the quality of audit opinion by improving these attributes of an audit engagement. Moreover, the overall responses indicate a stronger biasness towards agreeing. This suggests the practitioners who are working in the audit profession feel there is a strong chance that DA will provide benefits in these areas and eventually will have an overall effect on audit quality.

5.6 Factor Analysis

Factor analysis is run to reduce a large set of variables or scale items down into a smaller and more manageable number of factors (Pallant, 2011). The responses to the 50 items were collected to determine the perception, regarding each factor's influence in implementing DA in audit procedure. This section discusses the results of factor analysis conducted for all items that measured the factors that influence the implementation. The Factor analysis was carried with a sample of 118 responses. This would validate the survey scale and will prepare the data for further studies.

5.6.1 Cronbach's Alpha

In this study, Cronbach's Alpha tests were utilized, because of its relevance to a questionnaire based on the Likert-type five-point scale, and measures the internal consistency of the questionnaire, based on the average inter-item correlation of the items (Salkind, 2009). A reliability test using Cronbach's alpha was conducted to measure the internal consistency of the items in the survey instrument. This test was conducted on all variables. The result of Cronbach's Alpha demonstrates an alpha of 0.9499. The result of 0.9499 is acceptable as Nunally & Bernstein, (1978) identified 0.7 and above is a good value where the general guideline says that alpha value above 0.8 indicates good reliability (Field, 2009).

5.6.2 Kaiser-Meyer-Olkin (KMO) and Bartlett Test of Sphericity

Before proceeding with factor analysis, Kaiser-Meyer-Olkin (KMO) and Bartlett's Test of Sphericity (BTOS) needed to be measured. The KMO and BTOS measure whether the adequacy of sampling is appropriate to proceed with factor analysis. A small KMO value indicates the factor analysis may not be a good option. Kaiser, (1974) quoted that a KMO measure in the 0.90's is considered as 'marvelous', in the 0.80's as 'meritorious', in the 0.70's as 'middling', in the 0.60's as 'mediocre', in the 0.50's as 'miserable', and below 0.50's as 'unacceptable' for sample adequacy for factor analysis purposes (Norusis, 1992).

BTOS is a statistical test for the presence of correlations among the variables (Hair et al., 1998). BTOS provides the statistical significance that the correlation matrix has significant correlations among at least some of the variables. The result for the KMO and BTOS are shown in Table 5.20 below.

Table 5.20 KMO and Bartlett's Test

Bartlett test of sphericity	
Chi-square	4816.084
Degrees of freedom	1225
p-value (sig.)	0.000
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	
KMO	0.820

From Table 5-20, the KMO measure for the factors that influence the implementation of DA in the audit process showed a value of 0.880. The observed value of the Bartlett test of sphericity was also large (4816.084) and its associated significance level was very low (0.000). Combining the results of KMO measure and Bartlett test of sphericity, the items used to indicate the factors that influence the implementation of DA clearly met the conditions for subsequent tests of factor analysis.

5.6.3 Eigenvalues and Variances Percentage

Table 5.21 Eigenvalues

Factor analysis/correlation Number of obs = 118
Method: principal-component factors Retained factors = 10
Rotation: (unrotated) Number of params = 455

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	15.942	10.452	0.319	0.319
Factor2	5.491	2.436	0.110	0.429
Factor3	3.055	0.392	0.061	0.490
Factor4	2.664	0.651	0.053	0.543
Factor5	2.012	0.292	0.040	0.583
Factor6	1.720	0.210	0.034	0.618
Factor7	1.510	0.127	0.030	0.648
Factor8	1.384	0.074	0.028	0.676
Factor9	1.309	0.221	0.026	0.702
Factor10	1.088	0.094	0.022	0.724

According to Hair et al., (1998), during the factor analysis eigenvalue of less than 1 would be rejected and factors with eigenvalue more than 1.0 are considered to be significant and maintained for further analysis. The results of the test revealed that there were ten factors with an eigenvalue exceeding 1.0. As shown in Table 5.21 only the eigenvalues above 1 have been shown. The highest eigenvalue is 15.942 explaining 10.452 % of the variance. The lowest eigenvalue was 1.088explaining 0.094 % of the variance.

5.6.4 Scree Plot

The scree test consists of eigenvalues and factors(Cattell, 2012). A scree plot is a graph that plots each factor in factor analysis against its associated eigenvalues (Field, 2009). The scree test can be derived by plotting the latent roots against the number of factors in their order of extraction, and to assess the cut-off point, the shape of the resulting curve is used (Hair et al., 1998). The number of factors to be retained is the data points that are above the break (i.e., point of inflexion). To determine the 'break', researchers draw a horizontal line and a vertical line starting from each end of the curve. The scree plot in

Figure 5.1 shows that the plot slopes steeply downwards from one factor to two factors, and two factors to three factors, and then gently from three factors to four factors, before slowly becoming an approximately horizontal line.

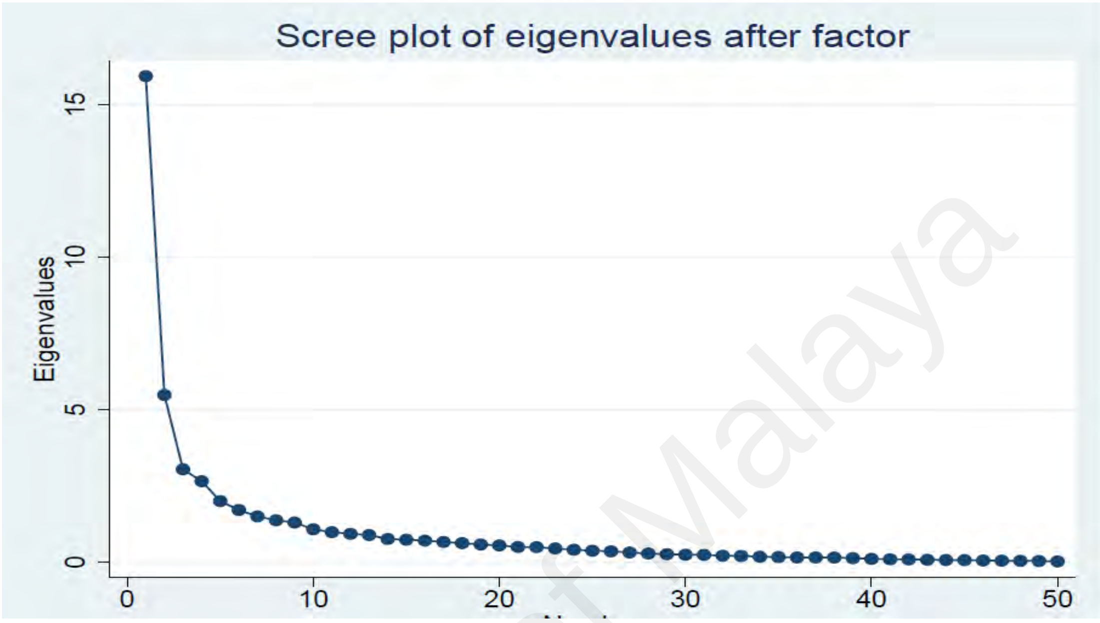


Figure:5.1 Scree Plot

Cattell, (2012) suggested that the cut-off point for selecting factors should be at the inflexion point of the curve. As can be seen in Figure 5.1, the point of inflexion occurs between the fifth and the sixth data point. According to Field, (2009), the factor to the left of the point of inflexion should be retained. However, it was decided that other factor which had an eigenvalue of more than 1.0 should be retained for further investigation, consistent with the results of the eigenvalue analysis shown in Table 5.21. The above factors were further tested with the principal component factors (PCF) analysis and orthogonal Varimax rotation method.

5.6.5 Factor Loading Based on Rotated Component Matrix

Factor analysis in this study was conducted using PCA and rotated using a Varimax method with factor loading more than 0.50. The Varimax method was selected because it is the most commonly orthogonal approach used, which attempts to minimize the number of variables that have high loadings on each factor (Pallant, 2011). The research uses a variety of cut-off points for individual factor loadings; however, our use of .4 is consistent with the prior audit quality research (Carcello, Hermanson, & McGrath, 1992; Shevlin & Miles, 1998) and is consistent with other exploratory factor analyses. Hair Jr, Black, Babin, Anderson, & Tatham, (2010) suggest that if the factor loadings are +0.50 or greater, they are considered to be very significant, and can be used for further analysis. So, for the purpose of this study. 0.5 has been used as the cut-off point to make sure the identified factors are significant and the scale is validated properly. The results are shown in Table 5.22. Based on the sorted rotated factor loadings, with orthogonal varimax rotation, Stata has extracted 10 factors, as seen in Table: 5.22. However, Factor 9 had only one component, and Factor 8 and 10 had only two components which are not enough to form a separate factor. Since the factor loading for factor 9 (0.510), factor 8 (0.592 & 0.588) and factor 10 (0.592 & 0.588) are quite high, instead of ignoring them we put factor 9 under previous stated factors to make it more sensible. The component under factor 9 has been included in factor 6 and the components under factor 8 and 10are combined together to form a separate factor, to give them a much more meaningful view. The table 5.23 below shows the final factors after the extraction of factor loading. These have been grouped into eight (8) components and each of them were named and labelled according to their specifications.

Table 5.22 Rotated Component Matrix

Factor analysis/correlation — Number of obs = 118
Method: principal-component factors — Retained factors = 10
Rotation: orthogonal varimax — Number of params = 455

Rotated factor loadings (pattern matrix) and unique variances sorted

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7	Factor8	Factor9	Factor10	Uniqueness
q1211	0.837	-0.000	0.026	-0.082	0.039	0.063	0.064	0.117	0.063	-0.044	0.264
q126	0.790	0.188	0.048	0.033	-0.026	0.127	-0.067	-0.025	-0.290	0.052	0.229
q134	0.787	0.040	-0.064	0.025	0.155	0.043	0.227	0.027	0.144	-0.005	0.276
q135	0.773	0.104	0.022	0.051	0.168	0.219	0.283	0.018	0.168	0.056	0.201
q1210	0.758	0.132	0.229	0.011	-0.021	0.005	0.082	0.092	-0.025	0.170	0.310
q133	0.751	0.021	-0.066	0.018	0.219	0.093	0.222	-0.029	0.220	0.136	0.257
q127	0.747	0.173	-0.004	0.227	0.011	0.027	0.042	-0.097	-0.157	-0.207	0.281
q125	0.744	0.224	0.100	0.042	-0.006	-0.196	-0.185	0.107	0.136	0.230	0.229
q122	0.708	0.216	0.140	0.263	0.018	0.123	0.163	-0.089	0.055	-0.178	0.279
q124	0.605	-0.016	0.036	0.223	0.076	0.244	-0.154	0.024	-0.345	-0.189	0.338
q128	0.525	0.407	0.258	0.280	-0.057	-0.114	0.165	-0.040	-0.023	-0.295	0.282
q121	0.504	0.336	0.227	0.230	-0.012	-0.081	0.278	-0.036	0.157	-0.104	0.407
q161	0.463	-0.196	-0.068	0.418	0.023	0.358	-0.162	-0.059	0.008	0.241	0.351
q141	0.234	0.796	0.224	0.179	0.110	0.041	0.070	-0.083	0.045	0.105	0.191
q142	0.139	0.784	0.193	0.193	0.071	0.200	0.116	-0.054	0.014	0.005	0.230
q143	0.095	0.766	0.149	0.230	0.194	0.268	0.082	0.077	0.146	0.072	0.181
q144	0.147	0.726	0.155	0.182	0.057	0.039	0.197	-0.021	-0.062	-0.055	0.343
q145	0.149	0.696	0.098	0.075	0.053	0.248	0.303	0.267	0.059	0.051	0.245
q153	0.148	0.464	0.290	0.265	0.049	0.295	0.115	-0.146	0.432	-0.123	0.283
q175	0.068	0.203	0.847	0.200	0.081	0.113	0.061	-0.018	-0.049	0.098	0.162
q174	0.128	0.048	0.821	0.172	-0.004	0.126	0.193	0.085	0.072	-0.113	0.200
q176	0.038	0.238	0.809	0.186	0.187	0.094	0.022	-0.051	0.137	0.118	0.173
q177	0.020	0.239	0.732	0.241	0.275	0.065	0.029	0.071	0.083	0.117	0.242
q173	0.042	0.156	0.605	0.166	0.245	0.330	-0.042	0.261	0.008	-0.013	0.341
q123	0.212	0.340	0.397	0.019	0.016	0.153	0.260	-0.339	0.017	-0.107	0.464
q163	0.128	0.283	0.057	0.837	0.079	0.071	0.036	-0.061	0.097	-0.014	0.174
q164	0.133	0.131	0.229	0.783	0.221	0.085	0.053	-0.099	0.018	-0.044	0.229
q165	0.077	0.136	0.281	0.758	0.120	0.073	0.168	0.026	0.053	0.120	0.256
q162	0.043	0.269	0.163	0.751	0.078	0.144	0.002	-0.037	0.118	0.072	0.288

q166	0.040	0.079	0.350	0.691	0.040	0.025	0.147	0.098	-0.116	0.196	0.308
q183	0.285	0.091	0.121	0.128	0.750	-0.017	0.005	-0.048	-0.112	0.104	0.291
q182	0.303	0.015	0.085	0.283	0.671	0.052	-0.043	0.114	0.321	0.030	0.249
q185	-0.036	0.248	0.231	0.180	0.636	-0.050	0.396	0.009	-0.048	0.078	0.280
q184	-0.141	0.224	0.280	-0.035	0.575	0.122	0.012	0.148	-0.128	-0.152	0.444
q181	0.037	0.088	0.313	0.143	0.569	0.101	0.259	0.180	0.197	0.171	0.371
q155	0.065	0.356	0.210	0.228	0.020	0.706	0.131	-0.059	0.098	0.002	0.244
q157	0.318	0.259	0.200	-0.051	0.003	0.680	0.180	0.052	-0.024	0.162	0.265
q154	0.052	0.360	0.207	0.156	0.093	0.599	0.071	-0.230	0.309	-0.085	0.272
q156	0.101	0.331	0.338	0.259	-0.041	0.543	0.174	0.076	-0.153	-0.020	0.343
q136	0.293	0.299	0.070	0.148	0.083	0.153	0.682	-0.135	-0.018	0.019	0.284
q131	0.225	0.296	0.132	0.157	0.102	0.079	0.621	0.012	0.044	-0.099	0.406
q132	0.183	0.296	0.154	0.092	0.213	0.283	0.608	0.110	0.298	0.150	0.227
q129	0.260	0.209	0.319	0.156	-0.006	0.148	0.462	0.225	-0.098	-0.316	0.367
q171	0.194	-0.050	0.056	-0.046	0.097	-0.040	0.043	0.819	-0.167	0.044	0.242
q172	-0.139	0.190	0.414	-0.043	0.105	-0.076	0.017	0.608	0.281	-0.109	0.294
q186	0.066	0.152	0.272	0.393	0.419	-0.067	0.320	-0.451	-0.081	-0.000	0.252
q152	0.167	0.427	0.246	0.407	-0.024	0.116	0.172	-0.021	0.510	-0.055	0.256
q151	0.130	0.487	0.301	0.192	0.044	0.311	0.022	-0.211	0.491	-0.120	0.220
q167	-0.099	0.301	0.220	0.420	0.087	-0.028	0.116	-0.018	0.002	0.592	0.302
q168	0.433	-0.017	0.202	0.261	0.296	0.195	-0.066	0.048	-0.154	0.588	0.203

Table 5.23 Factor Loading, Mean & Standard Deviation of new factors

Factor	Code	Item	Factor Loading	Mean	Std. Dev.
Factor 1	q1211	Auditors will be able to provide more than reasonable assurance on financial statements using DA	0.837	3.72	.75
	q126	Improve accounting disclosures	0.790	3.686	.884
	q134	ISAs encourage use of various analytical methods to detect misstatement	0.787	3.788	.749
	q135	If ISAs provides guidance on how to use audit analytics tools in auditing procedures, I will be willing to use audit analytics	0.773	3.898	.841
	q1210	Identifying risk of material misstatement will be easier	0.758	3.856	.83
	q133	ISAs encourage use of advanced analytics methods to enhance audit function reliability	0.751	3.814	.703
	q127	Sufficiency of audit evidence collected using DA	0.747	3.771	.81
	q125	Improve accounting estimates	0.744	3.737	.81
	q122	Lead to better improvement in professional audit judgement	0.708	3.932	.688
	q124	Able to test 100% of population	0.605	3.407	1.006
	q128	DA will improve identification of outliers and exceptions in audit sampling	0.525	3.89	.624
	q121	An existing audit methodology to follow	0.504	3.873	.661
Factor 2	q141	Improvement in data reliability	0.796	4.017	.599
	q142	Data security concerns	0.784	4.051	.625
	q143	IT Specialist’s role in audit will increase	0.766	4.161	.627
	q144	Data accessibility from different type of system will be difficult	0.726	4.034	.612
	q145	Storing and retaining data for audit trail	0.696	4.102	.646
Factor 3	q175	Appropriate quality controls need to be in place for using DA	0.847	4.093	.627
	q174	Reliance on client’s internal audit data	0.821	4.034	.666

	q176	Maintaining ethics and professionalism when using DA	0.809	4.059	.644
	q177	Legal/Regulatory challenges in using DA	0.732	4.034	.64
	q173	Reliance on external or third-party data	0.605	3.949	.714
Factor 4	q163	Complexity in client's general IT controls	0.837	3.898	.709
	q164	Understanding the data in use (Clients' Data)	0.783	4.008	.647
	q165	Support provided by client's IT personnel	0.758	3.958	.684
	q162	Strengths of client's IT infrastructure	0.751	3.856	.683
	q166	Clients business size	0.691	3.992	.734
Factor 5	q183	Input from academicians, universities and researchers will be needed	0.750	3.763	.623
	q182	Shifts in business environment will require auditors to use and adopt DA	0.671	3.949	.611
	q185	Issuance of Non- Authoritative guidance by Standard setters for using DA	0.636	3.873	.634
	q184	Auditors may be over reliant on technology	0.575	3.763	.844
	q181	DA should be defined more clearly in terms for auditors use	0.569	3.992	.577
Factor 6	q155	Manage workloads on multiple audit engagement	0.706	3.966	.679
	q157	Demand in auditor's promotion policies	0.680	3.839	.784
	q154	Instructed by the management to use DA	0.599	3.975	.633
	q156	Financial budget on audit engagement	0.543	4.042	.659
	q152	Re- training or Re- Skilling existing auditors	0.510	4.161	.554
Factor 7	q136	Developing a principle based standard rather than rule-based standard	0.682	3.881	.73
	q131	Collaborative work is required from auditors, standard setters & oversight authorities on ISAs related to DA application in audit	0.621	3.864	.612
	q132	Current ISAs should provide guidance on application of DA in audit	0.608	4.025	.745
Factor 8	q171	Use of DA will be time consuming	0.819	3.254	.898

	q172	Implementing DA will require huge cost	0.608	3.89	.825
	q167	Whether SMEs and SMPs clients are ready to use DA	0.592	3.966	.773
	q168	Whether DA can be used in group audits	0.588	3.847	.791
Items Dropped	q161	DA will enhance the capability of understanding client's business environment & internal control	0.463		
	q153	Full support from top management	0.464		
	q123	Professional skepticism needs to be in exercise when using DA	0.397		
	q129	Amount of audit documentation will increase	0.462		
	q186	Future audit might need to use different features of DA like predictive algorithms/text mining/blockchain/continuous auditing	0.451		
	q151	Skills of auditors as data analyst	0.491		

5.7 New Labelled Factors

Table 5.24 Cronbach Alpha value and Label for new Factors

Factors	New Label	Cronbach Alpha
Factor 1	Audit Profession Factors	0.9272
Factor 2	Technological Factors	0.9114
Factor 3	Factors relating to Quality Controls	0.9103
Factor 4	Client Factors	0.9020
Factor 5	External Factors	0.7723
Factor 6	Organizational Factors	0.8288
Factor 7	Factors relating to Audit Standards	0.8042
Factor 8	Inhibiting Factors	$0.4959 \approx 0.5$

5.7.1 Factor 1 Audit Profession Factors

Table 5.25 Descriptive Analysis of Audit Profession Factors

Factor 1	**Descriptive Analysis of Audit Profession Factors**						
	Factor Loading	Mean	Std. Dev.	Cronbach Alpha	BTOS Chi-square	P-value	KMO
				0.9272	934.672	0.000	0.912
Lead to better improvement in professional audit judgement	0.708	3.932	.688				
If ISAs provides guidance on how to use audit analytics tools in auditing procedures, I will be willing to use audit analytics	0.773	3.898	.841				
DA will improve identification of outliers and exceptions in audit sampling	0.525	3.89	.624				
An existing audit methodology to follow	0.504	3.873	.661				
Identifying risk of material misstatement will be easier	0.758	3.856	.83				
ISAs encourage use of advanced analytics methods to enhance audit function reliability	0.751	3.814	.703				
ISAs encourage use of various analytical methods to detect misstatement	0.787	3.788	.749				
Sufficiency of audit evidence collected using DA	0.747	3.771	.81				
Improve accounting estimates	0.744	3.737	.81				
Auditors will be able to provide more than reasonable assurance on financial statements using DA	0.837	3.72	.75				
Improve accounting disclosures	0.790	3.686	.884				
Able to test 100% of population	0.605	3.407	1.006				

The first factor which was generated had the highest factor loading and was labeled as Audit profession factors. The professional category includes all the aspects within the audit profession. The audit process or methodology category refers to the specific procedures and practices followed by the audit team. This is the first factor been created and is labeled as Audit Profession Factors. There are 12 attributes for this factor which explains the overall factor. This factor explores the perception of auditors on attributes relating to standard, risk of material misstatement, accounting disclosures, reasonable assurance, guidance on standards. Accounting estimates, the sufficiency of audit evidence, professional audit judgment, and sampling bias. It analyses what the auditors perceive whether these attributes will influence the implementation of DA.

All the attributes under this factor have a positive response from the auditors. Each of the items previously was measured in the survey by agreement through a Likert scale represented by 1 to 5, where 1 strongly disagrees and 5 strongly agree. This shows that auditors in Malaysia believe these factors will have an impact or influence the implementation of DA in the audit profession. The highest mean for this factor was 3.932 as shown in table 5.25, for "Lead to better improvement in professional audit judgment" and the lowest mean was 3.407 for "Able to test 100% of the population". The respondents believe that if improvement in professional judgment can be seen through the use of DA, then it will affect its implementation process. Also, a higher response can be seen for "DA will improve identification of outliers and exceptions in audit sampling" (3.89), "if ISAs provides guidance on how to use audit analytics tools in auditing procedures, I will be willing to use audit analytics" (3.898). The scale represents a high Cronbach alpha of 0.9272, which shows a high internal consistency between the attributes, and are closely related as a group. The factor test gives a P-value of 0.00

representing high significance and KMO of 0.912 which shows a very high measure of sampling adequacy and is suitable for further analysis. These values validate and measures the scale reliability and are therefore satisfactory at all level.

5.7.2 Factor 2 Technological Factors

Table 5.26 Descriptive Analysis of Audit Technological Factors

Factor 2	Descriptive Analysis of Technological Factors						
	Factor Loading	Mean	Std. Dev.	Cronbach Alpha	BTOS Chi-square	P-value	KMO
				0.9114	388.685	0.000	0.864
IT Specialist's role in audit will increase	0.766	4.161	.627				
Storing and retaining data for audit trail	0.696	4.102	.646				
Data security concerns	0.784	4.051	.625				
Data accessibility from a different type of system will be difficult	0.726	4.034	.612				
Improvement in data reliability	0.796	4.017	.599				

The second factor has been named as Technological Factors. Most of the attributes relating to this factor concerns about data. Five attributes explain the overall factor. This factor explores the perception of auditors on attributes relating to data reliability, data security concerns, data accessibility, storing and retaining data for audit trail, and IT Specialist's role in audit. All the attributes under this factor have a very high positive responses form the auditors, anchoring from agreeing to strongly agree. This shows that auditors in Malaysia believe these factors will have an impact or influence the implementation of DA in the audit profession. The highest mean for this factor was 4.161 as shown in table 5.26, for "IT Specialist's role in audit will increase" and the lowest mean was 4.034 for “Data accessibility from a different type of system will be difficult”. The respondents believe that the role of IT specialists will play a big factor in the implementation of DA. Audit firms are recruiting many experienced data scientists to offer expertise to auditing and other areas of their businesses (Salijeni, 2018), but this does not necessarily mean that chartered professional accountants need to become data scientists or computer engineers to benefit from the coming data revolution (Tschakert et al., 2016). Data accessibility will also be a major since the shift in focus will most likely relate to the timely accessibility of the relevant data as stated by Brown-Liburd & Vasarhelyi, (2015). Storing and retaining audit data (4.102) would be an important attribute for an audit trail. Alles, Brennan, Kogan, & Vasarhelyi, (2006) mentioned any system has to retain sufficient information to provide evidence that the necessary audit procedures were indeed carried out, and the documentation requirement will suffice as an audit trail. The scale also represents a high Cronbach alpha of 0.9114, which shows a high internal consistency between the attributes, and are closely related as a group. The factor test gives a P-value of 0.00 representing high significance and a Kaiser-Meyer-Olkin (KMO) of 0.864 which shows a very high measure of sampling adequacy and is suitable for further analysis. These values validate and measures the scale reliability and are therefore satisfactory at all level.

5.7.3 Factor 3 Factors relating to Quality Controls

Table 5.27 Descriptive Analysis of Quality Control Factors

Factor 3	**Descriptive Analysis of Quality Control Factors**						
	Factor Loading	Mean	Std. Dev.	Cronbach Alpha	BTOS Chi-square	P-value	KMO
				0.9020	427.826	0.000	0.849
Appropriate quality controls need to be in place for using DA	0.847	4.093	.627				
Reliance on client’s internal audit data	0.821	4.034	.666				
Maintaining ethics and professionalism when	0.809	4.059	.644				

using DA Legal/Regulatory challenges in using DA	0.732 4.034 .64
Reliance on external or third-party data	0.605 3.949 .714

The third factor which was generated from the factor loading consists of five attributes. This factor is named Quality Control Factors because the items listed under this component are related to the controls which are required to maintain if DA is implemented in the audit process.

There are five attributes that explain the overall factor. This factor explores the perception of auditors on attributes relating to Reliance on the client's internal audit data, Maintaining ethics and professionalism, Legal/Regulatory challenges, and external or third-party data. The attributes under this factor also show high positive responses form the auditors, ranging from agreeing to strongly agree. Malaysian Auditors consider these attributes to be important for the implementation of DA. The highest mean for this factor was 4.093 as shown in table 5.27, for "Appropriate quality controls need to be in place for using DA" and the lowest mean was 3.949 for "Reliance on external or third-party data" which still falls along with the agreement. The respondents believe ensuring quality controls will be an important issue when it comes to adopting and using DA in the audit process. Alles et al., (2006) mentions the importance of continuous monitoring of business process controls when implementing continuous auditing. a big factor in the implementation of DA. The effectiveness of internal control and client audit control depends on high ethics and professionalism (Alzeban & Gwilliam, 2014). Implementing DA in audit processes will also need to focus on these aspects of reliance on the client's data and maintaining ethics and professionalism. Relying on clients' internal audit data (4.034) can be difficult. As explained by Appelbaum, (2016), if a client-based their valuation method depending on social media, the reliability of tweets and other external social media is hard to verify. The scale also represents a high Cronbach alpha of 0.9020, which shows a high internal consistency between the attributes, and are closely related as a group. The factor test gives a P-value of 0.00 representing high significance and a Kaiser-Meyer-Olkin (KMO) of 0.849 which shows a high measure of sampling adequacy and is suitable for further analysis. These values validate and measures the scale reliability and is therefore satisfactory at all level.

5.7.4 Factor 4 Client Factors

Table 5.28 Descriptive Analysis of Client Factors

Factor 4	**Descriptive Analysis of Client Factors**						
	Factor Loading	Mean	Std. Dev.	Cronbach Alpha	BTOS Chi-square	P-value	KMO
				0.9020	405.438	0.000	0.790
Understanding the data in use (Clients' Data)	0.783	4.008	.647				
Clients business size	0.691	3.992	.734				
Support provided by the client's IT personnel	0.758	3.958	.684				
Complexity in client's general IT controls	0.837	3.898	.709				
Strengths of client's IT infrastructure	0.751	3.856	.683				

The fourth factor that was generated from factor analysis is labeled as client factor. There are five items under this factor and all of them relate to the auditor's client environment and support. This factor explores the perception of auditors on attributes relating to the client's IT control, client's data, client's support, and strengths of infrastructure and client's business size. These show positive responses form the auditors, ranging between neutral to agree. Malaysian Auditors consider these attributes to be important for the implementation of DA. The highest mean for this factor was 4.008 as shown in table 5.28, for "Understanding the data in use (Clients' Data)" and the lowest mean was 3.856 for "Strengths of client's IT infrastructure". The respondents reflect on the idea that understanding the client's data will have significant importance when data analytics software will be used for audit. Clients can have unusual sources for their data, they might be generating financial valuations of some assets based on information provided by external social media sources (Appelbaum, 2016) but understanding those data will be difficult and to some extent might not be possible even by using DA. Apart from that client's business size (3.992) will also be important in whether to use DA or not. The motivation of audit companies to invest in analytics tools relies primarily on the size of the company (Dagilienė & Klovienė, 2019). As prior research shows that technological competence is a prerequisite for the adoption of technology innovation (Lin, Shih, & Sher, 2007), so strengths of the client's IT infrastructure (3.856) will be an important criterion as presumed by the respondent auditors. The factor test for this new scale also represents a high Cronbach alpha of 0.9020, which shows a high internal consistency between the attributes, and are closely related as a group. The factor test gives a P-value of 0.00 representing high significance and a Kaiser-Meyer-Olkin (KMO) of 0.790 which shows a good measure of sampling adequacy and is suitable for further analysis. These values validate and measures the scale reliability and are therefore satisfactory at all level.

5.7.5 Factor 5 External Factors

Table 5.29 Descriptive Analysis of External Factors

Factor 5	**Descriptive Analysis of External Factors**						
	Factor Loading	Mean	Std. Dev.	Cronbach Alpha	BTOS Chi-square	P-value	KMO
				0.7723	161.734	0.000	0.791
DA should be defined more clearly in terms for auditors use	0.569	3.992	.577				
Shifts in business environment will require auditors to use and adopt DA	0.671	3.949	.611				
Issuance of Non-Authoritative guidance by Standard setters for using DA	0.636	3.873	.634				
Input from academicians,	0.750	3.763	.623				

universities and researchers will be needed			
Auditors may be over reliant on technology	0.575	3.763	.844

The fifth factor that was generated from factor analysis was labeled as External Factors. There are five items under this factor and all of them relate to external issues relating to the implementation of DA. This factor explores the perception of auditors on attributes relating to shift in the business environment, issuance of guidance, over-reliance on technology, and inputs from academicians and researchers. A range of positive responses was recorded ranging mostly towards agree. Malaysian Auditors consider these attributes to be quite important for the implementation of DA. The highest mean for this factor was 3.992 as shown in table 5.29, for "DA should be defined more clearly in terms for auditors use" and the lowest mean was 3.763 for "Auditors may be over-reliant on technology". Over-reliance on technology could be a factor that auditors need to be always aware of. One of the findings presented in (Omoteso, Patel, & Scott, 2008) was auditors may become over-reliant on automated procedures to pick up errors and you may ignore other factors. Shifts in the business environment will require auditors to use and adopt DA (3.949), which has always been an important issue to be pondered about for auditors. Auditors need to be more proactive rather than reactive due to the everchanging business environment. As concluded by Tarek, Mohamed, Hussain, & Basuony, (2017), the rapid advances in information technology have greatly affected the auditing profession in many ways, and hence transforming the traditional audit process to more technology-based audit. The factor test for this new scale also represents a high Cronbach alpha of 0.7723, which shows a good internal consistency between the attributes, and are closely related as a group. The factor test gives a P-value of 0.00 representing high significance and a Kaiser-Meyer-Olkin (KMO) of 0.791 which shows a good measure of sampling adequacy and is suitable for further analysis. These values validate and measures the scale reliability and are therefore satisfactory at all level.

5.7.6 Factor 6 Organizational Factors

Table 5.30 Descriptive Analysis of Organizational Factors

Factor 6	Descriptive Analysis of Organizational Factors						
	Factor Loadin	Mean	Std. Dev.	Cronbach Alpha	BTOS Chi-square	P-value	KMO
				0.8288	227.886	0.000	0.777
Re- training or Re-Skilling existing auditors	0.510	4.161	.554				
Financial budget on audit engagement	0.543	4.042	.659				
Instructed by the management to use DA	0.599	3.975	.633				
Manage workloads on multiple audit engagement	0.706	3.966	.679				
Demand in auditor's promotion policies	0.680	3.839	.784				

The Sixth factor that was generated from factor analysis was labeled as Organizational Factors. There are five items under this factor and all of them relate to issues relating to the organization or the firm itself. This factor explores the perception of auditors on attributes relating to shift in the business environment, issuance of guidance, over-reliance on technology, and inputs from academicians and researchers. All responses show the positive feedback from the auditors with the mean for each item is more than 3.0. Each of the items previously was measured in the survey by agreement through a Likert scale represented by 1 to 5, where 1 strongly disagrees and 5 strongly agree. A range of positive responses was recorded ranging mostly towards agree. Malaysian Auditors consider these attributes to be quite important for the purpose of the implementation of DA. The highest mean for this factor was 4.161 as shown in table 5.30, for "Retraining or Re- Skilling existing auditors" and the lowest mean was 3.839 for "Demand in auditor's promotion policies". Retraining the workforce is something that the firms need to be well aware of if the implementation DA takes place. Changing the auditor's mindset to gathering audit evidence from the use of data analytics compared to traditional techniques will require time and investment in training (IAASB, 2016). Financial budget on audit engagement (4.042) might rise due to the expensive software being used due to DA implementation. The factor test for this new scale also represents a high Cronbach alpha of 0.8288, which shows a good internal consistency between the attributes, and are closely related as a group. The factor test gives a P-value of 0.00 representing high significance and a Kaiser-Meyer-Olkin (KMO) of 0.777 which shows a good measure of sampling adequacy and is suitable for further analysis. These values validate and measures the scale reliability and are therefore satisfactory at all level.

5.7.7 Factor 7 Factors relating to Audit Standards

Table 5.31 Descriptive Analysis of Audit Standard Factors

Factor 7	**Descriptive Analysis of Audit Standards**						
	Factor Loading	Mean	Std. Dev.	Cronbach Alpha	BTOS Chi-square	P-value	KMO
				0.8042	112.937	.00	0.711
Current ISAs should provide guidance on the application of DA in audit	0.608	4.025	.745				
Developing a principle based standard rather than rule-based standard	0.682	3.881	.73				
Collaborative work is required from auditors, standard setters & oversight authorities on ISAs related to DA application in audit	0.621	3.864	.612				

The seventh factor that was generated from factor analysis was labeled as Audit Standards. There are three items under this factor and all of them relate to issues relating to the International Standards of Audits (ISAs). This factor explores the perception of auditors on attributes related to developing a principle-based standard rather than a rule-based standard, collaborative work on standards, and the state of current ISAs. All responses show the positive feedback from the auditors with the mean for each item is more than 3.0. Each of the items previously was measured in the survey by agreement through a Likert scale represented by 1 to 5, where 1 strongly disagrees and 5 strongly agree. A range of positive responses was recorded ranging mostly towards agree. Malaysian Auditors consider these attributes to be quite important for the purpose of the implementation of DA. The highest mean for this factor was 4.025 as shown in table 5.31, for "Current ISAs should guide the application of DA in the audit" and the lowest mean was 3.864 for "Collaborative work is required from auditors, standard setters & oversight authorities on ISAs related to DA application in the audit". Guidance regarding the standards is a prerequisite for implementing DA. Without Guidance, most of the firms won't be able to implement DA so in turn, this will affect the implementation of DA. As mentioned in Byrnes et al., (2014), there is virtually no professional auditing guidance on the theory and practice of applying new data analytic, continuous auditing, and other techniques and technologies to auditing. The factor test for this new scale also represents a high Cronbach alpha of 0.8042, which shows a good internal consistency between the attributes, and are closely related as a group. The factor test gives a P-value of 0.00 representing high significance and a Kaiser-Meyer-Olkin (KMO) of 0.711 which shows a good measure of sampling adequacy and is suitable for further analysis. These values validate and measures the scale reliability and are therefore satisfactory at all level.

5.7.8 Factor 8 Inhibiting Factors

Table 5.32 Descriptive Analysis of Inhibiting Factors

Factor 8	**Descriptive Analysis of Inhibiting Factors**						
	Factor Loadin	Mean	Std. Dev.	Cronbach Alpha	BTOS Chi-square	P-value	KMO
				0.4959	69.947	0.000	0.371
Whether SMEs and SMPs clients are ready to use DA	0.592	3.966	.773				
Implementing DA will require huge cost	0.608	3.89	.825				

Whether DA can be used in group audits	0.588	3.847	.791
Use of DA will be time consuming	0.819	3.254	.898

The last factor that was generated from factor analysis was labeled as Inhibiting Factors. This factor was created by combining two different factors which had only two items under each of them. Only two items are not strong enough or do not give a proper identification of a factor. There are four items under this factor and all of them relate to which would restrict the use or implementation of DA in the audit process. This factor explores the perception of auditors on attributes related to time consumption, cost, SMEs and SMPs, and Group Audits. All responses show positive feedback from the auditors with the mean for each item is more than 3.0. Each of the items previously was measured in the survey by agreement through a Likert scale represented by 1 to 5, where 1 strongly disagrees and 5 strongly agree. A range of positive responses was recorded ranging mostly towards agree except one which is more towards neutral. Malaysian Auditors consider these attributes to be quite important for the purpose of the implementation of DA. The highest mean for this factor was 3.966 as shown in table 5.32, for "Whether SMEs and SMPs clients are ready to use DA" and the lowest mean was 3.254 for "Use of DA will be time-consuming". Whether using DA will be time-consuming or will free up more time is still a debate, as we see the response rate is towards neutral. It is expected for DA to be more time-efficient and freeing up more time for Auditors. According to Yoon, Hoogduin, & Zhang, (2015) audit quality can be improved with the increased use of data DA, freeing auditors from time-consuming manual tests and allowing them to focus more on substantive tasks. The factor test for this new scale also represents a Cronbach alpha of 0.4959, which is close to the cut-off point of 0.5 and shows a reliable internal consistency between the attributes and are closely related as a group. The factor test gives a P-value of 0.00 representing high significance and a quite low Kaiser-Meyer-

Olkin (KMO) of 0.371 which is not a good measure of sampling adequacy. This could be due to the effect of combining two different sets of attributes, however, if more responses can be collected this could also show a much better value.

5.8 Summary of Chapter

This chapter centers on the analysis of the questionnaire and the results obtainable therefrom. The chapter has highlighted the quantitative data analysis and the findings from the survey questionnaire. There are three main parts of this chapter. The first part discussed the profiles of the audit firms and the auditors. The results have been tabled accordingly to give an idea regarding the background of the respondents. The second part showed a descriptive analysis of the current usage of data analytics regarding Malaysian auditors. The result also will give an overview of the implementation of Data Analytics in Malaysia. An exploratory factor analysis was conducted to validate the scale of the survey. The analysis was carried out using varimax orthogonal rotation. The analysis gave out eight new variables that were labeled according to their factor loading. These were further discussed depending on the factor's Cronbach value and KMO.

CHAPTER 6 CONCLUSION

The final chapter gives an overview of the study is presented, the results are summarised, and the contributions are discussed together with the limitations of, and future extensions to the study. The chapter begins with a general overview of the study and a summary of the study's findings.

6.1 Summary of Research Findings

At the outset, this study aimed to explore the factors affecting the implementation of Data Analytics in the audit process. This was further validated in the context of Malaysia by taking perceptions from auditors of Malaysian Audit firms. The research aim was subsequently broken down into three main objectives:

i. To explore the perceptions of relevant Stakeholders on factors affecting the implementation of Data Analytics in the audit process

ii. To explore the current usage of Data Analytics among auditors in Malaysia.

iii. To further validate the factors identified for the implementation of DA in the context of Malaysia

The above objectives above were then reconstructed into six research questions, after having an extensive look at the existing literature. Initially, the emphasis was given on literature relating to IT adoption on auditing, then to further refine the objective of the study focused on literature relating to Data Analytics, Big Data, continuous auditing. In general, this study has focused on the following questions:

RQ1: What are the factors which will have a significant influence in implementing Data Analytics in the Audit process

RQ2: What is the current state of DA usage among auditors in Malaysia?

RQ3: Which factors are relevant and important for the implementation of DA in external auditing?

6.2 Perceptions of Stakeholders

Based on the content analysis of the feedback collected in response to the IAASB DAWG paper, several issues have emerged relating to the use of DA in the audit. A various range of audit stakeholders has responded, whereby the most of responses were recorded from Member bodies & Professional Organizations (15), and the second most was from professional Accounting Firms (10). The results from the analysis indicate that factors like "Revising/Challenges in developing new Standard or Current ISAs not suitable for DA" represented a 72% response rate from the respondents. This was one of the most prominent factors and has been discussed widely. "Whether DA can be used as substantive testing, Test of control or Test of details" has a 54 % response rate, and issues regarding "Audit Quality/Audit Judgement" has a response rate of 52% making them quite significant issues to be discussed and validate further.

The importance of these findings suggests that these factors need to be looked in detail before we can start implementing DA in audit procedures, without solving the issues raised about these factors, standard setters cannot expect practitioners to use DA in their Audit engagements. To increase the implementation of DA in audit, an authoritative pronouncement is required among both auditors and preparers. The evidence of adopting DA is still scarce and factors like 'Audit Quality', 'Audit Judgement', 'Challenges in Developing new standard' are some of the inhibitors which have emerged from the content analysis. Auditors and Accounting firms are reluctant in using DA since the standards still don't suggest enough about using DA and at the same time standard setters or regulators are not doing enough to make sure the Standard take these things into considerations.

Factor like 'Testing 100 % of the sample'(42%) has been presumed to be one of the most convincing benefits of using DA. However, as expressed by a lot of stakeholders it is not as straightforward as it seems. The idea of testing all the samples gives rise to a lot of different conclusions and raises different ambiguity. So, standard setters should look into this factor and help auditors and clients understand to realize the true and proper benefits of this factor. Guidance notes and other such pronouncements may be required to raise the general awareness about adopting DA. The technical proficiency of the auditor will clearly be critical to conduct an audit using DA. Moreover, factors like 'Audit Judgement'(52%), "professional skepticism while using DA"(26%) were very vocalized factors among stakeholders, will remain to be important.

External auditors did not invent data analytics but they do have a history of demonstrating to management how new techniques work before management gets the hang of it (ICAEW, 2016a). As businesses are currently learning about data analytics from auditors, ultimately auditors and professional firms are the ones who will need to step on the gas to implement DA. Some view that Data analytics is genuinely revolutionary and game-changing, a ground-breaking technology that will ultimately change the audit fundamentals (ICAEW, 2016a).

The issues which were most highlighted are focused within audit standards setting, audit practice issues, and the development of better audit data analytics. Each and every attribute had several perspectives, which needs to be considered individually before we can move into this new era of auditing.

6.3 Current State of DA usage in Malaysia

The study explored the current state of DA usage through perceptions taken from Malaysian Auditors. The analysis suggests that 94 % of the responding auditors have used some form analytics software in the Audit procedure of their firm. 65 % of the respondents indicated that their firm has been using DA for more than one year. However, 31 % of the smaller practices have very little to no knowledge of using DA in audit engagements. Whereas 19% of the respondents who are from big and mid-tier firms have been using DA for more than two to three years.

As expected, the bigger firms are well equipped with modern technology and conduct their engagement accordingly. However, the frequent usage of DA does not explain the bigger picture. What we really needed to know was what sort of software and techniques have been used by these firms and auditors in Malaysia. The findings suggested that 54 % of the respondents prompted using Advance Excel only. There was other software which was suggested in the survey, for business intelligence analytics the study suggested IBM, Oracle, SAS, etc, and visualization, software like Tableau, Power BI, etc were suggested. Very few portions of the respondents suggested the use of this other software. However, 11% of the respondents said they have used In-House applications like Audit Express, TeamMate, etc. 24 % of the respondents have used excel along with some additional software relating to the list of software provided in the list.

Survey results suggest that Malaysian small and mid-tier firms have not yet fully got accustomed to the use of advanced analytics, which is in line with most of the other countries as well. The most used techniques in different areas of Audit have been Visualizations and Descriptive Statistics. 50% of the respondents used visualization and descriptive statistics for determining the level of materiality, 46 % used the same techniques to perform the test of controls. A higher number of participants indicate not using any sort of specific technique in these procedures representing not applicable. Other than visualization, 14 % and 11 % of the respondents have used optimization and advanced statistical analysis respectively, for audit analytical procedures. 22 to 23 percent of the respondents also indicated that they have always used some sort of data analytics, to perform audit planning, to determine the level of materiality, and to perform substantive testing.

Eventually, the overall findings suggest that although Malaysian practitioners have started developing the use of DA in audit procedures there are significant limitations in the use. They have constrained themselves to some specific software and some specific areas of the audit. The overall picture of DA implementation is very similar worldwide and the low level of implementation of DA techniques in audit has been inherently due to the complexity of those techniques which in most cases requires understanding that is beyond auditors' current level of IT knowledge (Kostić & Tang, 2017). Earley, (2015) has pointed out that audit engagements have lagged the use of DA than any other practices and this is due to some of the unique challenges and hurdle which has been focused earlier on this study.

6.4 Factors that Influence the implementation of Data Analytics

The empirical evidence for factors affecting the implementation of DA is still scarce. This study provides exploratory evidence on factors such as audit quality, authoritative guidance (auditing standards), data quality and benefits, and costs are some of the motivating and inhibiting factors affecting the implementation of DA in external audit. A huge number of suggestions have been received from the respondents to optimize the use of DA. A few of these issues are outlined as a concluding remark while others have been discussed at length in previous chapters. Firstly, the main concern, like any other software, is the issue of user friendly. As DA will be used by accountants or explicitly auditors, the software should be built from their experience and perspectives rather than from the general IT experts' perspective. IFAC (2007) states that accountants should be IT-competent, the technology still needs to be developed to match their use by non-IT professionals. DA needs to be more user friendly, which will help non-IT auditors to understand its usage in a more simple and easy way. According to the analysis, stakeholders want more comprehensive guidelines relating to ISA and DA so that it would be more standardized. The respondents also believe that the emergence of a data-driven audit would require a new set of skills for auditors, or the audit firms need to hire data analysts for the purpose. However, retraining and reskilling employees will also have a major impact on the audit firm's intention to adopt DA.

Several contributing factors have emerged and perceived to be important in affecting the implementation of DA in external auditing by the audit practitioners. The attributes with the highest factor loadings and highest means are presumed to be vital in the implementation of DA, as more professional auditors seem to agree to those points and can be discussed further.

Firstly, the main concern, like any other software, is the issue of the features with DA being user friendly. As DA will be used by accountants or explicitly auditors, the software should be built from their experience and perspectives rather than from the general IT experts' perspective. IFAC, (2009) states that accountants should be IT-competent, the technology still needs to be developed to match their use by non-IT professionals. DA needs to be more user friendly, which will help non-IT auditors to understand its usage in a more simple and easy way. The respondents also believe that the emergence of a data-driven audit would require a new set of skills for auditors, or the audit firms need to hire data analysts for the purpose. Thus, the attributes of retraining and reskilling external auditors, under organizational factors have a high mean of 4.16. The respondents seem to agree to the fact that more training is required for external auditors and will also have a major impact on the audit firm's intention to adopt DA.

Secondly, the DA needs to be developed with more flexibility and compatibility. The analysis refers to the attributes of principle-based audit guidance rather than rules-based guidance, which has the highest factor loading under Factors relating to Audit Standards. The attributes also have a mean of 3.881, suggesting that most of the respondent auditors believe that it is more compatible with the emergence of more technological aspects. This means the use of DA should be adaptable to work with data from the client and consistent to operate in any computing environment, either in terms of different operating systems or probably in different hardware technologies.

Thirdly, under audit profession factors, a higher number of respondents tend to believe that auditors will be able to provide more than reasonable assurance on financial statement audit when using DA. This has the highest factor loading and a mean of 3.7. But, the question arises, whether this will increase the expectation to another level of assurance? Changes in audit techniques through the use of data analytics may create an unintended expectations gap. In the future, audit opinions will be presented quantitatively and/or qualitatively, and most importantly, in real-time (CarLab, 2017). Accountancy Europe, (2017), a professional organization stated that if DA would enhance the quality of audit compares to traditional audit, it would be unfair to express a similar opinion, so, even though the definition of reasonable assurance is unlikely to warrant a change, the perceptions of what it signifies, or its values should capture the relative developments which are brought about by DA.

Fourthly, the consensus among respondent auditors was very high, with a mean of close to 4, about the attribute, "DA will lead to better improvement in professional audit judgment". This attribute under audit profession factors suggests that audit judgment can be improved through the use of DA and can eventually impact the audit quality positively. According to several interviews conducted by Kostić and Tang, (2017) for their research, majority respondents suggests that audit quality can be improved in the future through automation. Cao, Chychyla, and Stewart,(2015) pointed out that the increased implementation of DA can lead to an improvement in the efficiency and effectiveness of financial statement audits. However, the EFAA, (2017) mentioned that data analytics will not automatically lead to a better audit. For instance, ACCA, (2017) mentioned in their reports that it is important to understand where the value in data analytics really lies. Data analytics may contribute to better audit quality either by increasing efficiency or by permitting a greater depth of auditor inquiry.

The next attribute relates to IT specialists, who will have a much bigger role to play when performing DA in external auditing. This attribute under Technological factors has a very high mean of 4.161 and a high factor loading of 0.766, suggesting an overall correlation between the factors. IT professionals from both the audit firm and client must strive to work together to overcome conceptual challenges and ensure that systems are producing reliable data.

The next attribute has a mean of over 4.0 suggesting a very affirmative view on the issue from the respondents. Auditors believe that "current ISAs should provide guidance on the application of DA in the audit". At this moment there is a strong need for guidance from standard setters and also regulators. The guidance should explain their point of view regarding procedures to be followed and documentation criteria that have to be met in adopting DA (CPA, 2017). AUASB, (2017) has notified that there is a need for standard setters to provide practical guidance on how the implementation of data analytics can improve audit quality and efficiency. Deloitte, (2017) expressed that the issuance of non-authoritative guidance with practical examples of using data analytics in the audit will provide auditors with the most effective reference materials that would both help to further advance the application of data analytics. Such guidance will ultimately align the motivation of auditors and the concerned stakeholders to adopt DA in the auditing process.

One of the key challenges of DA use is how to apply quality control processes when developing tools, and to assess the reliability of the tools and technology utilized, to avoid a potential 'overconfidence in technology'. This attribute is presented under quality control factors with a mean of 4.093 and a high factor loading of 0.847. Respondents tend to agree to the fact that quality control procedures are required to secure the integrity of the tools against unauthorized access, and the protection of the entity's data privacy and confidentiality. IAIS, (2016) mentioned in their report in response to IAASB, that there should be a strong quality control processes over the use of analytics by auditors in these procedures. The required competence and training should make sure appropriate controls are set by the engagement partner and is also known by the staff to use and interpret the results of Data Analytics.

Lastly, a crucial attribute mentioned under external factors was the requirement for auditors to use and adapt to this shift in the business environment. It has a mean of 3.949 which shows the respondent auditors mostly view this in a positive manner and realizes the potential of DA. Rapid advancements in both the ability to access significant amounts of data and to apply unique technologies to such data require us to revisit the current auditing standards and interpretative literature. The environment in which audits are performed today continues to evolve and become increasingly complex. The increasing availability of data as well as analytical technology and tools have advanced very rapidly. Whilst the nature, timing, and extent of the impact that technology will have on the audit are difficult to predict, emerging technologies like automation, artificial intelligence, blockchain, and even drones have the potential to transform the way an audit is conducted whilst enhancing audit quality (KPMG, 2017). Therefore, prompt initiation and development of discussions are thought to be crucial. However, there are always concerns that an over-reliance on the use of data analytics might lead to less direct interaction and discussion with the client about the entity's operational activities thereby potentially inadvertently reducing the extent of the auditor's understanding of the entity. Auditors need to make sure they do not over-rely on a technique without making any professional judgment.

6.5 Research Contribution

The multi-stage method of this study has been developed to allow for a better understanding of the status of DA implementation in the audit profession. In general, this study contributes by offering insights, as well as obtaining a better understanding of the issues of the implementation of DA as a whole and also precisely in the context of Malaysia. The results of this study would be a very critical contributor to the accounting profession, standard setters, regulators, and as well as academicians. Currently, there is a lack of skills relating to Data analytics among professional accountants (Fay & Negangard, 2017). However, the potential skills of Data Analytics to improve decision making within a company or increase the effectiveness and efficiency of an audit cannot be ignored further.

From the content analysis of all those concerned stakeholders' responses, it can be perceived that the profession would like to move towards the use of data analytics, but with some reassurance from regulators and standard setters. Since the study confabulated all the ideas and viewpoints from different stakeholders in one place it would be easier for standard setters or any other users, to identify all the issues. It also contributes to the existing literature of DA in audit, by providing a very wide diverse perspective of stakeholders.

The quantitative analysis of this study ensured the factors that influence the use and implementation of DA among Audit practices. Each and every factor has been discussed from different angles, making sure the adopters of DA are well aware of the concerning issues and the benefits. These suggested research issues, along with various proposals will help to move toward greater use of Data Analytics. In the end, further empirical research needs to be conducted to validate these theoretical approaches before they can be implemented by the audit profession. The statistical analysis also contributed by helping to understand the current stage of DA implementation in Malaysia, which will act as empirical evidence in this field. The research was based on the on-line survey and physical survey to obtain further feedback from audit practitioners across the country.

The study has also contributed in that respect as well by ensuring a proper method has been followed through.

6.6 Research Implication

The findings of the study would provide additional insights to policymakers and regulators who can use it as a stepping-stone for the implementation of DA in audit practice and can also help them to apprehend the challenges and benefits of DA. Through the content analysis, the study confabulated all the ideas and viewpoints from different stakeholders in one place it would be easier for standard setters or any other users, to identify all the issues. It also contributes to the existing literature of DA in audit, by providing a very wide diverse perspective of stakeholders. Each factor has been discussed from different angles, making sure the adopters of DA are well aware of the concerning issues and the benefits. These suggested research issues, along with various proposals will help to move toward greater implementation of Data Analytics in external audits. Moreover, the empirical analysis from the study allows for a better understanding of the status of DA implementation in the audit profession. In general, this study will have further implications through obtaining a better understanding of the issues of the implementation of DA in practice. The findings of the study would implicate additional insights to policymakers and regulators who can use it as a stepping-stone for the implementation of DA in audit practice and can also help them to apprehend the challenges and benefits of DA. The study has further implications on Malaysian audit capabilities. The findings suggest that although Malaysian practitioners have started developing the use of DA in audit procedures there are significant limitations in the use. They have constrained themselves to some specific software and some specific areas of the audit. The overall picture of DA implementation is very similar worldwide and the low level of implementation of DA techniques in audit has been inherently due to the complexity of those techniques which in most cases requires understanding that is beyond auditors' current level of IT knowledge (Kostić & Tang, 2017). Earley, (2015) has pointed out that audit engagements have lagged the use of DA than any other practices and this is due to some of the unique challenges and hurdle which has been focused earlier on this study. External auditors did not invent data analytics but they do have a history of demonstrating to management how new techniques work before management gets the hang of it (ICAEW, 2016). As businesses are currently learning about data analytics from auditors, ultimately auditors and professional firms are the ones who will need to step on the gas to implement DA. Some view that Data analytics is genuinely revolutionary and game-changing, a ground-breaking technology that will ultimately change the audit fundamentals (ICAEW, 2016).

6.7 Limitations of the Study

A Master's research work inherently has some constraint and restrictions on the extent of scope and coverage due to time and financial constraints. Due to the limitation of the time frame and access to external auditors, there was a limitation in data being collected. The study didn't have enough data available to run any further analysis. Furthermore, the analysis had to be based on Malaysia only, it would be more meaningful and complete if we could represent more countries and see the implementation and then compare it accordingly. Therefore, the findings could not be generalized at the global level because auditing in other parts of the world might not be similar. Furthermore, the research data consisted of mainly small and medium firms. Very few Auditors from the Big Four firms responded to the survey. So, an important viewpoint was missing in that aspect. Therefore, the results of this study can only be applied to such types of firms. One of the biggest challenges was to get responses from Auditors. It was hard to convince them to spare 15 minutes to fill up the survey. Since the study did not provide any sort of incentive for filling up the surveys, respondents were inherently disinterested. Similar limitations came into limelight in the work of Ahmi & Kent, (2012) and Omoteso, (2006).

6.8 Recommended areas for Future Research

Future researches can be conducted stemming from these issues and arguments by approaching firms who are already adopting DA in their audit approach. Based on the findings of this study, future researchers can take further perceptions from auditors to see whether they truly believe what has been stated from stakeholders around the world. This would also further validate the findings and will make the case of DA implementation stronger. Future researches can explore further with the findings of this study.

A large number of issues have been raised throughout the studies. First, of all the research can be carried further from where this study has left off. By gathering more responses and sample, the study can explore further by using the validated scale of factors affecting the implementation of DA. Further research can examine the association between these factors and their impact on Audit Quality. How do these factors react when they have associated with Audit Opinion and whether the use of DA results in better assurance? Secondly, researches can examine what sort of audit evidence can be gathered using DA and whether using DA gives better audit evidence? Thirdly, researchers will be able to look into what sort of changes are required in Audit Standards to implement DA in audit procedures? Practical evidence can be gathered on these aspects by cooperating with audit firms and the findings could be reported back to find a more sophisticated implementation process for the implementation of DA. Apart from professional firms, academicians and regulatory bodies need to be in constant engagement to make sure all the loopholes are being covered. It is important for standard setters to work closely with academics, as accountants and auditors need to develop different skills through increased education in technology and analytic methods. Greater research is required by both accounting firms and academics on how and which audit procedures and audit standards may be changed, not just to improve the audit process but also to allow it to truly evolve (CFA, 2016).

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Appendix A Ethics Clearance