Critical issues of the audit expectation gap in the era of audit digitalisation

By: Lazarus Elad Fotoh and Johan Ingemar Lorentzon

Abstract

This study aims to conceptually examine how a paradigm shift from traditional audits to digital audits could impact critical and recurring issues of the expectation gap. The findings indicate that digital platforms such as data analytics systems supported by machine learning can facilitate the identification of anomalies in data which can be investigated manually by auditors. Also, big data can be used in the audit process to interrogate an entire population of journal entries, transactions, and unstructured data, enabling auditors to focus on transactions displaying unusual patterns identified through artificial intelligence. Furthermore, drones could equally facilitate stock counts, compliance, and the attainment of operational objectives. In a nutshell, existing extant literature and commentaries underscore the significance of these digital technologies in enhancing internal controls and facilitating fraud prevention and detection. This study further contributes to the extant literature by projecting new avenues where the expectation gap is likely to emerge due to a paradigm shift from traditional audits to digital audits, enabling the auditing profession to take pre-emptive measures to prevent the exacerbation of an already worsening trust and confidence in the audit profession by financial statement users.

Keywords: Audit Expectation gap, Fraud prevention and detection, Internal control, Digital technologies

1. Introduction

The audit expectation gap has been evident for decades and is still plaguing the audit profession. However, the audit profession is currently experiencing a paradigm shift from traditional audits with samples to digital audits of complete data analysis due to breakthroughs in digital technologies. These changes may have substantial impact on the expectation gap in general. Contemporary studies are yet to examine how this paradigm shift will impact on the

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expectation gap, especially on aspects where the gap is most evidenced. The aim of this study is to fill up this gap by conceptually exploring the impact of this paradigm shift on two of the most critical issues of the gap: auditors´ fraud prevention and detection responsibilities and auditors´ responsibility for maintaining internal control.

The audit expectation gap (AEG) is an existential and polemical issue in the audit profession (Stevenson, 2019) and a pandemonium plaguing the audit profession for decades even before the term officially came to existence (Humphrey et al. 1993; Koh & Wo 1998). The expectation gap is broadly the differences in beliefs and desires between auditors and financial statement users regarding the duties of auditors. Substantial research has been conducted over the last two decades on the dimensions of the gap, especially after prominent accounting scandals and corporate failures (Dennis 2010; Gold et al. 2012, Hassink et al. 2009, Pourheydari & Abousaiedi 2011). A commonality of the findings of these studies is that the gap is conspicuous on two key issues; auditors' responsibility for fraud prevention and detection (Alleyne & Howard, 2005; Best et al., 2001; Desira & Baldacchino, 2005; Dixon et al., 2006; Fadzly & Ahmad, 2004; Gay et al., 1997; Gloeck & De Jager, 1993; Hassink et al., 2009; Lin & Chen, 2004; Onumah et al., 2009; Pourheydari & Abousaiedi, 2011; Porter et al., 2012; Sidani, 2007; Siddiqui et al., 2009), and auditors' responsibility for maintaining the soundness of internal control (Best et al., 2001; Fadzly & Ahmad, 2004; Desira & Baldacchino, 2005; Dixon et al., 2006; Pourheydari & Abousaiedi, 2011; Onumah et al., 2009). The detection of financial reporting fraud remains a daunting task for auditors and remains an issue of grave concern to the audit profession (Hammersley 2011). It is worth mentioning that fraud prevention and detection (IFAC 2009) and the maintenance of internal control are the responsibility of those charged with governance and management (IFAC 2019).

A broad spectrum of contemporary studies has focused on narrowing the expectation gap (Sidani 2007; Noghondari & Foong 2013) by providing recommendations on narrowing the gap. Despite the plethora of recommendations and numerous institutional changes over several decades (Gold et al. 2012), there is demonstrable evidence indicating the continuous existence and persistence of the gap (Gold et al. 2012; Koh and Woo 1998; Ruhnke & Schmidt, 2014; Sidani 2007; Noghondari & Foong 2013) across time and national borders (Gold et al. 2012). Therefore, the prevailing proposed solutions have not resulted in the elimination of the expectation gap or at the minimum, critical issues of the expectation gap. This partly results from the differences in perceptions and beliefs of different stakeholders (Fulop et al. 2019). Therefore, it is crucial to examine how this inevitable paradigm shift will impact critical issues of the expectation gap. Since It should be noted that the continuous existence of the expectation gap severely deteriorates trusts and confidence in the audit profession (Fadzly & Ahmad 2004; Porter 2014), impairs the value of auditing, the reputation and credibility of auditors (Lee et al. 2009), and decimates the legitimacy of the audit profession as a whole (Ruhnke & Schmidt 2014) which has already been exacerbated by recent prominent corporate malfeasances. Under the current traditional audit paradigm of sample audits, the expectation gap continues to exist on key issues such as; auditors' fraud prevention and detection responsibilities, and auditors' responsibility for maintaining the soundness of internal controls.

It is worth noting that auditing is currently at a critical juncture (Byrnes et al. 2018, Lombardi et al. 2015) and crossroad (Lombardi et al. 2015) resulting from breakthroughs in technological developments such as robotics and artificial intelligence (Goertzel 2007, Nowak et al. 2018), data analytics (Alles 2015, Cukier and Mayer-Schoenberger 2013, Richins et al. 2017), blockchains (White 2017), workflow automation, mobile applications, collaboration platforms, and so on, which are significantly altering the way audits are performed as many labour-intensive and tedious manual tasks are being eliminated (Brennan 2016, Meuldijk 2017, Raphael 2017). There is significant evidence alluding to the influence of technologies on the development of the audit profession in recent years (Dai 2017; Vasarhelyi et al. 2010; Vasarhelyi et al. 2015). Audit firms are beginning to develop and incorporate cutting-edge technologies into the audit process (Agnew 2016), especially the big four audit firms. Further, routine audit processes are being automated resulting in intelligent and predictive audits which generally enhances audit quality (Alles et al. 2006; Dai & Li 2016; Jans et al. 2014; Moffit et al. 2018). The adoption of these digital technologies has been precipitated by audit clients who have exponentially adopted these digital technologies (Meuldijk 2017) resulting in the urgency for the audit profession to jump on the bandwagon (Appelbaum et al. 2017). These technologies are gradually resulting in a paradigm shift from the traditional audit paradigm of sample audits to the digital audit paradigm or "Audit 4.0" with a new era of methodologies (Brown-Liburd et al. 2015; Cao et al. 2015; Dai 2017).

It is against this backdrop this study aims to examine how a change in paradigm from traditional audits to digital audits could affect the critical and recurring issues of auditors' fraud prevention and detection responsibilities and auditors' responsibility for maintaining internal controls. To achieve this aim, we perform an analysis of the existing literature together with commentaries from the audit industry on the expectation gap and audit digitalisation.
Consequently, the following research questions are posed;

RQ1: How will a shift in paradigm from traditional audits to digital audits affect the expectation gap on issues related to auditors' fraud prevention and detection duties?

RQ2: How will a shift in paradigm from traditional audits to digital audits affect the expectation gap on issues related to auditors' responsibility for maintaining the soundness of internal controls?

This study is one of the first of its kind to examine how audit digitalisation will impact the expectation gap. The contribution to the extant literature is twofold. Firstly, this study uses sensemaking techniques to uncovers how a paradigm shift from traditional audits to digital audits will impact areas where the gap is widest and commonly observed. As previously mentioned it is imperative for the expectation gap to be narrowed as a whole especially the critical issues due to the fact that the continuous existence of the gap decimates the trust and confidence of users and reduces the value of audits. Furthermore, this study adds value to the expectation gap discourse by projecting areas where the gap is likely to emerge due to the paradigm shift to digital audits. We, therefore, underscore that it is critical for the audit profession takes pre-emptive measures to narrow these emerging new gaps in order to further prevent the deterioration of financial statement users trust and confidence.

The remainder of this paper is structured as follows: the next section contains the conceptual background literature, the ensuing section contains the analysis and discussion, while the final section ends with a conclusion, contribution, limitation, and suggestion for future research.

2. Conceptual Background

2.1. Audit Expectation gap

The expectation gap has been an existential issue even before the term was first used in auditing (Sidani 2007). The expectation gap remains a contentious issue (Stevenson 2019) still subject to debates (Lee et al. 2010) and not limited geographically (Porter et al. 2012). The term was initially introduced in the audit literature by Liggio (1974, p. 27) who referred to it as the difference between the expected level of performance "as envisioned by both the user of financial statements and the independent accountant." Similarly, Humphrey (1997, p.9) defines the expectation gap as "a representation of the feeling that auditors are performing in a manner at variance with the beliefs and desires of those for whose benefit the audit is carried out." Several studies have uncovered the existence of the expectation gap globally especially during the last decade (Ruhnke & Schmidt 2014). As previously stated, a recurring finding of these studies is that the gap is most evident on issues related to auditors' responsibility for fraud prevention and detection and auditors' responsibility for maintaining internal controls.

The Association of Certified Fraud Examiners (2016) estimates that organizations typically lose 5% of their revenue annually to fraud. The global fraud losses equate to 6.05% of GDP which amounts to 5.127 trillion US dollars (Gee & Button 2019). It is worth noting that the International Standards on Auditing (ISA) 240, paragraph 5 requires an auditor to obtain only reasonable assurance, instead of absolute assurance that financial statements taken as a whole are free from material misstatements resulting from either fraud or error (IFAC 2009). Similarly, the Statement of Auditing Standards (SAS), section 200, No. 122/123 requires that auditors provide reasonable assurance that financial statements taken as a whole are free from material misstatement resulting from fraud or error (AICPA 2011). Furthermore, ISA 240, paragraph 3 notes that although auditors may suspect as well as identify fraud, auditors do not generally make a legal assessment of the occurrence of fraud (IFAC 2009). Instead, ISA 240, paragraph 4 notes that those charged with governance and management of an entity are responsible for fraud prevention and detection (IFAC 2009).

Regarding the maintenance of internal control, ISA 315, paragraph 12M underscores that those charged with governance and management have the responsibility to design, implement, and maintain a system of internal controls which provides reasonable assurance that the attainment of an entity's objectives concerning financial statement reliability, effectiveness and efficiency of operations, and compliance with the relevant laws and regulations (IFAC 2019). Therefore, it is management's responsibility for maintaining internal controls and not the auditor's responsibility. However, ISA 315, paragraph 7 expects auditors to obtain an understanding of an entity's environment, its relevant financial reporting framework, and its system of internal control to identify and assess the risk of material misstatement (IFAC 2019). Similarly, SAS No. 107 requires auditors to evaluate the risk associated with weaknesses in internal control and fraudulent financial statements (AICPA 2007).

Other areas where the gap has observed include; auditors' responsibility for exercising judgment in selecting audit procedures (Best et al., 2001; Dixon et al., 2006; Siddiqui et al., 2009), and issues related to auditors' independence (Humphrey et al., 1993; Schelluch, 1996; Dewing and Russel, 2002; Hassink et al., 2009). While prior studies (Liggio 1974; The Cohen Commission 1978) on the expectation gap focused on establishing its foundation and rationale (Fossung et al. 2020), contemporary studies have been focused on addressing the extent of the gap, areas most affected by the gap, and possible measures to narrow the gap (Sidani 2007; Noghondari & Foong 2013).

Current recommendations on narrowing the expectation gap include; educating users on auditors' duties (Humphrey et al. 1992; Sidani, 2007; Siddiqui et al., 2009; Hassink et al., 2009; Noghondari & Foong, 2013; Fulop et al., 2019), structuring audit methodologies (Koh and Woo 1998; Lee et al. 2009a), providing more information through audits or the audit report in the form of the expanded audit report (Enes et al. 2016; Ruhnke & Schmidt, 2014), adjusting the language in which information is communicated (Schelluch & Gay 2006; Asare & Wright 2012),changing the content of the audit report (Vanstraelen et al. 2012), prohibiting the provision et non-audit services, mandatory rotation of auditors (Ruhnke & Schmidt 2014), monitoring auditors' performance to eliminate sub-standard performance (Porter 2014), or even aligning auditing standards in line with users' expectations and effectively communicating to users the extent and type of audit performed (McEnroe & Marten 2001; Salehi 2007). On the contrary, Fossung et al. (2020) note that an increase in the regulation and duties of auditors concerning the reliability and usefulness of audits and audited financial statements and auditors' skills further widens the expectation gap. Despite these proposed measures to narrowing the expectation gap, the gap has continued to persist (Sidani 2007; Noghondari & Foong 2013) under the prevailing audit paradigm of sample audits especially on the two issues of fraud prevention and detection, and auditors' responsibility for maintaining the internal control system of an entity.

2.2. Audit Digitalisation

The audit profession is currently experiencing a paradigm shift from traditional audits to digital audits or "Audit 4.0" a term derived from "Industry 4.0" (Hermann et al. 2015). Audit 4.0 was recommended as a framework to facilitate the transition towards a new era (Dai & Vasarhelyi 2016). Audit 4.0 is a prototype of Industry 4.0 and implements similar infrastructures as Industry 4.0 but from an auditing perspective. Industry 4.0 generally entails the use of smart sensors, Internet of Things (IoT), Internet of Service (IoS) cyber-physical systems, virtualisation, real-time capability, smart factories to enhance interoperability, service orientation, decentralisation, and modularity in manufacturing industries (Hermann et al. 2015).

It should be emphasised that one of the main objectives of audit digitalisation is to ease fraud detection and the quantification of a client's risk (Brown-Liburd et al. 2015). Data explosion and the inherent limitations of the traditional audit paradigm in understanding risk and the collection of audit evidence (Deloitte 2013) has resulted in a strong desire for audit firms to use technology and data analytics in the audit process (PwC 2014, Protiviti 2014). Big data and artificial intelligence are the commonest digital technologies used in the audit process today (Montes & Goertzel 2019), and it principally encompasses large and complex data sets enigmatic to analyse and handle using standard methods and tools (Cao et al. 2015). In general, big data is characterised by the five V paradigm of value (Gantz & Reinsel 2011), volume, velocity, variety (Gantz & Reinsel 2011, McAfee and Brynjolfsson 2012), and veracity (Wamba et al. 2015). Big data presents enormous opportunities to speedily access and examine voluminous, diverse, and typically structured data (Wamba et al. 2015) and to transform such information into useful knowledge (Constantiou & Kallinikos 2015; De Mauro et al. 2016). Also, big data provides new avenues for auditors in the form of new consulting opportunities especially pertaining to the provision of assurance regarding the authenticity of unstructured data (Richins et al. 2017).

Big data is often defined in relation to data analysis (Earley 2015). In this light, Alles and Gray (2014) underscore that in the accounting literature, instead of defining big data based on the data source, big data is often defined based on the types of analysis which can be conducted with such data, for example, predictive analytics and data analytics. Data analytics is defined as the "process by which insights are extracted from operational, financial, and other forms of electronic data internal or external to the organization" (KPMG 2012, p.2). Data analytics have the potentials of replacing numerous tasks performed by accountants and auditors (Richins et al. 2017). In view of the potential benefits of big data, Frey and Osborne (2013) predict that 94 percent of accounting and auditing jobs are likely to be automated. Also, data analytics can equally enable auditors to perform auditing on a real-time basis instead of the traditional sample-based approach (Richins et al. 2017). Consequently, public accounting firms are now racing to provide enhanced and comprehensive data analytic services to their clients (Earley 2015).

Artificial intelligence, on the other hand, could enhance the inventory process making it less prone to human errors (Nehmer & Appelbaum 2019) as well as improve auditing processes and standards (Tiberius & Hirth 2019). Also, artificial intelligence can facilitate visual patterns, language recognition, logical problem solving (Gershman et al. 2015), as well as detecting anomalies in accounting data (Tiberius & Hirth 2019). Similarly, blockchains could facilitate the restructuring of some financial statement assertions (Raphael 2017). Despite the tremendous technological breakthroughs and potential benefits of audit digitalisation, a Deloitte survey uncovered that only 7% of participants were in the advanced stages of incorporating big data and analytics in the audit process, 24% were still at the intermediate level, while a great majority (55%) were still at the elementary phase, while another 14% were unsure or had no capability to use big data and data analytics in the audit process (Deloitte 2018). For example, the use of big data analytics is not yet pronounced in auditing because accounting data is still too small from a big data perspective. In addition, accounting data is customarily well structured and it is worth noting that big data works best with unstructured data (Tiberius & Hirth 2019).

3. Methodology

In this study, we make use of the design science research (DSR) methodology, which entails creating information artefacts. The method was introduced by Hevner et al. (2004) and Peffer et al. (2007) and subsequently by other researchers like Appelbaum and Nehmer (2017). Furthermore, we equally implemented four out of the six major activities of the methodology which Geerts (2011) highlighted. It is noteworthy that, it is not a requirement to include all six activities in a proposal of research (Peffers et al. 2007, p. 73-74). The design science research method best suits research projects that cover a wide range of researchers, articles, and a period of development. The main activities include:

1. Problem identification and motivation
2. Defining the objectives of a solution
3. Designing and developing artefacts that meets (some of) the solution objectives
4. Demonstrating the solution
5. Evaluating the solution
6. Communicating the problem and the solution (usually an article).

The implementation of digital technologies in the audit process has generally been incremental. In this study, we focused on the first three and the last aspects of the DSR. The paper is designed to capture the selected four aspects. Table 1 below contains the selected four aspects of DSR in relation to how audit digitalization will impact the critical expectation gap issues of; auditors' responsibilities for fraud prevention and detection, and auditors' responsibility for maintaining internal control.

Table 1: The four selected main activities of DSR used to analyse how audit digitalization will impact critical issues of the expectation gap

Main DSR activities	**The impact of digital technologies on the expectation gap**
Problem identification and motivation	Businesses are beginning to use digital technologies to reduce cost, improve operational efficiency, and enhance internal control. Could these digital technologies be used to eliminate critical issues of the expectation gap?
Defining the objectives of a solution	The objective is to examine how digital technologies will impact critical issues of the expectation gap.
Designing and developing artefacts	A range of digital technologies and their potential impact on critical issues of the expectation gap are presented.
Communication of results	Digital technologies if adequately implemented in the audit process, have the

	potentials of eliminating if not narrowing critical issues of the expectation gap.

4. Discussion and Analysis

4.1. Audit digitalization in relation to fraud prevention and detection

Data analytics and fraud prevention and detection

It is now trendy to apply data analytics to fraud detection (Tang & Karim 2018) and the quantification of risks (Russom 2011). Data analytics has the potentials of improving audits through an increase in the sufficiency of audit evidence as auditors will be able to test a greater number of transactions than they currently do (Earley 2015). Under the prevailing traditional audit paradigm, auditors enforce the risk-based approach with a test of sample transactions to determine whether financial statements are fairly presented. However, data analytics will enable auditors to utilise digital technology to test a complete population of transactions (Earley 2015). For example, auditors can use big data analytics to analyse high risk areas such as cash transactions to uncover suspicious transactions and to ensure compliance with regulations such as money laundering regulations (Brown-Liburd et al. 2015) hence enhancing internal controls. Generally, it will be beneficial for audit firms to transition from the current traditional substantive tests, analytical tests, and tests of controls to enforcing a problem-oriented data analytic approach in big data (Titera 2013). From the professional perspective, James Liddy (Liddy 2014), the then KPMG's Vice Chair of Audit and Regional Head of Audit for the Americas noted that:

> In the future, using high powered analytics, auditors will have the capacity to examine 100 percent of a client's transactions. We will be able to sort, filter and analyse tens of thousands or millions of transactions to identify anomalies, making it easier to focus in on areas of potential concern and drill down on those items that may have the highest risks. This will enable us more than ever before to help assess risks and identify trends

> through the audit process. With smart data, each year's audit will also "learn" from prior years, exposing areas of possible risk and building a self-enriching knowledge base to better inform companies and their investors.

Liddy (2014) while addressing the increasing number of transactions and the shift from sample testing to complete transaction testing, emphasised a shift towards the identification and analysis of anomalies which is consistent with contemporary studies (Brown-Liburd et al. 2015, Capriotti 2014, Whitehouse 2014). Anomalies generally refer to instances of a mismatch between the data and auditors' expectations based on their knowledge of the business (Earley 2015). Anomalies are crucial red flags in predicting and subsequently detecting fraudulent activities. Importantly, data analytics has the potentials of enabling auditors to build a transferable database of knowledge about every audit engagement from year to year such that auditors can obtain an enhanced perspective of how previously identified anomalous transactions were resolved which will enable auditors in subsequent years to follow up with these cases as they develop their expectations (Liddy 2014).

Contemporary scholars agree that data analytics will enhance fraud detection in audits (Capriotti 2014; Gogtas et al. 2007, Gray & Debreceny 2014, McGinty 2014) by unmasking rounded numbers typically used by fraudsters (Nigrini 2018 O). For example, in November 2014, during a meeting of the Public Company Accounting Oversight Board's (PCAOB) Standing Advisory Group (SAG) where auditors' fraud detection responsibility was the focal point of three-panel discussions, the issue of how data analytics could be used to enhance fraud detection was explored between panellists and SAG members (PCAOB 2014). Generally, there was a unanimous agreement that data analytics is auspicious for fraud detection due to the availability of software that facilitates the analysis of large data sets efficiently and cost-effectively to audit firms (AICPA 2014). Similarly, KPMG (2015) concurs with this position by noting that "using D&A we make the analysis of the past more insightful. Rather than sampling transactions data to test a snapshot of activities, we can now analyse all transactions processed, allowing us to identify anomalies and drill down on the items that show the greatest potential of being high risk. Our systems automate this process, increasing its ability to produce high quality audit evidence". Consequently, auditors can potentially detect all fraud by making use of data analytics tools that facilitate the testing of all transactions and uncovering anomalous transactions that have the potentials of predicting fraudulent activities. Additionally, data analytics can facilitate the use of non-financial data (NFD) and external data to enhance the audit planning process especially risk assessment as well as to effectively audit issues requiring auditors' judgment, for example, going concern or valuation (Earley 2015).

Artificial Intelligence and Big Data and fraud prevention and detection

Artificial intelligence and data mining techniques can equally be implemented in the audit process to identify patterns from journal entries to uncover fraud (Debreceny & Gray 2010, PwC 2019). Also, machine learning, an application of artificial intelligence, could further facilitate the review of entire populations enabling auditors to test for items out of the norm (ACCA 2019). Artificial intelligence mechanisms are growingly capable of scanning keywords and identifying complex documents as well as extracting supporting data from sources such as; invoices, sales, and contracts (Agnew 2016) for subsequent substantive testing (Brennen et al. 2017). Thus, artificial intelligence mechanisms can facilitate the identification of potentially fraudulent transactions. For example, artificial intelligence tools can facilitate the detection of abnormally high sales values recorded before the end of the financial year, or unusually high payment values made after the end of the financial year (Rapoport 2016). Also, Machine learning could be used to facilitate risk assessment particularly "supervised learning algorithms can be used to help identify specific types or characteristics that warrant greater scrutiny; and improve targeting areas of focus for the audit." (ACCA 2019, p.20). Additionally, the backward and forward prediction nature of machine learning offers valuable opportunities for risk management, fraud detection, and uncovering inaccuracies through the comparison of historical data to current information thereby facilitating risk assessment (ACCA and CA ANZ 2019).

Further, an obvious use of big data is to detect fraud (EY 2014). Big data possesses rich data sources that facilitate the identification of potentially fraudulent activities. It is generally difficult for fraudsters to manipulate all upstream non-financial transactions to make up for financial statement fraud (Alles & Gray 2016). Besides, integrating big data as supplementary audit evidence aids in anomalies detection and fraud prediction which generally result in an increase in audit quality (Yoon et al. 2015). Broadly speaking, big data analytics has the potentials of reducing the number of false positives and uncovering important anomalies for further consideration (Issa & Kogan 2014, Cao et al. 2015). Since big data contents can generally be separated both physically and conceptually from accounting data, it is onerous for fraudsters to manipulate existing big data elements to whitewash fraud (Alles & Gray 2016). Also, Big data facilitates the analysis of an entire population with an increased probability for discovering red flags, suspicious outliers (Alles & Gray 2016), and patterns in a large data population almost impossible to detect in samples and smaller data sets (Alles 2013). It is worth noting that, under the current traditional audit paradigm, there is ample evidence highlighting that auditors are not adept in identifying patterns in both financial and non-financial data (Bierstaker et al. 1999; Asare et al. 2000). Therefore, Big data makes up for this loophole and facilitates the identification of patterns and areas susceptible to fraud.

Drones, Image Recognition and Robotic Process Automation and fraud prevention and detection

Additionally, the potentials of unmanned drones are currently being implemented by the big four audit firms for inventory inspection especially in cases where physical scale or distribution is a major issue (ACCA & CA ANZ 2019). Therefore, these unmanned drones can facilitate stock counts to confirm inventory balances reported in financial statements (PwC 2019) as well as uncovering inventory fraud. In the same manner, image recognition although not evident in accounting could facilitate the count of certain categories of inventories (Kokina & Davenport 2017). Cathy Engelbert, the then CEO of Deloitte LLC for examples speculated by noting;

> This might sound a little sci-fi to you, but drones could do physical inventory observations. Maybe you wouldn't have to send people out to look at that kind of thing. Take it one step further. We could use imaging technology to look at things like storage tanks and grain silos. We could use it for a variety of things as you look at the industrial internet of big things (Cohn 2016).

Therefore, image recognition facilitates the identification of any discrepancies between the recorded inventory and the actual inventory, thus enabling the detection of fraud and potential fraud-prone areas. Similarly, robotic process automation (RPA) can strengthen the value of audits by facilitating the testing of an entire revenue population enabling auditors to analyse the risk of revenue material misstatement (Moffit et al. 2018) thus facilitating fraud prevention and detection. It is worth noting that revenue is a high-risk area that is subject to frequent audits (Moffit et al. 2018). The Public Company Accounting Oversight Board (PCAOB) has consistently noted that revenue is subject to habitual audit deficiencies (PCAOB 2017). Therefore, RPA can be of immense significance to the audit profession by eliminating these lapses and evaluating potential material misstatements or fraud.

Issues and remedies of digital technologies in fraud prevention (estimation)

It should be noted that digital audit tools possess the inherent limitation of not being able to detect managements' intention to commit financial statement fraud. This results from the inability to automate management's intentions, motivations, opportunity, and the inability to rationalise fraud related to financial statements due to the fact that these assessments require social intelligence (Frey & Osborne 2013). However, hypothesis-based predictive analysis can be used to forecast the plausibility of financial events and malfeasance (Tschakert et al. 2016). Digitally advanced tools (such as data mining) and data analytics tools (such as predictive modelling) are effective tools in analysing and examining big data to determine fraud risks (Humpherys et al. 2011, Bochkay & Levine 2013). In general, fraud risk assessment and detection of fraud intentions entail an extensive knowledge of the client's business environment, operations, and motivations (Peecher et al. 2007). Consequently, the textual analysis of a company's disclosures and managements' conference call transcripts enables auditors to estimate the probability of misstatements and management fraud (Humpherys et al. 2011; Larcker & Zakolyukina 2012; Yoon et al. 2015). It should be underlined that the use of deceptive language by executives during conference calls can facilitate the identification of financial misstatements (Larcker & Zakolyukina 2012).

The ability of auditors to test entire data sets instead of samples is raising new expectations for auditing. For example, a participant of the ACCA and CA ANZ (2019) is quoted saying:

> I expect that my auditors will no longer test a sample of transactions, for example 100 items, and consider this to be sufficient evidence to form a conclusion for the entire population, when in fact we have tens of thousands of transactions coming in and out on a daily basis.

However, despite the promising nature of data analytics in testing complete data sets and rising expectations of users for auditors to perform a complete test of transactions, the International Auditing and Assurance Standard Board [IAASB] (2016) cautions that "Being able to test 100% of a population does not imply that the auditor is able to provide something more than reasonable assurance opinion or that the meaning of "reasonable assurance" changes." In effect, the IAASB is less likely to place more fraud responsibilities on auditors, although auditors will be able to perform a complete test on an entire data set during digital technologies.

4.2. Audit digitalization in relation to the soundness of internal controls

Digital technologies are transforming business models as well as control procedures, risk management, the overall control environment, and audits in general (PWC 2019). In this era of voluminous and complex data, digital technology and data analytics offers auditors with enormous opportunities of effectively and robustly understanding a client's business and environment, which further enhances auditors' risk assessment and response (IAASB 2016) about internal control. It should be stressed that a comprehensive and deeper insight by auditors into the auditee and its environment provides invaluable information to the auditee regarding its risk assessment and business operations (IAASB 2016) which is necessary for strengthening the auditee's system of internal control. Also, artificial intelligence is being used to monitor, visualise, and assess an entity's risk in real-time (PWC 2019) which is necessary to craft control measures to mitigate these risks. Furthermore, with machine learning, audit firms are "better able to identify unusual patterns and anomalies in huge amounts of data in an instant" (PWC 2017). It's worth mentioning that unusual patterns are not an indication of fraudulent circumstances, however, these could result in fraudulent situations. Therefore, the identification of these unusual circumstances and anomalies enables auditors to propose recommendations aimed and strengthening internal control systems.

Also, robotic process automation is being used by finance and operation departments to automate and improve controls (PWC 2019) thus reducing the risk of fraud.

Also, drones can be used to facilitate stocktaking especially in industries characterised by a large stock of inventories. PWC (2019) equally notes that drone technology offers tremendous benefits in enhancing internal controls in the construction industry where assets are constructed in a vast area. Drones typically facilitate the attainment of control objectives including; the verification, valuation, and keeps stock of the work in progress on projects. Drones can equally perform quick surveillance of a site to ensure compliance with health and safety measures. Additionally, drones can facilitate the achievement of operational objectives such as deterring employees from cutting corners as well as achieving a high quality of work (PwC 2019). Similarly, some face and voice recognition software could be implemented by audit clients prosaically to facilitate authorisation, separation of duties, and meta-controls (Issa et al. 2016).

Aspects of artificial intelligence such as Natural Language Processing (NLP) and algorithms (a component of machine learning) can perform scans of large text documents, check values, accuracy tests, and consistency with other documents (PwC 2019), thus strengthening internal control. Similarly, deep learning can be deployed in the audit process to perform a content analysis of news articles and social media postings which can potentially facilitate the identification of internal control risk, risk of management fraud, litigation risk, or business risk (Sun and Vasarhelyi 2018). Deep learning is equally efficient and effective in facilitating the extraction of sentiment scores which enables auditors to predict material weaknesses in internal control (Sun and Vasarhelyi 2018).

It's worth mentioning that auditors often implement the risk-based approach to facilitate the evaluation of the risk of material misstatement. Oftentimes, the assessment is done during the audit with a preliminary evaluation performed during the audit planning phase and on an ongoing basis during the internal control and substantive testing phases (Moffit et al. 2018). The ongoing risk assessment is usually performed on a review of sample transactions which are usually tested (PCAOB 2010). However, robotic process automation can facilitate the reconciliation (PwC 2019) and testing of an entire population of sales records which facilitates the effectiveness of internal controls and management's assertions (Moffit et al. 2018). It should be noted that testing a complete population facilitates the process of eliminating sampling and assess risks (Appelbaum et al. 2017). Robotic process automation will equally enable organisations to digitise error-prone manual processes and internal control with the potential of software bots, performing certain processes and control activities with enhanced reliability and at a lower cost (PwC 2019), hence enhancing the system of internal control. In this regard, a participant of the PwC (2019) survey is quoted saying "I believe that RPA will reduce the risk of human errors in internal controls as well as lessen the labour required for checking. Reducing human error will also improve data accuracy substantially." Therefore, the audit profession could consider encouraging audit clients to implement robotic process automation in their business processes which will further enhance internal controls.

Robotic process automation further has the potentials of documenting every step, process, and activity, thus, maintaining a complete digital audit trail (PwC 2019) which facilitates the auditor's task in evaluating a client's system of internal control. Similarly, blockchain technology can facilitate the integrity of records since transaction saved in blocks cannot be easily altered due to a mathematical formula which processes transaction contents and generates digital fingerprints for that (Kokina et al. 2017, PwC 2019). Therefore, blockchain technology can enhance the system of internal control and reduce the risk of fraud occurrence. Also, blockchains facilitate the establishment of complete audit trails and the review of exceptions originating from a population of transactions instead of from samples (Kokina et al. 2017). Moreover, blockchains can facilitate the authentication of transactions, the tracking of asset ownership, as well as the registration process, and inventory system of any type of asset (Baron 2017), which further enhances the internal control system of an entity and mitigates the risk of fraud occurrence. Therefore, audit digitalisation can make internal controls much more effective, efficient, and pervasive. Even fundamental automation can enhance internal controls by infusing some discipline in organising and standardising processes. However, for these digital tools to be effective, the processes and controls must be adequately designed (PwC 2019).

In summary, although under the prevailing sampled-based approach, ISA notes that although audits may be properly planned and performed (240:5), there is an unavoidable risk that some material misstatement may not be detected. We argue that using digital technology in the audit process will ultimately facilitate the process of fraud detection and will significantly serve as a deterrence (fraud prevention) mechanism for the occurrence of fraud considering the likelihood of all fraud being detected. We equally argue that systems of internal controls associated with this digital auditing technologies will easily identify fraudulent cases or anomalies, which will facilitate the implementation of control mechanisms to enhance internal controls.

4.3. Evolution Gap and Challenges of Audit digitalisation

Despite the promising nature of audit digitalisation in eliminating the never-ending expectation gap issue of auditors' responsibilities for fraud prevention, detection, and maintaining internal controls, there are numerous inevitable emerging new threats, risks, and challenges which the audit practice community will need to take into consideration.

A paradigm shift from the traditional audit-based approach to the digital audit paradigm will inadvertently result in an evolution gap due to technological advancement which will result in new expectations from financial statement users. However, the areas where the expectation gap will become prominent are not yet eminent. In general, auditors may face the expectation of validating and testing the reliability of data analytic tools (Appelbaum et al. 2017), robotic process automation (Moffit et al. 2018), as well as other digital technology tools which will be incorporated into the audit process. Also, auditors may be expected to learn how to implement their problem-driven approach to data analysis on larger data sets. Furthermore, financial statement users may expect auditors to develop competencies in analysing unstructured data sets that currently fall out of the purview of current auditing duties.

In dealing with these expectations, the audit practice community may need to be proactive by sourcing for solutions to these emergent expectation gaps and constraints before they become eminent. The audit industry must avoid falling into the old cycle of reputation loss and sourcing for measures to narrow this gap. Regarding risks, auditors may need to deal with new issues regarding cybersecurity, information security, and data privacy risks which prevailing internal control systems were not designed to address. The audit industry may equally have to deal with ethical concerns such as how to responsibly use these digital technologies and the permissible use of data. To mitigate these risks, it is imperative for the audit practice community to strike a balance between these digital audit innovations with enhanced safety and security. Although an armoury of apparatus has been deployed to combat fraud, fraudsters have equally refined their mechanisms. Therefore, the audit profession will need to be alert and take pre-emptive measures to mitigate the risk regarding those who use the benefits of digitalisation for nefarious reasons which undermine and target businesses.

In transitioning from traditional audits with samples to digital audits, the audit profession will incur a huge cost in training professionals in obtaining the relevant expertise to use these digital audit tools such as text mining, statistical software appropriate for unstructured data. Also, auditors will equally need to develop skills that will enable them to recognise patterns and analyse anomalies which have so far not been the focus of the current traditional audit paradigm (Earley 2015).

5. Conclusion

At both the theoretical and normative levels, it seems logical that the audit profession will transition from traditional audits to digital audits due to the frantic pace of digitalisation. However, the impact of this transition on the audit profession has not been fully investigated. In view of this, the present study sought to conceptually examine how a paradigm shift from traditional audits with samples to digital audits with full audits will impact critical and recurring issues of the audit expectation gap.

In line with the two research questions posed, our analysis reveals that digital platforms such as data analytics systems supported by machine learning can facilitate the identification of anomalies in data which can be further investigated manually by auditors. Also, big data can be implemented in the audit process to interrogate one hundred percent of journal entries, transactions, as well as unstructured data enabling auditors to focus on transactions displaying unusual patterns identified through artificial intelligence, unlike the limited traditional approach with random sampling testing. Furthermore, drones can facilitate stock counts, compliance, and the attainment of operational objectives. In summary, existing extant literature and commentaries from the audit profession highlight the significance of audit digitalisation in enhancing internal controls and facilitating the prevention and detection of fraud.

While our analysis does not expressively affirm that audit digitalisation will result in auditors preventing and detecting all fraud and maintaining internal controls, our analysis, however, highlights the important role of these digital platforms in facilitating fraud prevention and detection and in enhancing internal controls. Although these digital technologies can be implemented to facilitate the prevention and detection of fraud and enhancing internal controls, auditors' professional scepticism and judgment are required in the actual process of fraud risk assessment and fraud detection as well as the evaluation of the robustness of internal controls. We, therefore, argue that a paradigm shift from the traditional audit methodologies of samples to digital audits of complete transaction analysis is a potential game-changer that will likely result in the elimination of the two critical areas (fraud prevention and detection, and internal controls) of the expectation gap, while there is a likelihood for the emergence of new gaps resulting from the digitalisation of the audit process. Therefore, it is peremptory for the audit profession to take the necessary steps to eliminate these potential gaps before they surface.

Despite the promising nature, a plethora of opportunities, profound impact of digital technologies in enhancing audits, the audit profession has been slow in adopting these digital technologies in the audit process (Katz 2014; Whitehouse 2014). It is worth noting that one of the greatest possible risk confronting the audit profession is the slow implementation of big data (Griffin & Wright 2015) and other digital technologies in the audit process. The slow pace of adoption of these digital technologies partially results from the highly regulated nature of the audit industry (Issa et al. 2016). Audit clients are increasingly expecting auditors to use data analytics (IAASB 2016) and other digital technologies in the audit process which explains why these platforms are yet to be enforced to market expectations (FRC 2017). The International Standards on Auditing do not forbid nor trigger the use of data analytics (IAASB 2016) and other digital auditing technologies in the audit process. However, considering the rule-based nature of the audit profession, it is unlikely that auditors will adopt these digital platforms without encouragement from audit regulatory bodies. Hence, audit regulatory bodies may need to be more active and engaged in encouraging and facilitating the implementation of these digital tools through digital auditing standards.

In a nutshell, we argue that digitalisation offers tremendous opportunities for narrowing and eventually closing the expectation gap concerning the never-ending issues of fraud prevention and detection and auditors' responsibility for maintaining internal control. However, the audit industry needs to be cautious of some of the misrepresentations and false positives of the impact of digitalisation on auditing. We echo the recommendation of Alles and Gray (2016) who underscore the need for a formal theory for guidance as a countermeasure to these misrepresentations and false positives. To regain the already decimated reputation and credibility of the audit profession resulting from the persistence of the expectation gap, the audit profession needs to adopt digital audit technologies to narrow the expectation gap while being cautious of potential emerging areas of the gap and false positives of audit digitalisation. Hence, a paradigm shift from traditional audits to digital audits is a step in the right direction to eliminating critical expectation gap issues of auditors' responsibilities in fraud prevention and detection and the maintenance of internal control. Therefore, we assert that with the potentials of narrowing critical issues of the expectation gap, audit digitalisation can facilitate the audit profession to regain the already decimated trust and confidence of the public thus, enhancing users' perception of the value of audits and audit quality.

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