Factors Affecting the Use of Data Analytics in External Auditing

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ABSTRACT

This study examined perceptions of external auditors on the actual use of data analytics (DA) and factors affecting its use in external auditing. Based on survey questionnaire data, results from descriptive analysis showed a lack of use of advanced data analytic tools amongst the respondents. A majority of them agreed that further support was needed when asked about DA usage. DA was perceived by the respondents to be useful in fraud risks evaluation, audit planning and test of journal entries. The respondents also perceived benefits of DA include improvement in audit efficiency and effectiveness, and auditors' ability to detect material misstatements. A range of factors that included audit profession, technological, organizational, quality control and audit client were perceived to have an effect on the use of DA in external auditing. Analysis of top ten mean scores showed that amongst the attributes affecting DA use in audit practice were reliance on IT specialist, auditors' skills and knowledge, storing and retaining data for audit trail and quality controls within the use of DA. The findings of this study would be useful for accounting firms and policymakers to assess the motivating and hindering factors affecting the use of DA in external auditing. This study is one of the first that explored the use of DA within the context of external auditing in Malaysia.

Keywords: Data Analytics, External Auditing, Big Data, External Auditors

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INTRODUCTION

In the era of the industrial revolution 4.0 (IR 4.0), the use of technology by companies has affected its business and economic transactions system, thus, the way auditing is being performed today also needs to be changed (IAASB, 2018). Technology has resulted in a proliferation of business and accounting data in various forms and volume, hence, greater focus is being given to the use of data analytics (DA) in audit performance (Salijeni et al., 2018). Practices of audit in this manner would eventually provide greater assurance on audited financial statements (Tang & Karim, 2017). In addition, the IR 4.0 creates a greater expectation from stakeholders of audit services (such as audit clients, and regulators) on the continuous role of auditors in delivering more insights and value of audited financial statements to users (Forbes Insights, 2017). This means that auditors need to keep abreast with technology development in the business environment and to develop a more rigorous way of auditing.

Some scholars have suggested that the pace of audit data analytics (ADA) adoption in the audit field has been slower in comparison to other fields like advisory or forensic investigation practices (Katz & Margo 2014; Whitehouse, 2014). Despite DA being argued to be an effective tool in an audit engagement, information and knowledge about the use of DA in external auditing are limited (Wang & Cuthbertson, 2015). Thus, the Auditing and Assurance Standards Board's (IAASB) - Data Analytics Working Group (DAWG) had emphasized the need to understand the key factors affecting the use of DA in external auditing. While there is scarce research on factors affecting DA adoption, research evidence suggests that the characteristics of audit clients, auditors (such as system), audit firms (such as management support), and audit tools or techniques can also influence the use of DA in audit practices (Dagilienė & Klovienė, 2019; Eilifsen et al., 2020). The focus of the research is in line with the call made by the IAASB on 'the need to consider circumstances and factors that exist in the current business environment that could influence the use of DA within the context of financial statement audits (IAASB, 2016, p. 5). Thus, building on the research framework for technology adoption in the audit context, the current study aimed to address the following research questions:

1. Research questions 1 (RQ1): What is the current status of the use of DA in external auditing?
2. Research question 2 (RQ2): What are the most important factors and attributes affecting the use of DA as perceived by external auditors?

The remainder of this paper is organized as follows: Section 2 outlines the literature review, Section 3 describes the methodology, Section 4 presents the findings and discussion of the study, and Section 5 concludes the study.

LITERATURE REVIEW

Data Analytics in Audit

Auditing has gone through many faces of technology adoption. Starting from adopting computer-based auditing to using computer assisted audit techniques (CAATs) and generalised audit software (GAS) and now to the era of DA. The increasing use of audit technology as well as its improvements and sophistication have been due to the advancement in technology that helps to automate the audit (Byrnes et al., 2018). Some audit practitioners have argued that it is not clear whether there is any difference between CAATs and DA. For example, CPA, Australia has also mentioned in their response letter to the International Federation of Accountants (IFAC), that it is not clear whether there is any difference between a CAAT and DA (CPA, 2017). They opined that it is hard to put CAATs, GAS and DA in different categories, except for the level of sophistication they pose and the benefits you can nurture from its use. In the end, these are all audit tools that aid auditors during the conduct of an audit.

DA is the method of analysing raw information to come to a conclusion and to facilitate decision-making. DA encompass the variety of functions and applications used, from basic business intelligence (BI) to reporting, and from online analytical processing (OLAP) to multiple modes of advanced analytics (Jacky & Sulaiman, 2022). The term, audit data analytic (ADA), refers to the use of sophisticated software tools, and advanced statistical procedures (such as cluster analysis predictive models, data layering, visualizations) to evaluate massive sets of audit-relevant information. This information comes from internal and external sources; they serve as evidence for the various parts of the audit process (such as analytical procedures, control testing, risk assessment, and substantive procedures (Tschakert et al., 2016). The audit profession has, of late, come to recognize the emergence and the growing use of DA in external audits (Alles & Gray, 2016; Brown-Liburd & Vasarhelyi, 2015; Vasarhelyi et al., 2015) . However, Eilifsen et al. (2020) suggest the use of DA is relatively limited and use of more "advanced" DA is rare. The prevalence of big data techniques in external audit practice also remains largely unknown and so is the case of DA to some extent (Gepp et al., 2018; Kend & Nguyen, 2020).

Eilifsen et al. (2020) found auditors' attitudes toward DA usefulness as positive. Earley (2015) stated that there are four primary benefits of using DA on audits: (1) auditors can test a greater number of transactions than they do now, (2) audit quality can be increased by providing greater insights into clients' processes, (3) easier to detect fraud because auditors can leverage on the tools and technology which they are already using, and (4) auditors can provide services that are beyond current capabilities and solve problems for their clients by utilizing external data to inform audits. Thus, DA is perceived to increase audit quality and efficiency (Dagilienė & Klovienė, 2019; Krieger et al., 2021; Manita et al., 2020; Salijeni et al., 2018). For instance, accessing a large volume of data, when compared to a risk-based selection, would eliminate sampling bias, hence assisting auditors to obtain audit evidence with more efficiency (IAASB, 2016). With the large coverage and a shift from sampling to total population audits, there is more audit credibility (Newman et al., 2021). Although the benefits of DA are recognized, its adoption has not advanced as rapidly as was expected (Buttigieg & Ellul, 2021; Appelbaum et al., 2017).

Most DA studies in auditing are conceptual (Salijeni et al., 2018), with scholars discussing the factors affecting the use of DA in audit practices. It was found that greater audit coverage, audit efficiency, and quality audit evidence motivated the use of DA in practice while data accessibility and integrity inhibited its use (Alles & Gray, 2015; Alles & Gray, 2016; Krahel & Titera, 2015). Empirical data drawn from interviews showed that auditors had perceived issues, such as reliability of audit evidence, lack of audit guidance, and integration of DA in the audit approach to be barriers when implementing DA in audit practices (Salijeni et al., 2018). Likewise, the interviews conducted by Dagiliene and Kloviene (2018) highlighted that financial resources, client structure and technology, regulations, education, and intended outcomes were the key factors affecting the use of DA in audit practices. The setback in DA adoption in external auditing can be ascribed partially to the absence of new directives, guidance or/and auditing standard issues by the standard setters of the auditing profession (Liu & Vasarhelyi, 2014). Further, A total of 85% of managers who were surveyed by KPMG had noted that one of their biggest challenges in using DA was not knowing the best way to analyse the data collected due to lack of skills and knowledge (KPMG, 2014). The recent study by Eilifsen et al. (2020) showed that environmental issues and audit clients' pressures, cost and benefits, the role of regulators, and the quality of evidence can both motivate and inhibit the use of DA.

Overall, prior research in DA had provided some evidence related to factors affecting the use of DA by external auditors. However, most of the empirical work was exploratory, with interviews used as the main research method. There is limited research that examined perceptions of external auditors on the current use of ADA and rated key factors affecting its use in external auditing.

RESEARCH METHOD

A survey instrument was developed to solicit the required data and to fulfil the objective of this study. Exploratory factor analysis was performed to determine the underlying components of the measurable constructs. Descriptive analysis was then conducted to understand the current use of DA by audit practitioners. Further, analysis of the mean scores was then performed to identify the relative importance of the individual attributes.

Research Design

Instrument Development and Validation

The research instruments of this study were adapted from research by Ahmi and Kent (2013), Dagiliene and Kloviene (2018) and Salijeni et al. (2018). In addition, selected response letters to the consultation paper published by the IAASB project: Data Analytics Working Group: Exploring the Growing Use of Technology in the Audit, with a Focus on Data Analytics was also used to identify the relevant attributes in the usage of DA in external auditing (IAASB, 2016). The questionnaire had a total of 4 sections. The sections were segregated as organizational profile, demographic information, usage of DA and factors that influence the use of DA in the audit practice. The measurable constructs used in this study comprised seven factors consisting of fifty attributes which were evaluated by the 5-point Likert scale represented by 1 to 5, where 1 represents strongly disagrees and 5 represents strongly agree.

The questionnaire was pretested by five audit practitioners and ten academicians with prior knowledge of the subject. As a result, some minor changes were performed in the wording and sentence structures of the questionnaire to improve its clarity. Following this, a pilot test with 50 respondents was conducted to confirm the reliability and validity of the questionnaire. The reliability of the instrument was tested using Cronbach's alpha score (Hair et al., 1998) with a minimum of 0.7499 and a maximum of 0.8678 (see Table 1). Exploratory factor analysis (EFA) was then performed on the measurable constructs to validate the research scale. This was achieved by using PCA and the Varimax rotation technique, with the result showing factor loadings of more than 0.50, consistent with the recommendation of Pallant (2011). Results of the EFA are presented in Table 9.

Table 1: Cronbach's Alpha

	Cronbach Alpha	Number of Items
Overall	0.9455	50
Factor 1: Audit Profession	0.8678	11
Factor 2: Relating to International Standards of Auditing	0.8295	6
Factor 3: Technological	0.9243	5
Factor 4: Organizational	0.9139	7
Factor 5: Audit Clients	0.9410	8
Factor 6: Limitations and Challenges	0.8683	7
Factor 7: Other Relevant External Factors	0.7499	6

Administration of research instrument

Due to the low response of online questionnaires, this study then conducted a self-administered questionnaire. A total of 400 questionnaires were distributed to all levels of auditors from different audit firms who were attending the continuing professional development (CPD) training conducted by the Malaysian Institute of Accountants (MIA) between March to July 2019. A total of 131 responses were retrieved, but only 118 responses were found suitable for analysis, showing a response rate of 29.5%. The front page of the questionnaire explained the objective of the study and the target audience. It also specified the fact that if a participant had already participated, they need not participate again in the study.

Theoretical framework

This study adapted the framework of use of audit technology proposed by Ahmi and Kent (2013). This framework is based on theoretical frameworks of the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM). This study adapted this framework because it focussed on the use of technology (ADA) and recognizing perceived factors affecting its use in the external auditing setting. The framework outlines a range of factors relevant to the auditing context such as audit profession, technological, personal, client, organizational, external factors that can give effect to the use of technology in audit practice.

FINDINGS AND DISCUSSION

Demographic Analysis

Table 2 illustrates the demographic analysis of this study. While 67% of the respondents were males, and 51% were females, the breakdown of the respondent's position in the audit firm showed that 35% were partners. Quite a high number or 32% of the overall responses were derived from senior associates and directors. The "other" category included anyone who did not fall in the above-mentioned category such as interns undergoing audit training in the audit firm. Around 56% of the auditors had more than 10 years of experience. The demographic data further indicated that the auditors were quite experienced in their careers, with over 50% of them having a minimum experience of about six years. Respondents were also asked about their general IT skills, and nearly 27% indicated that they had very basic IT skills, with 48% stating that they have an adequate number of skills required to carry out the audit processes.

The size of the audit department, based on the number of auditors within the audit firms varied, with 33 out of 118 audit firms having less than five auditors. This showed that about 28% of the total respondents had five to nine auditors. Table 2 shows that only 3% of the firms had more than 50 auditors. The number of employees owned by firms was used as a measure to indicate firm size. Most of the mid-tier practices had employees ranging from 10-999 while smaller practices had employees ranging from 10-99 employees.

Table 2: Demographic Analysis

Items	Frequency	Percentage (%)
Gender Profile		
Male	67	56.78
Female	51	43.22
Age of Respondent		
18 to 24 years	3	2.54
25 to 34 years	48	40.68
35 to 44 years	27	22.88
45 years & above	40	33.90
Auditor's current position in Firm		
Director	9	7.63
Partner	41	34.75
Manager	21	17.80
Assistant Manager	11	9.32
Senior Associate	28	23.73
Associate	3	2.54
Others	5	4.24
Auditor's Experience		
0 to 5 years	28	23.73
6 to 10 years	26	22.03
11 to 15 years	20	16.95
16 to 20 years	13	11.02
21 years & above	31	26.27

Auditor's Experience with computerized auditing		
None	10	8.47
0 to 5 years	47	39.83
6 to 10 years	40	33.90
11 to 15 years	12	10.17
16 to 20 years	7	5.93
21 years & above	2	1.69
Auditor's IT Skills		
Very good	2	1.69
Good	26	22.03
Adequate	57	48.31
Basic	28	23.73
Very basic	5	4.24
Category of Audit Firm		
Big four firm	2	1.69
Mid-Tier firm	32	27.12
Smaller firm	84	71.19
Size of Audit Department		
Less than 5 auditors	33	27.97
5 to 9 auditors	30	25.42
10 to 19 auditors	29	24.58
20 to 50 auditors	22	18.64
More than 50 auditors	4	3.39
Size of Audit Firm		
Less than 10 employees	26	22.03
10 to 49 employees	63	53.39
50 to 99 employees	18	15.25
100 to 499 employees	7	5.93
500 to 999 employees	2	1.69
More than 1000 employees	2	1.69

Analysis of the Current Use of DA – RQ1

Types of Audit Software Used

Excel Advanced seems to be the most popular audit software used among the respondents (see Table 3). Excel Advanced has been used for its techniques like Macros, VBA, Miner, and Solver for auditing. Around 12% of the mid-tier and smaller firms also developed their own in-house applications to cater for computerized auditing. Results suggest that respondents of this study had predominantly been using excel, advanced excel, SQL and UBS. However, sophisticated DA tools like SAS, Visual Analytics and Power BI has not been used widely for auditing purposes.

Table 3: Types of DA Used

	Tabulation of Usage of DAs Software				
	Big Four Firm	Mid-Tier Firm	Smaller Firm	Total	Percent
Excel advanced	0	16	45	61	54.46
Business intelligence analytics	0	0	1	1	0.89
Database management systems	0	1	3	4	3.57
Visualization	0	4	8	6	5.36
In-house application	0	5	8	13	11.61
Excel & a combination of the above software*	2	6	19	27	24.11

Level of Satisfaction in Usage of DA

The respondents were asked about their level of satisfaction in using DA in their audit procedures (see Table 4). About 42% of them stated that they would require further support whereas 40% of them were reasonably satisfied with their current software.

Table 4: Satisfaction of DA Usage

	Tabulation of Respondent's satisfaction in using DA				
	Big Four Firm	Mid-Tier Firm	Smaller Firm	Total	Percent
Very satisfied	**0**	**3**	**4**	**7**	**6.03**
Reasonably satisfied	0	11	35	46	39.66
Need further support	2	14	35	49	42.24
Dissatisfied	0	4	5	9	7.76
Very dissatisfied	0	0	5	5	4.31

Level of DA Usage at Different Stages of the Audit

About 20% of the auditors claimed to have always used DA for audit planning, whereas 19% claimed to have always used DA for completion, and 11% claimed to have always used it for evidence gathering (see Table 5).

Table 5: Level of DA Usage

	Tabulation of level of DA usage at different stage of Audit						
	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

Usage of DA at Different Areas of the External Audit

To further explore the usage of DA in external audit, the respondents were asked to highlight how often they used DA in different areas of their external audit (see Table 6). The highest mean of 3.475 was for performing substantive procedures. The lowest mean of 2.432 was for the reviewing board and audit committee meeting, followed by minutes. Apart from these, a higher mean was noted in the following: analytical procedures (3.331), audit planning (3.424), and determining the level of materiality (3.373). Interestingly, testing 100% of the population, instead of just the samples, showed a lower mean (2.754).

Table 6: Extent of DA Usage

	Tabulation of the extent of DA usage at different areas of Audit						
	Never	Rarely	Sometime (3)	Often	Always	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 BOD/AC meeting minutes	34	32	24	23	5	118	2.432

DA Techniques Used

Table 7 shows that the respondents perceived visualization and descriptive statistics and advanced statistical analysis were widely used in the planning stage of an audit. While data optimization was used widely in identification of fraud risks and test of journal entry. The data optimization process made use of sophisticated data quality tools with the aim to access, organize, and cleanse data. Advanced statistical software like SAP, Oracle and ACL can be used in audit planning and in procedures to identify and assess risk of misstatements by analysing data to identify patterns, correlations, and fluctuations. Text mining was mainly used for understanding the client's operations and performance and to examine financial statements disclosures and notes. A small number of respondents indicated they used a combination of techniques in different areas of audit performance.

Table 7: DA Techniques Used in Different Stages of Audit

	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*	Total
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	7	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

Perception on Benefits of Using DA

Audit efficiency and effectiveness were perceived as key benefits of using DA in the external auditing (see Table 8). This was followed by "using DA to improve the ability to detect material misstatements", with mean score of 3.839. Findings also showed that the auditors believed that DA can enhance the accuracy of audit opinions. While "using DA to improve the audit of client's satisfaction" was perceived to be the least benefits of DA with a minimum means of 3.508.

Table 8: Perceptions on the Benefits of Using DA

	Tabulation of Respondent's perception on the benefits of using DA						
	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Mean	Std. Dev.
Using DA improves audit efficiency		4	21	79	14	3.873	.648
Using DA improves audit effectiveness		4	24	74	15	3.856	.670
Using DA improves ability to detect material misstatements		4	24	77	13	3.839	.653
Using DA improves ability to report misstatements		7	28	68	15	3.771	.744
Using DA improves accuracy of audit opinions		5	33	71	9	3.712	.668
Using DA ensures audit has been conducted in accordance with prescribed standards and regulatory requirements	3	8	30	71	6	3.585	.799
Using DA reduces earnings management		10	35	69	4	3.568	.698
Using DA reduces financial restatements	1	8	43	59	7	3.534	.747
Using DA improves audit client's satisfaction	2	7	49	49	11	3.508	.814

Overall, the analysis showed that majority of the responding auditors had used some form of analytics software in their audit procedures. This finding is consistent with the study conducted by CPA Canada (Canada CPA, 2017) where 65 % of the respondents indicated that their firms had been using some sort of DA for more than a year. The current study has also noted that the smaller audit firms had very little to no knowledge in using DA in audit engagements in comparison to the respondents from big and mid-tier firms that responded their firms have been using DA for more than two to three years. The findings of this study suggested that more than half of the respondents widely use Advance Excel rather than more of advanced analytics tool such as IBM, Oracle, SAS and visualization, Tableau and Power BI in the course of an audit. Thus, from the above findings it can be implied that Malaysian small and mid-tier firms had not yet gotten accustomed to the use of advanced DA. This outcome seems to concur with the scenario of other countries on the use of DA in external auditing (Dagilienė & Klovienė, 2019; Eilifsen et al., 2020). The findings of this study also showed that most firms used different techniques, such as visualizations and descriptive statistics, in different areas of auditing. The respondents indicated that DAs had been widely used in the performance of substantive tests, audit planning and determining the level of materiality. A higher number of respondents mentioned not using any specific techniques in these procedures, which were then deduced as being not applicable.

Analysis of EFA and Attributes Affecting the Use of DA in External Auditing – RQ2

Factor Loading

Based on the sorted rotated factor loadings, with orthogonal varimax rotation, it was observed that Stata extracted 10 factors. Based on the sorted rotated factor loadings, with orthogonal varimax rotation, Stata extracted 10 factors. However, Factor 9 had only one component, and Factor 8 and 10 had only two components which were 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) were quite high, instead of ignoring them we put factor 9 under previous stated factors to make it more sensible. The component under factor 9 were included in factor 6 and the components under factor 8 and 10 are combined together to form a separate factor, to give them a much more meaningful view. These were grouped into seven (7) components or factors, with each of them named and re-labelled according to their specifications (see Table 9).

Mean Score of Each Attribute

Factor 1: Audit Profession

Table 9 lists the mean score of each attribute that perceived affecting the use of DA in external auditing. The first factor generated had the highest number of items, with high factor loading which was labelled as audit profession factors. The professional category included all aspects listed within the audit profession. 12 attributes explained the overall factor. All the attributes under this factor leaned towards agreeable response, which indicated that auditors perceived these attributes to be influential when it comes to usability of DA in audit practices. The highest mean of 3.932 was for "lead to better improvement in professional audit judgment" while the lowest mean of 3.407 was for "ble to test 100% of the population". The respondents believed that if improvement in professional judgment can be seen using DA, then it would definitely affect the process of using. A higher response was also noted in other factors: "DA will improve identification of outliers and exceptions in audit sampling" (3.89), and "if ISAs provides guidance on how to use audit analytics tools in auditing procedures, I will be willing to use audit analytics" (3.898). Moreover, using DA can improve accounting estimates like fair value measurements and other assumptions required for disclosure during an audit.

Factor 2: Technological

The second factor termed as technological factors were mostly concerned with data quality and reliability. The five attributes explored the perception of auditors on the attributes related to data reliability, data security concerns, data accessibility, storing and retaining data for audit trail, and IT specialist's role in audit. The highest mean of 4.161 was for "IT specialist's role in audit will increase", and the lowest mean of 4.034 was for "data accessibility from different types of system will be difficult". The respondents believed that IT specialists had a big role to play in the use of DA. Audit firms will be recruiting many experienced data scientists who were deemed to be able to offer their expertise to auditing and other areas of their businesses (Salijeni et al., 2018). Data accessibility was also noted to be a major influence since the shift in focus would also be likely to relate to the timely accessibility of the relevant data (Brown-Liburd & Vasarhelyi, 2015). Storing and retaining audit data (mean: 4.102) would be an important attribute for audit trail. Alles et al. (2006) had mentioned that a system, or any system, has to retain sufficient information in order to provide evidence that the necessary audit procedures were performed. In this regard, the documentation requirement would suffice as an audit trail.

Factor 3: Quality Controls

The quality control factor generated from the factor loading consisted of five attributes that were related to controls that need to be maintained if DA was implemented in the audit process. This factor explored the perceptions of auditors on attributes related to reliance on client's internal audit data, maintaining ethics and professionalism, legal/regulatory challenges, and external or third-party data. These attributes obtained high positive responses from the auditors, ranging from agree to strongly agree. The highest mean of 4.093 was observed for "appropriate quality controls need to be in place for using DA" while the lowest mean of 3.949 was noted for "reliance on external or third-party data". Respondents believed that ensuring quality controls would be an important issue when adopting and implementing DA in the audit process. Alles et al. (2006) also mentioned the importance of continuously monitoring the business process controls when implementing DA in auditing. The effectiveness of internal controls, and clients' audit control, tend to depend on high ethics and professionalism (Alzeban & Gwilliam, 2014). Hence, the use of DA in audit processes would require significant focus be given to these aspects of reliance on clients' data and the maintaining of ethics and professionalism. Relying on clients' internal audit data (mean: 4.034) can be difficult. As explained by Appelbaum (2016) if clients based their valuation method on social media, there would be a difficulty since the reliability of tweets and other external social media is complicated and difficult to verify.

Table 9: Attributes Loading, Mean Score and Rated of Each Attributes

Factor	Item	Cronbach Alpha	Factor Loading	Mean	Rank By Mean	Overall Rank (Top 10)
Factor 1 **Audit Profession**	Leads to better improvement in professional audit judgement	0.9272	0.708	3.932	**1**	
	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	**2**	
	DA will improve identification of outliers and exceptions in audit sampling		0.525	3.89	**3**	
	An existing audit methodology to follow		0.504	3.873	**4**	
	Identifying risk of material misstatement will be easier		0.758	3.856	**5**	
	ISAs encourage use of advanced analytics methods to enhance audit function reliability		0.751	3.814	**6**	
	ISAs encourage use of various analytical methods to detect misstatement		0.787	3.788	**7**	
	Sufficiency of audit evidence collected using DA		0.747	3.771	8	
	Using DA will improve accounting estimates		0.744	3.737	**9**	
	Auditors will be able to provide more than reasonable assurance on financial statements using DA		0.837	3.72	**10**	
	Improves accounting disclosures		0.790	3.686	**11**	
	Able to test 100% of population		0.605	3.407	**12**	
Factor 2 **Technological**	IT Specialist's role in audit will increase	0.9114	0.766	4.161	**1**	**1**
	Storing and retaining data for audit trail		0.696	4.102	**2**	2
	Data security concerns		0.784	4.051	**3**	**5**
	Data accessibility from a different type of system will be difficult		0.726	4.034	**4**	**7**
	Improvement in data reliability		0.796	4.017	5	9
Factor 3 **Quality Controls**	Appropriate quality controls need to be in place for using DA	0.9020	0.847	4.093	**1**	**3**
	Reliance on client's internal audit data		0.821	4.034	**2**	**7**
	Maintaining ethics and professionalism when using DA		0.809	4.059	**3**	**4**
	Legal/Regulatory challenges in using DA		0.732	4.034	**4**	**7**
	Reliance on external or third-party data		0.605	3.949	**5**	

Factor	Item	Cronbach Alpha	Factor Loading	Mean	Rank By Mean	Overall Rank (Top 10)
Factor 4 **Audit Client**	Understanding the data in use (Clients' Data)	0.9020	0.783	4.008	**1**	**10**
	Clients business size		0.691	3.992	**2**	
	Support provided by client's IT personnel		0.758	3.958	**3**	
	Complexity in client's general IT controls		0.837	3.898	**4**	
	Strengths of client's IT infrastructure		0.751	3.856	**5**	
Factor 5 **External**	DA should be defined more clearly in terms for auditor's use	0.7723	0.569	3.992	**1**	
	Shifts in business environment will require auditors to use and adopt DA		0.671	3.949	**2**	
	Auditors may be over reliant on technology		0.575	3.763	**3**	
Factor 6 **Organizati-onal**	Re- training or re-skilling existing auditors	0.8288	0.510	4.161	**1**	**1**
	Financial budget on audit engagement		0.543	4.042	**2**	**6**
	Instructed by the management to use DA		0.599	3.975	**3**	
	Manage workloads on multiple audit engagement		0.706	3.966	**4**	
	Demand in auditor's promotion policies		0.680	3.839	**5**	
Factor 7 **Audit standards and other guidelines**	Current ISAs should provide guidance on application of DA in audit	0.8042	0.608	4.025	**1**	8
	Developing a principle-based standard rather than rule-based standard		0.682	3.881	**2**	
	Issuance of Non- Authoritative guidance by Standard setters for using DA		0.636	3.873	**3**	
	Collaborative work is required from auditors, standard setters & oversight authorities on ISAs related to DA application in audit		0.621	3.864	**4**	

Factor 4: Audit Client

This factor explored the perception of auditors on attributes relating to clients' IT control, clients' data, clients' support and strength of infrastructure, and clients' business size. The highest mean of 4.008 was for "understanding the data in use" and the lowest mean of 3.856 was for "strengths of client's IT infrastructure". The respondents reflected on the idea that understanding clients' data would have significant importance when DA tools were implemented for auditing. It is undeniable that clients can have unusual sources for their data. For instance, they might be generating financial valuations of some assets based on information provided by external social media sources (Appelbaum, 2016). Nonetheless, understanding those data would be difficult, even with the use of DA. Apart from that, clients' business size (mean: 3.992) also needs to be taken into account since it influences whether DA should be used or not. The motivation for audit firms to invest in analytic tools primarily relies on firm size (Dagilienė & Klovienė, 2019). As prior research had shown, technological competence is another prerequisite for the adoption of technology innovation Lin et al. (2007), hence, strengthening clients' IT infrastructure (mean: 3.856) would be an important criterion.

Factor 5: External Factors

The fifth factor generated from the factor analysis was labelled as external factors. The highest mean of 3.949 for "a shift in the business environment would thus require auditors to use and adopt DA" and the lowest mean of 3.763 was for "auditors may be over-reliant on technology". Tarek et al. (2017) opined the rapid advances in information technology have greatly affected the auditing profession in many ways. In this regard, it would be more advantageous to transform traditional audit processes to more technology-based auditing.

Factor 6: Organizational Factors

Organizational factors comprised of five attributes that were related to issues regarding the organization. The highest mean of 4.161 was for "re-training or re-skilling existing auditors", and the lowest mean of 3.839 was for "demand in auditor's promotion policies". Changing the auditors' mind-set in gathering audit evidence from the use of DA as compared to traditional techniques would require time and investment in training (IAASB, 2016). This means that financial budgets on audit engagements (mean: 4.042) may increase due to the use of expensive software.

Factor 7: Audit Standards and Other Guidelines

The seventh factor was mainly related to issues regarding International Standards of Auditing (ISAs). The attributes of this factor were geared towards a principle-based standard, collaborative work on standards, and the state of current ISAs. It appears that the Malaysian auditors in this study had considered all these attributes to be important for the use of DA. The highest mean of 4.025 was for "current ISAs should provide guidance on the application of DA in audit" while the lowest mean of 3.864 was for "collaborative work is required from auditors, standard setters, and oversight authorities on ISAs related to DA application in audit". As mentioned in Byrnes et al. (2018) there is virtually no professional auditing guidance on the theory and practice of applying new DA, continuous auditing, and the use of other techniques and technologies for auditing.

Overall, all of the factors were perceived to be affecting the use of DA in external auditing. Specifically, factors related to technological and quality control scored higher mean values in comparison to other factors.

Ten Highest Rated Attributes Affecting DA Use in External Auditing

Table 9 outlines ten highest rated attributes affecting use of DA by the respondents. "IT specialist role in audit will increase" was rated the highest attribute affecting the use of DA in external auditing. It was noted that IT specialist would have a bigger role to play when DA is used in external auditing. With less exposed knowledge in the field of IT, 'traditional' auditors would generally need to rely on IT specialist and experts to understand how DA software can be used in audit practice. In terms of DA, apart from IT specialist external auditing would also be looking into data analyst or data scientist who would be more capable with the use of sophisticated DA software. Since DA would be used explicitly by accountants or auditors, the software should be built based on their experiences and perspectives, rather than the perspectives of the general IT experts. Therefore, DA tools need to be more user-friendly as this would help non-IT auditors to understand its usage. The use of the term ‘data scientist’ is becoming more commonplace in auditing, which suggests auditors’ preference to imagine themselves as sophisticated experts, at least as far as data processing and analysis is concerned (Salijeni et al., 2018).

“Re-training and re-skilling external auditors”, was one of the attributes rated high by the respondents. This implied that the respondents were agreeable that more training was required for external auditors on the use of DA. Undeniably, this would have a major influence on the audit firm’s intention to use DA. If the skills required of modern auditors become skewed towards more technical, ‘number-crunching’ types of competencies, this would have implications for the manner in which practice provides a suitable environment for the development of auditors as professionals (Turley et al., 2016).

Another technological aspect which carried a significant value from the respondents was the attribute of “storing and retaining data for audit trail”. Storing and retaining audit data would be an important aspect for an audit trail. Alles et al. (2006) mentioned every 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 accessibility of these data at a later stage of the audit or for next year audit will also be of major concern since the shift in focus will most likely relate to the timely accessibility of the relevant data as stated by Brown-Liburd and Vasarhelyi (2015).

The need of “appropriate quality control” was also one of the top ranked attributes affecting use of DA in external auditing. One of the key challenges of DA use is in the application of quality control when developing or using the analytic tools. Further, caution needed to be exercised on the assessment of the reliability of the analytic tools. In this regard, respondents tended to agree with the fact that quality control procedures were required in order to secure the integrity of the tools and to guard against unauthorized access. This would offer protection for the entity’s data privacy and confidentiality. The IAIS (2016) mentioned in their report, in response to IAASB, that there should be a strong quality control process over the use of analytics by auditors. These auditors require competence; hence, training should be made available to these auditors so that appropriate controls can be set. This would further prevent the auditors being overconfident with technology or as it has been mentioned in our top ranked attributes as "auditors may be over reliant on technology".

"Maintaining ethics and professionalism" when using DA was another attribute that had a very high response rate from the respondents and consequently was in the top ten ranked attributes. Due to the huge amount of data being used and the sensitivity of these data from the client's perspective, it would be vital for auditors to maintain their ethical stance. There will be an issue of trust, independence and data governance between third parties and the client. It is important to have a proper guideline on any ethics and independence issues that might be aroused through the increased use of data analytics in the financial reporting and auditing process. The effectiveness of internal control and client audit control depends on high ethics and professionalism (Alzeban and Gwilliam, 2014).

Maintaining confidentiality of external or third-party data was to some degree the auditor needs to be well aware of. "Data security concerns" from client perspective is the attribute which explains this issue. This attribute under the quality control factor was ranked highly due to the concern posed by the respondents. Alles et al. (2006) mentioned the importance of continuous monitoring of business process controls when implementing continuous auditing, which is a big factor in the implementation of DA. Implementing DA in audit processes will also need to focus on these aspects of reliance on the client's data and their security concern over those data. Audit firms may also need to tackle the "legal and regulatory challenges" in relation to the access, and storage of client data when it comes to use of DA in audit.

Another top ten ranked attribute is "Current ISAs should provide guidance on the application of DA in audit". Companies and audit firms are investing in data analytics in unprecedented ways they are questioning the sufficiency of auditing standards in light of data analytics (Austin et al., 2021). At this moment, there is a strong need for proper guidance to be set by the standard setters and regulators. As pointed out by Salijeni et al. (2018) several participants in their study highlighted significant obstacle to more widespread use of BDA related to the fact that DA has not been specifically discussed in the auditing standards. While some auditors perceive this lack of guidance as an opportunity to innovate without worrying about possibly substantial regulatory restrictions, others commented that they would refrain from fully engaging with BDA unless the standard setters eliminated what they see as uncertainties around BDA use (IAASB, 2016).

The last two attributes in the top ten ranked list with highest mean scores were “improvement in data reliability” and “understanding the data in use (clients’ data)”. Many audit engagement clients are now integrating different sources of data (e.g big data) in their businesses with new and complex business analytical approaches to generate intelligence information for business decision making purposes (Appelbaum et al., 2017). Auditors are expected to match this level of sophistication being in par with their clients’ data and analysis. So, it is vital for auditors to both understand what clients’ data entails while at the same time assessing how reliable these data are. 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 but understanding those data will be difficult and to some extent might not be possible even by using DA (Appelbaum, 2016). There is a need to further clarify on what constitutes sufficient appropriate evidence when using a data analytics tool in the audit performance. Debreceny et al. (2005) opined compromise of clients’ data to be of concern when it comes to limitations of using DA in practice. Consequently, this is going to be a valid concern in terms of implementing DA in external auditing.

Overall, it can be deduced that a number of factors can affect DA use in external auditing which include technological, organizational, quality controls and client factors. While some of the highest rated attributes affecting use of DA includes role of IT specialist, auditors’ skills and IT competencies, issue of data security and reliability and standards to guide on the DA application in the external auditing.

CONCLUSION

The outcome derived from the findings of the first research question offer a better understanding of the status of the actual use of DA in external auditing.

It can be concluded that, DA use is limited and the use of more sophisticated DA tool seems uncommon although the respondents agreed on the potential benefits of DA to the audit performance. One possible implication of this is that the audit profession and regulators should carry out a details assessment to understand the reason for audit firms not adopt DA in external auditing. This is important to ensure the auditing profession is not lagging behind with the technology development in the business environments.

The findings of the second research question of this study showed several contributing factors perceived to be influential in the use of DA in external auditing. Overall, three factors related to technological, organizational and quality controls are perceived of significant in motivating the use of DA in external auditing. Amongst the key attributes rated high in influencing the use of DA were: role of IT specialist, auditors' re-training and re-skilling, storing and retaining data for audit trail and appropriate quality controls need to be in place for using DA. Earley (2015) had pointed out that audit engagements are lacking in the use of DA when compared to other practices. This deficiency could be due to some unique challenges which has been attributed to the complexity of the technique which requires a deeper understanding that is beyond the auditors' current level of IT knowledge (Kostić & Tang, 2017). One of the conclusions of this study is auditors' DA competency is still lacking. The implication of this would be for accounting firms, educators, and regulators to work together in designing the right trainings for audit practitioners and curriculum for the accounting students. Another conclusion that is derived from the findings is technological advancement in the business setting influences the use of DA in practice. Thus, it implied the audit profession should pay more attention on the increasing reliance on the role of IT specialist in the audit engagement while considering issue of data security and reliability in audit performance.

Like all studies, this study is also subject to some limitations. First, the analysis was derived from the context of Malaysia only, hence it would be more insightful and complete if we could have more studies looking at other countries. The outcome would enable research and practice to see how the adoption of DA prevails throughout the world. In this regard, our findings cannot be generalized at the global level since auditing in other parts of the world varies. Second, the research data were generated from mainly small and medium firms. Very few auditors from the Big 4 firms responded to the survey. Thus, an important viewpoint could be missing in that aspect. Therefore, the results derived from the current study can only be applied to such types of firms. One of the biggest challenges faced in the current study was to get the responses from auditors, and similar limitations were also noted in the works of Omoteso (2006).

Future research can, therefore, aim to gather more responses from Big 4 auditors so as to further explore the validated scale of the factors affecting the use of DA. The association between these factors and their influence on audit quality can also be examined so as to understand how these factors reacted when they were associated with audit opinion, and whether the use of DA resulted in absolute level of audit assurance. Second, future research may focus on whether the use of DA leads to higher quality of audit evidence. Third, researchers need to look into the changes required in audit standards in order to implement DA in audit procedures. Practical evidence can be gathered on these aspects by cooperating with audit firms. Findings can then be reported back so as to find a more sophisticated process for the adoption of DA. More investigations need to be conducted by both accounting firms and academics. Academics can help to gather perceptions of stakeholders and can point out to things which can be implemented to have a better quality in audit, whereas the firms would be the one who will implement it in workplace so as to understand how and which audit procedures and audit standards may be changed, besides looking at how to improve the audit process.

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REFERENCES

Ahmi, A., & Kent, S. (2013). The Utilisation of Generalized Audit Software (GAS) by External Auditors. *Managerial Auditing Journal, 28*(2), 88–113.

Alles, M., & Gray, G.L. (2015). The pros and cons of using big data in auditing: A synthesis of the literature and a research agenda. Working paper.

Alles, M., Brennan, G., Kogan, A., & Vasarhelyi, M.A. (2006). Continuous Monitoring of Business Process Controls: A Pilot Implementation of a Continuous Auditing System at Siemens. *International Journal of Accounting Information Systems, 7*(2), 137–61.

Alles, M., & Gray, G. L. (2016). Incorporating Big Data in Audits: Identifying Inhibitors and a Research Agenda to Address Those Inhibitors. *International Journal of Accounting Information Systems, 22*, 44–59.

Alzeban, A., & Gwilliam, D. (2014). Factors Affecting the Internal Audit Effectiveness: A Survey of the Saudi Public Sector. *Journal of International Accounting, Auditing and Taxation, 23*(2), 74–86.

Appelbaum, D. (2016). Securing Big Data Provenance for Auditors: The Big Data Provenance Black Box as Reliable Evidence. *Journal of Emerging Technologies in Accounting, 13*(1), 17–36.

Appelbaum, D. A., Kogan, A., & Vasarhelyi, M. A. (2017). Big Data and Analytics in the Modern Audit Engagement: Research Needs. *Auditing: A Journal of Practice & Theory, 36*(4), 1–27.

Austin, A. A., Carpenter, T.D., Christ, M.H., & Nielson, C.S. (2021). The Data Analytics Journey: Interactions Among Auditors, Managers, Regulation, and Technology. *Contemporary Accounting Research, 38*(3), 1888–1924.

Brown-Liburd, H., & Vasarhelyi, M.A. (2015). Big Data and Audit Evidence. *Journal of Emerging Technologies in Accounting,12*(1), 1–16.

Buttigieg, R., & Ellul, L. (2021). Benefits and Challenges of Applying Data Analytics in Government Auditing. *Journal of accounting finance and auditing studies (JAFAS), 7*(3), 1–33.

Byrnes, P.E., Al-Awadhi, A., Gullvist, B., Brown-Liburd, H., Teeter, R., Warren, J.D. & Vasarhelyi, M. (2018). Evolution of Auditing: From the Traditional Approach to the Future Audit. In *Continuous Auditing*, 285–97.

Canada CPA. (2017). *Audit Data Analytics Alert: Survey on Use of Audit Data Analytics in Canada — Results and Possible Implications*.

CPA. (2017). The International Federation of Accountants (IFAC) *Exploring the Growing Use of Technology in the Audit, with a Focus on Data Analytics Feedback Statement*. Melbourne.

Dagilienė, L., & Klovienė, L. (2019). Motivation to Use Big Data and Big Data Analytics in External Auditing. *Managerial Auditing Journal*, *34*(7), 750–82.

Debreceny, R., Lee, S. L., Neo, W., & Toh, J.S. (2005). Employing Generalized Audit Software in the Financial Services Sector: Challenges and Opportunities.ed. Jagdish Pathak. *Managerial Auditing Journal, 20*(6), 605–18.

Earley, C. E. (2015). Data Analytics in Auditing: Opportunities and Challenges. *Business Horizons*, *58*(5), 493–500.

Eilifsen, A., Kinserdal, F., William F. Messier Jr, W. F., & McKee, T. E. (2020). An Exploratory Study into the Use of Audit Data Analytics on Audit Engagements. *Accounting Horizons, 34*(4), 75–103.

Forbes Insights. (2017). Forbes Insights *Audit 2020 The Future Is Now*.

Gepp, A., Linnenluecke, K. M., O'Neill, T.J., & Smith, T. (2018). Big Data Techniques in Auditing Research and Practice: Current Trends and Future Opportunities. *Journal of Accounting Literature, 40*, 102–15.

Hair, J. F., Anderson, R. E., Tatham, R.L., & Black, W.C. (1998). *Multivariate Data Analysis*. Prentice hall Upper Saddle River, NJ.

IAASB. (2016). Exploring the Growing Use of Technology in the Audit , with a Focus on Data Analytics.

IAIS. (2016). International Association of Insurance Supervisors (IAIS) *Exploring the Growing Use of Technology in the Audit, with a Focus on Data Analytics Feedback Statement*

Jacky, Y., & Sulaiman, N. A. (2022). The Use of Data Analytics in External Auditing: A Content Analysis Approach. *Asian Review of Accounting* 30(1), 31-58.

Katz, L. F., & Margo, R. A. (2014). Technical Change and the Relative Demand for Skilled Labor: The United States in Historical Perspective. In *Human Capital in History: The American Record*, University of Chicago Press, 15–57.

Kend, M., & Nguyen, L. A. (2020). Big Data Analytics and Other Emerging Technologies: The Impact on the Australian Audit and Assurance Profession. *Australian Accounting Review* 30(4), 269–82.

Kostić, N., & Tang, X. (2017). The future of audit: Examining the opportunities and challenges stemming from the use of big data analytics and blockchain technology in audit practice.[Master Thesis, Lund University]. Lund University Research Repository. https://lup.lub.lu.se/luur/download?fileOId=8916733&func=downloadFile&recordOId=8916727

KPMG. (2014). *Going beyond the Data: Achieving Actionable Insights with Data and Analytics. Amstelveen, Netherlands: KPMG International Cooperative.*

Krahel, J. P., & Titera, W.R. (2015). Consequences of Big Data and Formalization on Accounting and Auditing Standards. *Accounting Horizons*, 29(2), 409–22.

Krieger, F., Drews, P., & Velte, P. (2021). Explaining the (Non-) Adoption of Advanced Data Analytics in Auditing: A Process Theory. *International Journal of Accounting Information Systems, 41*, 100511.

Lin, C., Shih, H., & Sher, P. J. (2007). Integrating Technology Readiness into Technology Acceptance: The TRAM Model. *Psychology & Marketing,* 24(7), 641–57.

Liu, Q., & Vasarhelyi, M. A. (2014). Big Questions in AIS Research: Measurement, Information Processing, Data Analysis, and Reporting. *Journal of Information Systems,* 28(1), 1–17.

Manita, R., Elommal, N., Baudier, P., & Hikkerova, L. (2020). The Digital Transformation of External Audit and Its Impact on Corporate Governance. *Technological Forecasting and Social Change*,150, 2-10

Newman, W., Muzvuwe, F., & Stephen, M. (2021). The impact of the adoption of data analytics on gathering audit evidence: A case of KPMG Zimbabwe. *Journal of Management Information and Decision Science*s, 24(5), 1-15.

Omoteso, K. (2006). The Impact of Information and Communications Technology on Auditing.(Doctoral Dissertation, DeMonfort University, Leicester United Kingdom).

Pallant, J. (2011). *Survival Manual. A step by step guide to data analysis using SPSS.*

Salijeni, G., Taddei, A. S., & Turley, S. (2018). Big Data and Changes in Audit Technology: Contemplating a Research Agenda. *Accounting and Business Research,* 49(1), 95–119.

Tang, J., & Karim, K. E. (2017). Big Data in Business Analytics: Implications for the Audit Profession. *The CPA Journal,* 34–39.

Wang, T., & Cuthbertson, R. (2015). Eight Issues on Audit Data Analytics We Would like researched. *Journal of Information Systems*, 29(1), 155-162.

Tschakert, N., Kokina, J., Kozlowski, S., & Vasarhelyi, M. (2016). The next Frontier in Data Analytics - Journal of Accountancy. *Journal of Accountancy,* 222(2), 58–63.

Turley, S., Humphrey, C., Taddei, A.S., Siddiqui, J., Woods, M., Basioudis, I.G., & Richard, C. (2016). *Skills, Competencies and the Sustainability of the Modern Audit*. Institute of Chartered Accountants of Scotland.

Vasarhelyi, M. A., Kogan, A., & Brad M Tuttle, B. M. (2015). Big Data in Accounting: An Overview. *Accounting Horizons,* 29(2), 381–96.

Whitehouse, T. (2014). Auditing in the Era of Big Data.*Compliance Week,* 11(126), 28–67.