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The Impact of Using Data Analytics in the Audit Process on the Audit Report lag: Evidence from Egypt

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A B S T R A C T

This research aims to study and test the impact of the auditor's using of data analytics (DA) on the audit report lag (ARL) in the professional practice environment. Data was obtained from a sample of companies listed on the Egyptian Stock Exchange. The COVID-19 pandemic has exposed the accounting profession to new dangers, difficulties, and significant concerns that have an impact on audit efficiency. This paper uses an empirical research method to test the hypotheses. A difference-in-difference (DID) design will be used to predict the influence of DA on the dependent variable. The results suggest that DA has significant effect on audit report lag. Because of the data analytics tools work to meet the needs of the auditors in obtaining accurate information in a timely manner that is characterized by reliability. Also, the results found that the Control variable leverage is positively impacts the audit report lag ARL.

1. INTRODUCTION

Developments in technology have made it possible for auditors to employ data analytic tools more frequently. These advancements have made it easier to create more complex data analytics tools, which enhance auditors' abilities in a number of ways, including assessing the population and locating all outliers (deviations) in accordance with applicable criteria (Barr-Pulliam et al. 2022). Predictive modelling and the analysis of unstructured, non-traditional data, such texts and videos, are applications for data analytics. By incorporating data analytics into the audit process, auditors will be able to shift their focus from labor-intensive activities to those that call for more professional judgment. Testing the population is now feasible and may be a potential solution to problems with audit sampling as a result of the development of data analytics and machine learning. Through the idea of "exception auditing" which allow auditors to utilize data analytics to discover odd or out-of-the-ordinary transactions and prioritize them for the audit process, The population as a whole is put to the test, As a result, the auditing procedure can be made more effective and efficient(Botez, 2018).

Audit processes often include an examination of client’s assertions that use big data and analytics to stay competitive and relevant in today's business environment. Additionally, many clients are now integrating big data with new and complex analytical methodologies to make decisions (Kend & Nguyen, 2022). In 2020, Amazon delivered nearly 4.2 billion packages in the United States, which is equivalent to more than 11 million packages per day. These transactions represent a significant portion of Amazon's revenue, and shipping costs are one of Amazon's most substantial expenses. Now, imagine the audit team attempting to perform an Audit process on 4.2 billion transactions delivered across the United States. Given the large number of transactions, the most feasible way to conduct audit procedures is to examine a sample of transactions (i.e., audit sampling) (Huang et al., 2022).Data analytics (DA) has the potential to transform the audit process by enhancing the quality and efficiency of audit procedures. Traditionally, the audit process relied heavily on manual sampling and testing of data to identify potential errors or irregularities. However, with the increased availability of data and technological advancements, auditors can now use data analytics tools and techniques to analyze large amounts of data quickly and effectively (Koreff, 2022).

Data analytics (DA) also provides an opportunity to maximize human efficiency. For example, technological solutions can reduce the amount of time spent on manual analysis, allowing auditors to spend more time on the most important aspects of analysis. Additionally, data analytics increases automation in the audit process, allowing auditors to focus on performing basic audit procedures and addressing the most complex and risky areas of the audit (Lombardi et al., 2014). The audit report lag (ARL) refers to the length of time that auditors spend analyzing the financial statements or the days between the accounting period’s conclusion and the date the independent auditor's report. According to past research, the consequences of the delay in audit reports are what give ARL its significance. The ARL is a crucial component of the audit results, and a short audit report lag (ARL) indicates audit effectiveness. A timely audit report improves information symmetry as well (Bajary, 2023).

The remainder of this paper is organized as follows. Section 2 outlines prior research on audit report lag (ARL) and Data analytics (DA).Then developing the Main hypothesis for the study. Section 3 includes the description of the research methods. Section 4 presents the empirical results of this study. Section 5 presents additional tests and the results. Section 6 presents a discussion of results and draw inferences and conclusions. Section 7 concludes and suggests areas for future research and include a research limitation.

2. LITERATURE REVIEW

2.1.Audit Report Lag (ARL):

After an exhaustive search of studies dealing with the audit report lag (Abdillah et al., 2019; Abernathy et al., 2017; Mitra et al., 2015; Knechel & Sharma, 2012), we can say that (ARL) is one of the most important metrics for the efficiency of the audit process. The timing of the audit report may provide insights into the efficiency of the audit process, as more efficient auditors are likely to perform audits in a timely manner. According to a study by MohammadRezaei and Mohd- Saleh (2018), when the audit market is more competitive, price pressures and costs can lead to increased audit efficiency, thereby reducing the audit report lag (ARL).The literature suggests that the audit report lag (ARL) varies depending on several factors, including the size of the audit firm, Big 4 versus non-Big 4 auditors, industry specialists versus non-specialist auditors. Big audit firms have a better opportunity to attract skilled employees and deploy these resources for training, using more powerful techniques, and therefore reducing audit work time. Moreover, the Big 4 audit firms have a competitive advantage in terms of resources, technology, and expertise, which can potentially lead to a reduction in the audit report lag compared to non-Big 4 auditors. According to Habib (2011), Industry specialists are also expected to have a better understanding of the complexities and risks of a particular industry, which can lead to a more efficient audit process and a shorter audit report lag.

Indeed, the busy season for audit firms is an important factor that affects the audit report lag (ARL). Many US public companies have fiscal year-ends in December, and their accounts are audited in the early months of the new calendar year. This creates significant pressure on audit firms during this time when they must perform many audit engagements within a short period of time. These pressures can result in resource constraints within audit firms and delays in issuing audit reports. Therefore, the issuance of the audit report may be postponed to a later time in the calendar year (Durand, 2019).

Audit report lag varies based on affiliation, for example, Big 4 versus non-Big 4 auditors, and industry specialists versus non-specialist auditors. Big audit firms have a better opportunity to attract skilled staff, deploy these resources for training, use more powerful techniques, and thus reduce audit time. On the other hand, big audit firms are more independent and thus more likely to resist client pressure in case of audit-related conflicts compared to smaller audit firms. Negotiating with clients takes time, and big audit firms are more likely to negotiate. Big audit firms are more cautious and carry out relatively more comprehensive audit procedures for a specific client because they have more to lose in lawsuits, thus increasing delay in audit report lag. (Habib et al., 2019)

Durand (2019) stated that, the audit report lag (ARL) is affected by various factors, including the complexity of the audit client's operations. When a company has more business segments and operates in multiple industries, the audit process becomes more complex and time-consuming, which can lead to a longer (ARL). A study by Abernathy et al (2017) pointed out that larger companies have shorter ARL, because they have access to more resources and have implemented better internal control systems, which reduces (ARL). On the other hand, companies that operate in industries with simple business models and fewer subsidiaries are likely to have a shorter (ARL). Furthermore, some industries, such as high-tech and financial services, are subject to more regulatory requirements and scrutiny, which can lead to a shorter (ARL) due to the need for timely reporting. In contrast, companies operating in industries with high litigation risk may require more detailed audit procedures, which can lead to a longer ARL. Overall, the complexity of the audit client's operations is a significant factor in determining the (ARL). The study by Chan et al (2016) discovered that the presence of extraordinary items raises audit complexity is positively correlated with audit reporting lag. In order to reduce any confusion or disagreement with management, auditors must perform more audit processes for transactions that are more complicated. For sophisticated audits, auditors must also fulfil more auditing standards, which results in a lengthier (ARL).

Basically, the importance of reducing audit report delay agrees with the theory of legitimacy, it stated that organizations will work efficient to ensure that they operate within social boundaries and norm. The company will try to gain confidence from the public in regard to the business activities being legal and legitimacy from the community is needed by the company because this is a supporting factor for the company's sustainability (Ginting & Hidayat, 2019).

In Egypt, according to Companies Law No. 159 of 1981 and Capital Market Law No. 95 of 1992, and article (46) of EGX rules of listing and delisting securities issued by the Financial Regulatory Authority (FRA), all listed firms on the EGX are required to publish their annual financial reports with a maximum of three months from the fiscal year.

2.2.Data Analytics (DA):

Big data refers to the vast amount of structured, semi-structured, and unstructured data that is so large that it is extremely difficult to process using traditional data processing techniques. Big data consists of very large datasets that can be analyzed using emerging technologies to uncover patterns, trends, and relationships among the data (Salijeni et al., 2019). A study by Anuradha in 2015 suggested that big data has five main characteristics: volume, velocity, variety, value, and veracity. Dealing with data of large volume, high velocity, and diverse types, whether structured or unstructured, requires the availability of the veracity element in that data to ensure reliability. This is essential to rely on the data in discovering different relationships and patterns. The term "big data" refers to a large volume of data, while "analytics" refers to the application of mathematical and statistical tools to a set of data to discover new patterns and relationships. These two terms have been combined into "big data analytics" to represent various advanced digital technologies developed to identify hidden patterns of information within large datasets (Wook et al., 2021).

Data analytics (DA) can be defined as the process of examining, filtering, transforming, and modeling big data to discover and communicate useful information and patterns, suggest conclusions, and support decision-making (Bender, 2017), also defined by AICPA (2017) as the science and art of pattern discovery, analysis, and anomaly identification and extract other useful information in the data through analysis, modeling and visualization. Data analytics (DA) refers to examining, cleaning, transforming, and modeling big data to identify and communicate valuable information and patterns, proposing conclusions, and supporting decision-making. Accordingly, computerized tools will allow patterns and anomalies in large and unstructured datasets to be identified, allowing the discovery of concealed information. Many domains of business are already utilizing data analysis (Hezam et al., 2023.p2). With the increasing adoption of information technology systems over the past three decades, technology has become increasingly important in obtaining audit evidence. One of the most important technologies in this regard is data analytics (DA), where all the technologies that are part of it are related to processing and analyzing data that differs from traditional audit procedures. Audit efficiency can be improved through the automation of audit procedures, and audit effectiveness can be increased by relying on data analytics (DA) technology to analyze the audit client's data. This allows for a more comprehensive view of the audit client's business operations, identification of related risks, and verification of the integrity of financial statements (Krieger et al., 2021).

The contingency theory is widely used in management research to explain the intentions of audit firms in using data analytics (DA). Given the complexity and dynamism of the audit process, there are various external and internal factors that affect the performance of the audit process to comply with accounting and auditing standards, regulations, and relevant laws. This theory seeks to understand how firms align their expected performance with the internal and external business environment. (Dagilienė & Klovienė , 2019) . In addition, the contingency theory suggests that the adoption of data analytics by audit firms is influenced by external factors, such as the level of competition in the audit market, the regulatory environment, and the availability of technological resources. Internal factors, such as the firm's culture, structure, and leadership, also play a significant role in shaping the firm's intentions to adopt data analytics.

The importance of using data analytics (DA) in the audit process stems from the emergence of big data, where big data is considered a complementary source of audit evidence (Gepp et al., 2018). While big data and data analytics are independent concepts, they can be interrelated. For many years, accounting and auditing firms have been using traditional data analysis tools (such as Excel or ACL) to analyze samples of data or accounting transactions. However, those firms began to move away from sampling (i.e., auditing 100% of transactions) and started using more advanced data analytics (DA) tools such as Tableau software (Alles & Gray, 2016).

Many studies (Eilifsen et al., 2020; Barr-Pulliam et al., 2017; Earley, 2015) agree that using data analytics (DA) improves the efficiency of the audit process. The increasing use of DA in the audit process will improve efficiency in several ways. New advanced technologies like DA allow for testing the population (transactions) in its entirety, instead of sampling, providing auditors with more certainty and accuracy about transactions and more evidence regarding internal control deficiencies. Furthermore, (DA) can highlight any transactions that deviate from the standard process.

Operations theory is the theory that describes the activities within the process and the organizational units within which those activities occur. It also describes how the process of adoption is affected by technological, organizational and environmental factors. Thus, it describes how something happens and the factors influencing it. According to the study of Krieger et al (2021), the theory of operations focuses on developing the use of data analytics (DA) across different organizational units that operate in the field of external audit, as it adopts data analytics techniques (DA) in practice through six activities represented in the following: ideation, evaluation, solution building, commitment of resources, deployment, and operational use), where the first four activities are related to the solution development process, while the last two are related to the solution development process deploy solutions in operational use.

Socio-Technical Systems Theory combines institutional theory, which explains how organizations change to adopt new technologies, with sociology to understand how organizations and societies influence the diffusion of technologies. This theory (ST) is also used to examine how the dissemination and use of data analytics occurs through a number of interactions between management, auditors and technology. The financial reporting environment includes social groups, such as managers and auditors, and regulations and laws. Managers and auditors form separate social groups because the members of each group share norms, standards, beliefs, and goals. The theory also suggests that technology is not static and does not evolve in isolation, it is an iterative process that involves dynamic interactions, and that technologies such as data analytics continue to evolve and spread over time; Because they interact with social norms and groups, whose needs continue to change (Austin et al., 2021).

As applied to the field of external auditing, there is a desire of auditors to connect directly and continuously with clients' systems to extract client data and load it into data analytics (DA) software, in order to increase the efficiency of the audit process. However, clients are not comfortable with auditors having access complete to their own systems and they are concerned about privacy and data security. Therefore, continuous co-evolution is necessary so that technology can be improved to meet customer interests, rules can be established to improve data security, so customers can become more comfortable with technology. It has been confirmed that data analytics has the ability to enhance audit quality. However, numerous obstacles to the widespread application of data analytics on audits have been noted. The research demonstrates that these issues are related to auditors' training and experience, data accessibility, relevance, and integrity, as well as regulatory requirements and financial statement users' expectations. Data destruction may be the biggest obstacle to employing data analytics in auditing. While screening the data or during any cyber-attack, the auditor could lose it. Another difficulty for an auditor is losing their job because everything will be automatic, including recording, regulating, and auditing data (Hezam et al., 2023).

2.3. Audit Report Lag and Data Analytics:

The emergence of the era of audit using data analytics (DA) has led to changes in the way the audit process is conducted. The constantly increasing complexity of business operations, corporate governance reform, risk management, global competition, and the growing demand for high-quality financial and non-financial reports require technology to update financial reporting processes. Data analytics (DA) in auditing is defined as the science and art of discovering and analyzing patterns, identifying outliers, and extracting other useful information in basic or audit-related data through analysis, modeling, and visualization for planning or performance purposes. In other words, data analytics (DA) allows auditors to use data to gain insights and make informed decisions in the audit process. It has become an essential tool for auditors to improve the efficiency and effectiveness of the audit process and to provide high-quality financial and non-financial reports to stakeholders (Ibrahim & Abdou, 2022).

The time used for performing manual testing can be better spent on audit functions with materiality. Due to human error, manual testing also involves some uncertainty and due to fatigue during testing, the auditor may switch up the invoice or the payment, which could result in further process delays. Taking longer time to complete the audit usually reflects that more work is required due to problems identified by the auditor, or higher assessments of inherent and/or control risk for the client. The auditors communicate low annual report readability by including additional language in their audit reports (Blanco et al., 2021). It is expected that the use of data analytics (DA) will have an impact on the efficiency of the audit process by reducing the audit report lag (ARL). This is accomplished by the ability to handle and process large amounts of data for analysis according to different criteria, and preparing various working papers within the file to perform audit process. Auditors can also use data analytics (DA) to download large financial transaction volumes for the audit client by connecting to data and information systems during the audit period, to assist in scoping and testing during the audit process.

In conclusion, the researcher finds that the audit report lag (ARL) is one of the most important indicators for the efficiency of the audit process from the perspective of stakeholders. Auditors present and convey their opinion on the accuracy and fairness of the financial statements in their report, and providing financial statements and audit reports to stakeholders in a timely manner is essential to maintain the relevance of the information in the financial statements. Delays in delivering financial statements and audit reports will cause the information in the financial statements to lose its ability to influence user decisions. With the use of data analytics (DA), auditors are able to complete the audit process faster and accomplish audit tasks within the agreed-upon timeframe. The period required to prepare financial reports reflects on the performance of the audit process, and rushing that period may negatively affect the efficiency and effectiveness of the audit process due to an increased workload. Therefore, it can be assumed that the use of data analytics (DA) in auditing can help reduce the audit report lag (ARL) and improve the overall efficiency of the audit process. Then the following hypothesis is developed:

H1: The auditor's using of data analytics has significant effect on the audit report lag for companies listed on the Egyptian Stock Exchange

3. MATERIALS AND METHODS

3.1.Data and Sampling Procedures

We obtain our data from the financial statements of companies listed on the Egyptian Stock Exchange and published on the Egyptian Stock Exchange website and Mubasher Egypt website. The research population involves all non-financial firms listed on the EGX, as banks and financial firms have their unique characteristics and different operations, which might require special audit efforts. The researcher relied on hand-collected data from financial statements of 30 non-financial publicly traded companies over a period of 5 years from 2018 to 2022 to reach the final sample. This process results in a final sample of 150 firm- year observations. The appendix A contains a list of the companies by their sector.

3.2.Research Model:

This study aims to test the main hypothesis of the research, as well as the relationship between the using of data analytics in the audit process by the auditor and the audit report lag, Also, the impact of the control variables on the dependent variable (ARL). This paper uses an empirical research method to test the hypotheses. A difference-in-difference (DID) design will be used to predict the influence of data analytics (DA) on the dependent variable. DID is a statistical technique which mimics an experimental research using observational data. A difference-in-difference (DID) calculate the effect of a treatment on an outcome, by comparing the average change over time for the treatment group with the control group (Bender, 2017).

$$\text{ARL} = \alpha + \beta 1 DAt + \beta 2\text{POST}t + \beta 3 DA\text{XPOST}t + \beta 4\text{frimsizet} + \beta 5\text{Loset} + \beta 6\text{Levt} + \varepsilon t \qquad (1)$$

The audit report lag (ARL) is measured as the number of days from the date of the end of the fiscal year until the date of the auditor signing his report. The auditor's use of data analytics is representing the variable of interest, it was measured as a dummy variable equal to (1) if the auditor's Office in partnership with Big audit firms, and zero otherwise. The variable data analytics (DA) explains the mean difference between treatment group and control group prior to the implementation of data analytics (DA). The effect of POST is measures by $\beta 2$, which describes changes in the control group after the implementation of data analytics (DA), the variable of interest in the regressions in DAXPOST. This variable measures the effect of data analytics (DA) after its implementation in the audit. If there exists a difference between the control and treatment group which is applicable to data analytics (DA) it will be captured by DAXPOST. The model is then improved by include control variables that can influence how the regression findings of the simple models come out.

The other elements serve as control variables to take into consideration. The first control variable (Lose) is a dummy for the result of the company's fiscal year, whether profit or loss. In the case of a loss, the value is taken as 1 and the value as zero in the case of a profit. The second control variable is (frim size), it measures by logarithmic of total assets. The third control variable is leverage (Lev). It measures the risk of non-payment of a company by dividing liabilities by total assets. It is expected that auditor will find it difficult to finish signing the report for the larger firms, with losses and more liabilities.

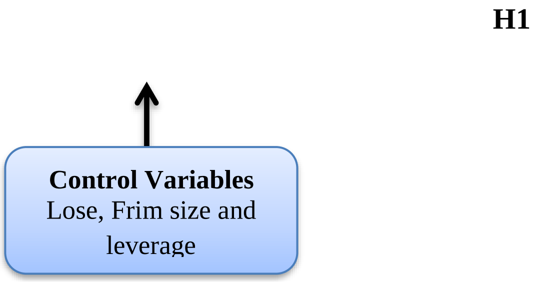

Figure 1: The Research Model

4. Empirical Results

4.1. Descriptive Statistics:

The descriptive statistics can be found in table (1), which involves 150 firm-year observations. It presents the summary statistics for variables of interest in Panel A and control variables in Panel B. As reported in Panel A, the variable audit report lag (ARL) has the mean value of 71.57 day; standard deviation is 29.059, with a minimum of 33 and maximum of 269, which is measured by the number of days from the date of the end of the fiscal year until the date of the auditor signing his report, indicating that the average period for the auditor to sign the audit report is 72 days for the sample companies. The variable data analytics (DA) is a dummy variable that takes the value (1) or (0). Table (1) shows that the mean of this variable is 0.49 and the standard deviation is 0.501, which means that around 49% of the sample used data analytics tools (74 firm-year observations), and 51 % of the sample did not used data analytics tools. In Panel B, the mean value of the variable (Lose) is 0.33, indicating that 33% of firm-year observations are made a loss and 67 % of the firms of the sample were making profits. The average of the variable (frim size) is 8.9152 and its standard deviation is 0.82785.

Table 1

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Panel A: Variables of interest					
ARL	150	33	269	71.57	29.059
DA	150	0	1	.49	.501
POST	150	0	1	.60	.492
DAXPOST	150	0	1	.31	.465
Panel B: Control variable					
Lose	150	0	1	.33	.473
Frim size	150	7.47	11.06	8.9152	.82785
Lev	150	.01	3.18	.5185	.34546
Valid N (listwise)	150				

4.2. Pearson Correlations:

Table (2) shows the Pearson correlations among variables, the correlations matrix shows that the variable audit report lag (ARL) is positively and significantly associated with (DA) at 1 % significance level (Pearson correlation = 0.318). It suggesting that the audit report lag is related to the use of data analytics techniques, which may lead to an increase or decrease in the timing of the audit process. Consistently, Pearson correlation matrix shows that the variable audit report lag (ARL) is positively and significantly associated with the variable (Lose) at 1 % significance level (Pearson correlation = 0.287), indicating that audit delay will increase in case of making a loss. The variable audit report lag (ARL) is positively and significantly associated with the variable (Lev) at 1 % significance level

(Pearson correlation = 0.290), As well, indicates the larger firms are likely to take more time for audit process because of its size.

Table 2

Correlations

		ARL	DA	POST	DAXPOST	Lose	Frim size	Lev
ARL	Pearson Correlation	1	.318**	-.160	.059	-.020	.287**	.290**
	Sig. (2-tailed)		.000	.051	.471	.806	.000	.000
DA	Pearson Correlation	.318**	1	.087	.694**	-.066	.507**	.291**
	Sig. (2-tailed)	.000		.289	.000	.422	.000	.000
POST	Pearson Correlation	-.160	.087	1	.552**	.029	.022	.048
	Sig. (2-tailed)	.051	.289		.000	.726	.793	.561
DAXPOST	Pearson Correlation	.059	.694**	.552**	1	.010	.321**	.189*
	Sig. (2-tailed)	.471	.000	.000		.902	.000	.021
Lose	Pearson Correlation	-.020	-.066	.029	.010	1	-.262**	.155
	Sig. (2-tailed)	.806	.422	.726	.902		.001	.058
	N	150	150	150	150	150	150	150
Frim size	Pearson Correlation	.287**	.507**	.022	.321**	-.262**	1	.322**
	Sig. (2-tailed)	.000	.000	.793	.000	.001		.000
Lev	Pearson Correlation	.290**	.291**	.048	.189*	.155	.322**	1
	Sig. (2-tailed)	.000	.000	.561	.021	.058	.000	

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

4.3.Hypotheses Testing:

To test the first research hypothesis (H1), which predicts that The auditor's using of data analytics has significant effect on the audit report lag, the author ran the first simple regression model (Model 1) using SPSS v23 on the research sample (150 firm-year observations) . The results of the regression for the first model can be found in table (3). The regression measures the effect of time before and after the application of data analytics (DA) on the audit for treatment firms. In table 3 the variable POST, which is a dummy for the time data analytics (DA) was implemented. It has an insignificant value. This result describes that for the treatment group there is no significant effect in time which changed the amount of audit hours before and after the implementation of DA for the treatment group. The variable DAXPOST in this regression captures the effect of data analytics (DA) on the audit report lag (ARL). As can been seen in table 3, variable DAXPOST has significant value. Therefore the results suggest that DA has an effect on audit report lag. Thus, the findings support H1.

In table 4, the control variables which are added in this regression model are based on prior literature. In the new model, data analytics (DA) stays significant and the variable POST remain insignificant. After the control variables were included in the regression model, the DAXPOST variable became insignificant. When leverage increases, going-concern risks increase. This model results shows that leverage positively impacts the ARL. This means that when the leverage worsens, the ratio increases, the amount of audit hours increases as well.

Table 3

Coefficients[a]

Tests without cor	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Adjusted R2	Observations
	B	Std. Error	Beta				
1 (Constant)	64.765	4.632		13.983	.000**		
DA	28.774	7.036	.497	4.090	.000**	0.136	150
POST	-3.881	6.198	-.066	-.626	.532		
DAXPOST	-15.551	9.054	-.249	-1.718	.088*		

a. Dependent Variable: ARL

*,**,*** Indicate significance at 0.10, 0.05 and 0.01 levels, respectively

Table 4

Coefficients[a]

Tests with control variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Adjusted R2	Observations
	B	Std. Error	Beta				
1 (Constant)	23.694	28.207		.840	.402		
DA	21.303	7.507	.368	2.838	.005***		
POST	-4.693	6.082	-.079	-.772	.442	0.171	150
DAXPOST	-14.073	8.910	-.225	-1.579	.116		
Lose	.578	4.939	.009	.117	.907		
Frim size	4.061	3.278	.116	1.239	.217		
Lev	16.079	6.946	.191	2.315	.022**		

a. Dependent Variable: ARL

*,**,*** Indicate significance at 0.10, 0.05 and 0.01 levels, respectively

5. Additional Tests

5.1. Alternative measurement of audit report lag

Depending on the Alkebsee et al (2020), the audit report lag (ARL) is measured as the natural logarithm of the time between the firm's fiscal end year and the audit report date. The appendix B contains Table 6 shows the regression results and exposes that the results are not consistent with the main result. The variable DAXPOST has no significant value. Therefore the results suggest that DA has no effect on audit report lag Thus, the findings not support H1.

5.2. Alternative measurement of frim size

We re-measured the second control variable frim size, it measured by logarithmic of total revenues. The untabulated results support the regression model after the control variables were included, the

DAXPOST variable became insignificant and the control variables (Lose and frim size) are insignificant. Finally the third control variable (Lev) still significant.

6. DISCUSSION

Because of big data and data analytics, the way companies are currently audited has changed. Businesses and organizations use big data to enhance strategy creation and decision-making. A fundamental issue that external auditors and the accounting science in general must address is a lack of appropriate education. As technology develops further, new challenges will arise. Therefore, it is vital for theorists, accounting and auditing professionals, as well as educational bodies, to integrate advancements technology in the profession. The external auditors must develop techniques for managing Big Data more efficiently.

Our findings demonstrate that the acceptance of technological by using data analytics (DA) is ultimately dependent on the technology's used ability to reduce the time for audit process so that the auditors could finish his report in a short time to achieve efficient in their work. This study agree with prior studies that indicate to the point of view of auditors can finish the audit process more quickly and complete audit activities within the predetermined time period by using data analytics (DA) and the financial statement information will become useless for influencing user decisions if financial statements and audit reports are sent late. In our setting, our sample period begins in 2018 and ends in 2022; the spread of the pandemic mostly at the end of 2019 is accompanied by additional risks and challenges in accounting and auditing work. Accordingly, the auditors will be necessitated to consume much time to perform all these procedures; such time is called audit report lag (ARL). As a result, we can observe that the Corona pandemic may have had an impact throughout the current study's time frame, but this was not taken into account.

7. CONCLUSIONS

The aim of this study is to better understand the interaction between audit report lag and using of data analytics and how this DA technology may have started to become embedded into existing audit spaces. We navigate our findings through the theoretical lens of Operations theory and Socio-Technical Systems Theory. To help fill this gap in the auditing literature, the present study extends prior studies by investigating these perspectives on using of data analytics (DA). Also, whilst prior research studies convey how DA shapes the dynamics of the audit work, the present study sought to investigate more specific issues related to the impact of DA on audit by investigating issues such as the most important indicators for the efficiency of the audit process from the perspective of stakeholders by an essential tool for auditors to improve the efficiency of the audit process (audit report lag).

The authors of this paper applaud the IAASB for beginning measures to strengthen the auditing standard on "audit evidence" in the latter half of 2020. Our analysis demonstrates that such regulatory advice is essential to the proliferation of technology, especially data analytics techniques which is important to remember while debating changes to audit standard. Our study is the first attempt that explores the Impact of Using Data Analytics in the Audit Process on the Audit Report lag in Egypt and providing empirical evidence about that research point.

However, our study is subject to some limitations. Due to the unavailability of some data, we were not able to include other variables such as the auditor's experience and academic qualification which may have an effect on the audit delay. The second limitation is that the sample focuses on non-financial sector companies. Analysis of stakeholders' awareness of DA in audits may make for an intriguing area of future research. For new research into the effects of large technological shifts on the dynamics of auditing regulation, academics should think about adopting qualitative methodologies.

The researcher suggests that audit firms pay more attention to the role of data analytics (DA) in increasing the level of transparency and reducing the information risk in financial statements. It is important to know that delaying audit report may deprive the companies from sources of funds for their investment opportunities. Also, the researcher recommends the accounting departments in public departments to hold scientific conferences to concentrate on the importance of using data analytics (DA) and its role in increasing audit efficiency and arrange some sessions to discuss their role in resource allocation decisions in audit firms.

REFERENCES

Abdillah, M. R., Mardijuwono, A. W., & Habiburrochman, H. (2019). The effect of company characteristics and auditor characteristics to audit report lag. Asian Journal of Accounting

Research, 4(1), 129-144.
Abernathy, J. L., Barnes, M., Stefaniak, C., & Weisbarth, A. (2017). An international perspective on audit report lag: A synthesis of the literature and opportunities for future research. International Journal of Auditing, 21(1), 100-127.
Alkebsee, R. H., Habib, A., Huang, H. J., & Tian, G. (2022). The gender-diverse audit committee and audit report lag: Evidence from China. International Journal of Auditing, 26(2), 314-337.
Alles, M. G. (2015). Drivers of the use and facilitators and obstacles of the evolution of big data by the audit profession. Accounting Horizons, 29(2), 439-449.
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.
Anuradha, J. (2015). A brief introduction on Big Data 5Vs characteristics and Hadoop technology. Procedia computer science, 48, 319-324.
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.
Bajary, A. R., Shafie, R., & Ali, A. (2023). COVID-19 Pandemic, Internal Audit Function and Audit Report Lag: Evidence from Emerging economy. Cogent Business & Management, 10(1), 2178360.
Barr-Pulliam, D., Brazel, J. F., McCallen, J., & Walker, K. (2020). Data analytics and skeptical actions: The countervailing effects of false positives and consistent rewards for skepticism. Available at SSRN 3537180.
Barr-Pulliam, D., Brown-Liburd, H. L., & Sanderson, K. A. (2017). The effects of the internal control opinion and use of audit data analytics on perceptions of audit quality, assurance, and auditor negligence.AUDITING: A Journal of Practice & Theory, AJPT-19-64.
Bender, T. (2017). The effect of data analytics on audit efficiency. Erasmus School of Economics.
Blanco, B., Coram, P., Dhole, S., & Kent, P. (2021). How do auditors respond to low annual report readability?. Journal of Accounting and Public Policy, 40(3), 106769.
Botez, D. (2018). Recent Challenge for Auditors: Using Data Analytics in the Audit of the Financial Statements. BRAIN. Broad Research in Artificial Intelligence and Neuroscience, 9(4), 61-71.
Chan, K. H., Luo, V. W., & Mo, P. L. (2016). Determinants and implications of long audit reporting lags: evidence from China. Accounting and Business Research, 46(2), 145-166.
Dagilienė, L., & Klovienė, L. (2019). Motivation to use big data and big data analytics in external auditing. Managerial Auditing Journal.٧٥٠-٧٨٢ ،(٧)٣٤ .
Durand, G. (2019). The determinants of audit report lag: a meta-analysis. Managerial Auditing Journal, 34(1), 44-75.
Earley, C. E. (2015). Data analytics in auditing: Opportunities and challenges. Business Horizons, 58(5), 493-500.
Eilifsen, A., Kinserdal, F., Messier, 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.
Gepp, A., Linnenluecke, M. K., 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, 102-115.
Ginting, C. U., & Hidayat, W. (2019). The effect of a fraudulent financial statement, firm size, profitability, and audit firm size on audit delay. International Journal of Innovation, Creativity and Change, 9(7), 323-341.

Habib, A. (2011). Audit firm industry specialization and audit outcomes: Insights from academic literature. Research in Accounting Regulation, 23(2), 114-129.
Habib, A., Bhuiyan, M. B. U., Huang, H. J., & Miah, M. S. (2019). Determinants of audit report lag: A meta-analysis. International journal of auditing, 23(1), 20-44.
Hezam, Y. A., Anthonysamy, L., & Suppiah, S. D. K. (2023). Big Data Analytics and Auditing: A Review and Synthesis of Literature. Emerging Science Journal, 7(2), 629-642.
Huang, F., No, W. G., Vasarhelyi, M. A., & Yan, Z. (2022). Audit Data Analytics, Machine Learning, and Full Population Testing. The Journal of Finance and Data Science.–١٣٨ ١٤٤http://www.keaipublishing.com/en/journals/jfds/
Ibrahim, M. S., & Abdou, R. M. (2022). Auditing New approach of Credit loss for Financial Institutions in The Audit Data Analytics Era: A field Study in Egypt. Journal of Contemporary Issues in Business and Government Vol, 28(04).
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), 269-282.
Knechel, W. R., & Sharma, D. S. (2012). Auditor-provided nonaudit services and audit effectiveness and efficiency: Evidence from pre-and post-SOX audit report lags. Auditing: A Journal of Practice & Theory, 31(4), 85-114.
Koreff, J. (2022). Are auditors' reliance on conclusions from data analytics impacted by different data analytic inputs?. Journal of Information Systems, 36(1), 19-37.

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, 100511.
Lombardi, D., Bloch, R., & Vasarhelyi, M. (2014). The future of audit. JISTEM-Journal of Information Systems and Technology Management, 11(1), 21-32.
Mitra, S., Song, H., & Yang, J. S. (2015). The effect of Auditing Standard No. 5 on audit report lags. Accounting Horizons, 29(3), 507-527.
MohammadRezaei, F., & Mohd- Saleh, N. (2018). Audit report lag: the role of auditor type and increased competition in the audit market. Accounting & Finance, 58(3), 885-920.
Salijeni, G., Samsonova-Taddei, A., & Turley, S. (2019). Big Data and changes in audit technology: contemplating a research agenda. Accounting and Business Research, 49(1), 95-119.
Wook, M., Hasbullah, N. A., Zainudin, N. M., Jabar, Z. Z. A., Ramli, S., Razali, N. A. M., & Yusop, N. M. M. (2021). Exploring big data traits and data quality dimensions for big data analytics application using partial least squares structural equation modelling. Journal of Big Data, 8(1), 1-15.

APPENDICES

Appendix A: Companies by their sector

Table 5

Sector	Firm-year observations
Real estate and Construction	**50**
Industrial	**35**

Food and Beverages	**30**
Chemicals	**25**
Basic Resources	**10**

Appendix B: Alternative measurements of audit report lag tests

Table 6

Coefficients[a]

Tests without co		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Adjusted R2	Observations
		B	Std. Error	Beta				
1	(Constant)	1.799	.023		78.897	.000**		
	DA	.125	.035	.442	3.622	.000**	0.126	150
	POST	-.028	.031	-.097	-.920	.359		
	DAXPOST	-.047	.045	-.154	-1.057	.292		

b. Dependent Variable: ARL

*,**,*** Indicate significance at 0.10, 0.05 and 0.01 levels, respectively