



LJMU Research Online

Al-Ateeq, B, Sawan, N, Al-Hajaya, K, Altarawneh, M and Al-Makhadmeh, A

Big data analytics in auditing and the consequences for audit quality: A study using the technology acceptance model (TAM)

<http://researchonline.ljmu.ac.uk/id/eprint/17750/>

Article

Citation (please note it is advisable to refer to the publisher's version if you intend to cite from this work)

Al-Ateeq, B, Sawan, N, Al-Hajaya, K, Altarawneh, M and Al-Makhadmeh, A (2022) Big data analytics in auditing and the consequences for audit quality: A study using the technology acceptance model (TAM). Corporate Governance and Organizational Behavior Review. 6 (1). pp. 64-78. ISSN

LJMU has developed **LJMU Research Online** for users to access the research output of the University more effectively. Copyright © and Moral Rights for the papers on this site are retained by the individual authors and/or other copyright owners. Users may download and/or print one copy of any article(s) in LJMU Research Online to facilitate their private study or for non-commercial research. You may not engage in further distribution of the material or use it for any profit-making activities or any commercial gain.

The version presented here may differ from the published version or from the version of the record. Please see the repository URL above for details on accessing the published version and note that access may require a subscription.

For more information please contact researchonline@ljmu.ac.uk

<http://researchonline.ljmu.ac.uk/>

BIG DATA ANALYTICS IN AUDITING AND THE CONSEQUENCES FOR AUDIT QUALITY: A STUDY USING THE TECHNOLOGY ACCEPTANCE MODEL (TAM)

Bara'ah Al-Ateeq^{*}, Nedal Sawan^{**}, Krayyem Al-Hajaya^{***},
Mohammad Altarawneh^{*}, Ahmad Al-Makhadmeh^{*}

^{*} Mu'tah University, Mu'tah, Jordan

^{**} Liverpool Business School, Liverpool John Moores University, Liverpool, the UK

^{***} Corresponding author, Mu'tah University, Mu'tah, Jordan

Contact details: Mu'tah University, P. O. Box 7, 61710 Mu'tah, Karak, Jordan



Abstract

How to cite this paper: Al-Ateeq, B., Sawan, N., Al-Hajaya, K., Altarawneh, M., & Al-Makhadmeh, A. (2022). Big data analytics in auditing and the consequences for audit quality: A study using the technology acceptance model (TAM). *Corporate Governance and Organizational Behavior Review*, 6(1), 64–78.

<https://doi.org/10.22495/cgobrv6i1p5>

Copyright © 2022 The Authors

This work is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0).
<https://creativecommons.org/licenses/by/4.0/>

ISSN Online: 2521-1889

ISSN Print: 2521-1870

Received: 23.09.2021

Accepted: 01.02.2022

JEL Classification: M4, M42, M48

DOI: 10.22495/cgobrv6i1p5

The study examines the impacts of using two dimensions of the technology acceptance model (TAM), perceived usefulness and perceived ease of use, on the adoption of big data analytics in auditing, and the subsequent impact on audit quality. Five hypotheses were developed. A questionnaire survey was undertaken with external affiliated audit companies and offices in Jordan. Eventually, 130 usable questionnaires were collected, representing a 72.22% response rate. Structural equation modelling (SEM) was employed for diagnosing the measurement model, and to test the hypotheses of the study. The study finds that perceived usefulness and perceived ease of use have a direct effect on audit quality, without mediating the actual use of data analytics. However, the use of big data analytics is shown to moderate the relationship between perceived usefulness and audit quality, but not between the perceived ease of use and audit quality. The study is one of the first to examine auditors' acceptance of big data analytics in their work and the impact of this acceptance and actual use on audit quality. It contributes to the existing literature in auditing through its application of SEM to examine the impact of big data analytics usage on audit quality by using the TAM.

Keywords: Audit Quality, Big Data, Big Data Analytics, Technology Acceptance Model

Authors' individual contribution: Conceptualization — B.A.-A. and K.A.-H.; Methodology — K.A.-H. and M.A.; Formal Analysis — B.A.-A. and N.S.; Writing — Original Draft — B.A.-A. and M.A.; Writing — Review & Editing — N.S. and K.A.-H.; Investigation — B.A.-A.; Funding Acquisition — N.S. and B.A.-A.; Visualization — N.S.; Supervision — A.A.-M.

Declaration of conflicting interests: The Authors declare that there is no conflict of interest.

1. INTRODUCTION

Currently, the world is experiencing an accelerating technological revolution, where information technology (IT) and electronic technologies are essential resources as important as their human and

material counterparts. The growth of IT in business is significantly increasing (Janvrin & Watson, 2017; Rezaee & Wang, 2017), with companies' incremental interest in IT, and their need to keep abreast of technological development and exploit IT to achieve their objectives.

The use of IT in the auditing field (e.g., computerised applications for auditing, continuous auditing, and big data analytics) is a contemporary issue emerging from auditors' awareness of the importance of technological tools in increasing the effectiveness and reliability of financial statements and thereby securing enhanced audit quality.

Twenty-five years ago, Sidek and Meng (1996) noted that with increased business size and complexity, the auditing profession has been faced with higher volumes of data of different types, and not surprisingly, this has led to auditors being involved in greater numbers of transactions. These researchers also noted that the challenges embodied in this change have highlighted the need to improve computer-based techniques to assist auditors and internal decision-making and that this has brought the requirement to improve auditors' skills in handling and auditing data from new geographically-distributed repositories (Sidek & Meng, 1996). That skill improvement has not generally been achieved, but as observed by Rezaee and Wang (2017), it may be accomplished by applying big data analytics in accounting and auditing. Earley (2015) notes that when auditors become skilled in using such analytics, their work becomes more reliable, reports more accurate, and overall better audit quality results.

Earley (2015) and Schneider, Dai, Diane, Ajayi, and Raschke (2015) argue that big data may influence auditing significantly and change the way auditors work. However, there is a potential risk associated with the use of big data as it requires the widespread use of large volumes of data in practice, education, and research (Griffin & Wright, 2015).

The large volume of data processed by audit firms has brought the need for data analytics techniques, which, according to the EY (2013) are transforming the audit process, and presenting certain challenges. The suggestion has been made that auditors should adopt computer-assisted auditing tools and techniques to improve audit efficiency and effectiveness, but audit firms usually find that auditors are unwilling to use new techniques like big data because, as noted by Gepp Linnenluecke, O'Neill, and Smith (2018), they are either unfamiliar with the techniques and have no appreciation of their usefulness, or indeed are untrained and unable to implement them. This promotes the need to focus on the personal attitudes of auditors towards the use of big data analytics, and this implies an understanding of the factors that might influence the use of big data analytics (Vasarhelyi & Romero, 2014; Vasarhelyi, Kogan, & Tuttle, 2015).

Consequently, the study employs the TAM as a vehicle for determining using users' attitudes, behavioural intention, and acceptance of new technologies and systems. This model can easily be applied in the context of the adoption of big data analytics, and therefore two of its dimensions are incorporated in the formulation of the following research questions:

RQ1: Does perceived usefulness influence the actual use of big data analytics?

RQ2: Does perceived ease of use influence the actual use of big data analytics?

RQ3: Does the usage of big data analytics have an impact on audit quality?

Given the discussion so far, it is seen that there is increasing attention to the factors affecting the use of big data and data analytics within the auditing function (Brown-Liburd, Issa, & Lombardi, 2015; Cao, Chychyla, & Stewart, 2015), yet to date, few studies have explored either the effect of perceived usefulness and ease of use on the auditor's attitude towards adopting big data analytics, or the impact of implementing big data analytics on audit quality, and this is especially the case in the developing country context. The current study attempts to address this shortcoming in the literature and investigates the extent to which auditors accept the use of big data analytics, using the dimensions of ease of use and usefulness to explore their attitudes. It then examines the effect of the actual use of big data analytics on audit quality.

The study findings are expected to make a substantial contribution to the contemporary auditing environment in four different ways. Firstly, they have importance to external auditors in providing them with an understanding of big data and an appreciation of its impact on the audit process. Secondly, they provide information about the TAM's perceived "usefulness" and "ease of use" dimensions that might encourage the acceptance of auditors in Jordan of big data analytics in their work, and potentially encourage other auditors in similar country contexts to do the same. Thirdly, the findings are helpful in creating awareness within audit companies of where they need to focus their attention to improve the usability of auditors of analytics provided by big data. And finally, the findings point to a reliable and validated model derived from the TAM that might function as a measurement tool relating to factors that might catalyse or hinder the personal use of big data analytics in auditing, and hence, be influential upon audit quality.

The remainder of this paper is structured as follows. Section 2 reviews the literature on audit quality and big data. It also presents a theoretical framework, hypotheses, variables, and models. Section 3 shows the research methodology, and Section 4 presents the analysis and findings from the data. Section 5 offers a discussion of the findings. Section 6 concludes the paper, providing a consideration of the study's contribution to academia and practice, the limitations of the study, and how these might be addressed in future research.

2. LITERATURE REVIEW

2.1. Audit quality and big data

Audit quality has yet to be universally defined and is thus difficult to measure since the definitions which have been advanced come from different perspectives and therefore vary in their expectations of what promotes quality (Rajgopal, Srinivasan, & Zheng, 2018; Masmoudi, 2021). As an example, high quality in the eyes of investors may be found in financial statements that do not contain material misstatements and that give due warning of any threats to investment (Carson et al., 2013), but from the viewpoint of regulators and other supervisory bodies, high quality might be associated with compliance with the standards set by those organisations, and when there is sufficient audit

evidence to support the opinions expressed by the auditors (United States Government Accountability Office [GAO], 2003; Velte & Loy, 2018); and there is also the perspective of audit professionals who believe that high quality is seen when due consideration has been given to the potential risks, and the audit plan has been constructed accordingly (Christensen, Glover, Omer, & Shelley, 2016; PwC, 2015).

Given these differing perspectives, audit quality has been measured by various proxies such as audit firm size, audit fees, provision of non-audit fees, auditor independence, industry expertise, differences across audit agents and countries (Francis, 2004; Francis, 2011; Christensen et al., 2016; Al-Hajaya, 2019). Two waves of interest in audit quality have been identified by Francis (2004), the first having its focus on firm size, and Big 4 firms, both of which were considered to be benchmarks of audit quality; and the second concentrating on industry expertise, differences across audit agents and countries as potential indicators where the Big 4 auditing firms are concerned. In an effort to design some model by which to test for audit quality, many researchers have constructed theoretical frameworks (e.g., Bedard, Johnstone, & Smith, 2010; Francis, 2011; Knechel, Krishnan, Pevzner, Shefchik, & Velury, 2013; DeFond & Zhang, 2014), but it has been suggested that these different models are overly-invested in discussing the elements of audit quality as opposed to innovating by considering the concept as something single and overarching (Christensen et al., 2016). Indeed, the components of audit inputs (e.g., expertise), outputs and opinions (e.g., restatements), audit processes (e.g., auditor judgments and work performed), and audit contexts (e.g., auditor tenure) are identified as separate entities all contributing to audit quality. In their attempt to consider the concept more holistically, Christensen et al. (2016) considered the opinions of both auditors and investors and presented a general audit quality framework comprised of audit inputs, processes, outputs and opinions, and post-opinion factors.

The auditing process is more effective, and hence, of better quality, if auditors can act independently, working and reporting objectively, free from influences from elsewhere in their organisations (Hosseiniakani, Inacio, & Mota, 2014). Likewise, if auditors have liability for their actions and accept their accountability to the regulators, audit quality is higher (Chung, Farrar, Puri, & Thorne, 2010). And professional competence may also have an impact on audit quality since this will affect an auditor's professional judgment (Hosseiniakani et al., 2014). All these aspects can be enhanced using big data analytics, which as defined by the Gartner website (<https://www.gartner.com/it-glossary/big-data/>), comprise data of high volume, velocity, and variety that require cost-effective, innovative forms of information processing to improve insight and decision-making.

The potential to change the way audits are conducted is noted by several researchers as being realised by the use of big data and analytics (BDA) techniques, which promote more efficient and effective audits (Krahl & Titera, 2015; Zhang, Yang, & Appelbaum, 2015; Arnold, 2018; Gepp et al., 2018). Using BDA allows for a broad range of tools

with relevance throughout the audit process (De Santis & D'Onza, 2021). Text-mining and sentiment analysis techniques are appropriate in the pre-engagement phase, to analyse various aspects of the media as a means of establishing a potential client's financial reputation and information about its key officers, e.g., CEO, CFO, and chair of the board (De Santis & D'Onza, 2021). At the same time, clustering techniques are helpful for the comparison of a potential client's financial statements with those from other companies in the same industry as a means of establishing the financial stability of an organisation (Rose, Rose, Sanderson, & Thibodeau, 2017; Appelbaum, Kogan, & Vasarhelyi, 2018). These BDA techniques are helpful in deciding whether or not to take on an audit contract, and what fee to charge. Moving to the planning phase, traditional analyses can be supported by clustering, descriptive analytics, and regression, which allow auditors to achieve a more detailed picture of the client's operation and thus gain more insight into risk and materiality thresholds (Cao et al., 2015; Earley, 2015).

There is also value in using BDA in respect of internal controls. For instance, compliance tests, such as a walkthrough, can be undertaken with process mining tools, thereby allowing auditors to establish non-compliance with segregation of duties controls or with other required procedures (Jans, Alles, & Vasarhelyi, 2013). BDA is also helpful in allowing greater scope in auditors' verifications (Dai & Vasarhelyi, 2016), as the techniques available allow for the simultaneous analysis and visualisation of all transactions within a given population rather than confining the process to one that looks only at samples of a population, hoping to identify anomalies for greater investigation. Furthermore, BDA supports comparisons of financial data with benchmarks and expectation models to establish whether inconsistencies exist (Stewart, 2015; Appelbaum et al., 2018).

Hence, it can be seen that BDA techniques complement traditional audit processes by providing opportunities for greater data-mining in a range of areas which thus supports auditors in their detection of accounting misstatements and corporate fraud (Moffitt & Vasarhelyi, 2013; Gray & Debreceeny, 2014; Cao et al., 2015; Yoon, Hoogduin, & Zhang, 2015).

Brown-Liburd et al. (2015) have indicated that while auditing standards provide auditors with guidance to complete their tasks, the audit process involves significant judgment about the type and amount of evidence collected. For example, based on Auditing Standard No. 1105 by the Public Company Accounting Oversight Board (PCAOB, 2010), audit evidence should be sufficient and appropriate; and this relies solely on the auditor's judgment, which creates the challenge for the auditing profession of how to extract value from big data and guarantee that audit judgments are based on quality information that is relevant and reliable (Brown-Liburd et al., 2015).

Earley (2015) and Lee (2017) have predicted that the use of big data is key to business survival and that organisations that cannot develop data analytics capabilities face a high probability of lagging behind their competitors in the future. Such capabilities increase the quantity and diversity of information, and this can improve the efficiency and

effectiveness of the auditors, helping to detect otherwise unknown patterns, and identifying high-risk areas that require constant monitoring (Brown-Liburd et al., 2015). Indeed, Russom (2011) observes the detection of fraud and quantification of risks as one of the top five benefits of analysing big data.

2.3. Prior research and hypotheses development

Previously, applied technology acceptance theories, such as the TAM and unified theory of acceptance and use of technology (UTAUT), have been used to understand auditors' behaviour. Kim, Mannino, and Nieschwietz (2009), for example, considered internal auditors' adoption of specific technology and extended the TAM by including technology features and complexity in addition to the traditional dimensions of perceived usefulness, and perceived ease of use. They found that path magnitudes were significantly changed by technology features and complexity. Perceived usefulness had more influence on feature acceptance when basic features were used, and perceived ease of use had more impact on feature acceptance when advanced features were used; as feature complexity increases, perceived ease of use decreases as consequently does system usage. Similarly, Uyar, Alnipak, and Guner (2015) employed the TAM to examine factors influencing auditors' adoption of IT, finding perceived usefulness and perceived ease of use to have a positive and statistically significant effect on IT usage, and perceived usefulness and the attitude towards usage to have a statistically significant effect on behaviour-oriented intention.

Janvrin, Lowe, and Bierstaker (2008) used the UTAUT model to explore auditor acceptance of computer-assisted audit techniques (CAATs), finding performance expectations, and facilitating conditions like organisational and technical infrastructure support to be influential in this respect. Likewise, Mansour (2016) used the UTAUT to investigate the absence of CAATs adoption in Jordan and the antecedents of this situation. He found the most important determinants of Jordanian external auditors' intentions to use CAATs technology to be performance expectancy, and facilitating conditions.

Big data and data analytics have been well researched, with scholars discussing big data concepts, applications, tools, and challenges. For example, Gandomi and Haider (2015) attempted to offer a broader definition of big data by integrating definitions from practitioners and academics, finding aspects such as velocity and variety to be as important as data size; and that the predictive analytics dealing with structured data overshadow the analytics applied to unstructured data. Additionally, the development of technology concerning storage and computations has enabled the cost-effective capture of the informational value of big data in suitable timeframes. Rodriguez-Mazahua et al. (2016), in their meta-analysis of the big data literature covering 2010–2014, identify the main challenges, areas of application, tools, and emergent trends of big data. They conclude the analysis to be the most important challenge for big data research because it is applied in all the areas of knowledge to gain insights into

the value of big data. They also determined the most popular frameworks and programming languages for big data applications.

Furthermore, Gepp et al. (2018) analyse the use of big data techniques in auditing in Australia. Initially, they introduced contemporary big data techniques to promote understanding of their potential application, showing that existing research extends across three other areas: financial distress modelling, financial fraud modelling, and stock market prediction and quantitative modelling. They subsequently concluded that auditing lags behind the other research streams in the use of valuable big data techniques.

Bender (2017) investigated the effect of data analytics (DA) on audit efficiency (measured by audit hours, audit costs, and billed costs). Their results indicate that data analytics did not improve audit efficiency since the audit hours, costs, and billed costs remained unaffected when data analytics were applied.

Likewise, Austin, Carpenter, Christ, and Nielson (2018) investigated the internal company use of data analytics focusing on the finance and accounting functions' preparation of financial statements, and fraud detection, and simultaneously also considered the use of data analytics by external auditors during their audits of those financial statements. They found that most companies and their auditors had made changes to the financial reporting and audit processes to incorporate data analytics, although there were differences in the manner in which data analytics were applied across audit firms. Furthermore, the challenges accompanying the use of data analytics previously mentioned were noted. Specifically, these related to finding employees with the right skill set, overcoming the financial cost, dealing with the lack of regulation, obtaining the data needed for analytics, and the lack of guidance and regulation around data analytics. The study also indicated that companies and their auditors view using data analytics as effective in improving financial statement misstatement and fraud detection capabilities. Finally, both clients and external auditors believe that the use of data analytics has strengthened their relationship.

Many studies have discussed audit quality and IT in the audit process in addition to the factors influencing audit quality. Mustapha and Lai (2017) highlight the use of IT by auditors at different levels and positions in audit firms in Malaysia, and influential factors in its use in the audit process, revealing IT to be widely used but mainly by the senior auditors and audit managers in their organisations. In addition, auditors were motivated to use IT in their work because of its time-saving and efficiency benefits.

In Turkey, Ada and Yardimcioğlu (2016) investigated and identified factors impacting the conduct of a quality independent audit. They found that the auditee, independent auditor, and legal regulations and institutions positively influence independent audit quality, while independent audit firm and IT use does not. The most influential factor on independent audit quality emerged as the independent auditor, and the second most influential factor was the auditee. The factor with the least impact on independent audit quality was legal regulations and institutions.

In another study by Alqatanani and Hezabr (2015) concerning the extent to which Bahraini auditors are aware of the possibilities of incorporating IT in auditing strategies, and the impact of this on the overall audit process, it was found that such awareness is poor, and there is very little use of IT in various fields. The researchers specifically identified the lack of material resources and software necessary for the implementation of audits, the absence of an appropriate level of scientific and practical training of employees to undertake audits using IT, the lack of confidence in electronic procedures, the fear of data loss and the inability to maintain data protection. Additionally, the fear among employees and the belief that expansion through the use of IT would precipitate the redundancy of some employees was expressed.

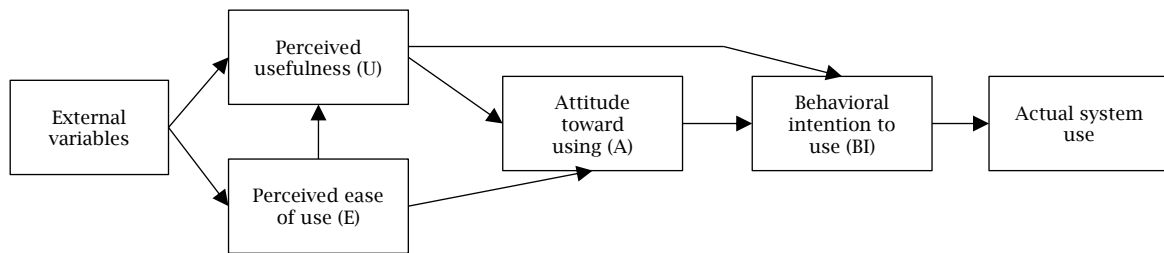
Clearly, this brief review illustrates the limitations of the literature addressing the factors that influence auditor acceptance of new technologies such as big data analytics in their work and exploring the consequences of lack of adoption on audit quality. Hence, there is a need to increase the general understanding of the role of the TAM

dimensions in big data analytics acceptance and use, and hence, the impact on audit quality. The current study draws on ideas mentioned in the literature review and aims to examine the acceptance of Jordanian external auditors of big data analytics, through a TAM.

There are many theoretical frameworks and models to study the acceptance of emerging technologies by individual users. However, after extensively reviewing the literature, Momani and Jamous (2017) concluded the TAM (Davis, Bagozzi, & Warshaw, 1989) to be the basis of all the extensions and developments that have evolved in this respect. Moreover, the use of the TAM in different fields, such as accounting, business, and others (Kim et al., 2009), supports that conclusion, and consequently, the TAM is used in this study. Essentially, this is upheld as one of the most popular models to predict the acceptance and use of information systems and technology by individual users (Surendran, 2012), and the model is now reviewed for its suitability for this study on big data analytics.

The TAM (Davis et al., 1989) is diagrammatically represented as follows:

Figure 1. Technology acceptance model (TAM)



Source: Davis et al. (1989, p. 985).

In the context of accounting, any new information system requires auditors to evaluate that system and develop attitudes towards it, from which behavioural intention to use or not to use it flows. Those attitudes are hypothesised to be a function of two beliefs regarding the system's perceived usefulness and perceived ease of use.

Perceived usefulness was defined as “the degree to which an individual believes that using a particular system would enhance his or her job performance” (Davis, 1986, p. 26). Perceived ease of use was defined as “the degree to which an individual believes that using a particular system

would be free of physical and mental effort” (Davis, 1986, p. 26). Perceived ease of use is theorised to influence perceived usefulness, and together these perceptions are believed to directly influence the attitude towards the system (Davis, 1986; Davis et al., 1989; Kim et al., 2009). External variables, presented as design features in Davis (1986) are theorised to directly influence both perceived usefulness and perceived ease of use.

For this study, the conceptual framework depicted in Figure 2 was developed to explore big data analytics, external auditor acceptance, and the subsequent influence upon audit quality.

Figure 2. The conceptual framework



In this model, perceived usefulness is defined as the degree to which external auditors believe that using big data analytics systems would enhance their performance. Other variables in the literature are found to be similar to perceived usefulness. For example, Venkatesh, Morris, Davis, and Davis (2003)

found performance expectancy to be similar to perceived usefulness, stating this to be “the degree to which an individual believes that using the tool will help him or her better attain significant rewards” (Venkatesh et al., 2003, p. 23).

Further support for the use of performance expectancy in the audit field was given by Janvrin et al. (2008) who explored auditors' acceptance of CAATs. Consequently, when external auditors believe that the big data analytics system is useful in their work and can enhance their performance, they are expected to use these analytics more frequently. The following hypothesis is thus derived:

H1: Perceived usefulness has a positive effect on the actual use of big data analytics.

Perceived ease of use is defined in the model as the degree to which external auditors believe that using big data analytics systems would be free from physical and mental effort. Venkatesh et al. (2003) found that effort expectancy is similar to perceived ease of use meaning and influence, stating that it is "the degree of ease associated with the use of the tool" (Venkatesh et al., 2003, p. 26). Again, Janvrin et al. (2008) provide support. Consequently, when external auditors believe that big data analytics systems are easy to use, they are expected to use them more. The following hypothesis is thus derived:

H2: Perceived ease of use has a positive effect on the actual use of big data analytics.

Further, perceived ease of use is theorised to influence perceived usefulness. For instance, when external auditors believe that big data analytics systems are easy and free from effort, they are expected to use these analytics systems more which will result in improving their performance. This idea is embodied in the following hypothesis:

H3: Perceived ease of use has a positive effect on perceived usefulness.

Finally, the actual use of big data analytics systems is expected to influence audit quality as indicated in the literature. The following hypothesis is derived:

H4: Using big data analytics by auditors positively affects audit quality.

3. RESEARCH METHODOLOGY AND SAMPLING

A quantitative survey involving the random distribution of a questionnaire to a sample of external auditors in Jordanian audit companies was used (a consensus was taken from participants in advance before conducting the survey). The scope of the current study was Jordan as a developing country for reasons of data accessibility.

The questionnaire was developed after reviewing the related literature: for example, big data (Gepp et al., 2018; Gandomi & Haider, 2015), technology acceptance model (Kim et al., 2009; Davis et al., 1989), and audit quality (Kilgore & Martinov-Bennie, 2014; Manita & Elommal, 2010). To establish the initial validity of the instrument, it was sent to a group of arbitrators and experts in fields related to the study for scrutiny and comment. It was then adjusted for use in the study. Consisting of two parts, the questionnaire began by asking demographic questions and establishing whether the respondents were users or non-users of big data analytics. The second part presented statements designed to measure the research variables (perceived usefulness, perceived ease of use, and audit quality) using a five-point Likert scale ranging between the values 5 — "strongly agree" and 1 — "strongly disagree".

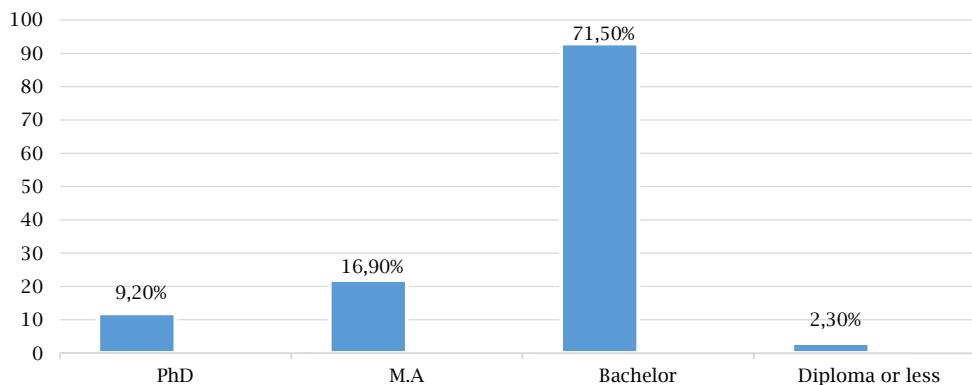
The questionnaire was distributed in the first week of December 2018 both personally and electronically. Reminders were subsequently given to participants to complete the questionnaires. Those in receipt of the questionnaire electronically were sent an email, whereas others were called on the telephone. As a result, of the 180 questionnaires distributed, 141 were collected, from which 11 were excluded because of incomplete answers. Therefore, 130 valid questionnaires were analysed, representing a response rate of 72.22%. Kaiser-Meyer-Olkin (KMO) test for sampling adequacy shown in subsection 4.3 indicated that the sample size is sufficient to get valid results from SEM analysis.

3.1. Respondent demographics

The information obtained from respondents about their educational level, experience, and professional certifications confirmed that external auditors in Jordan possess a high level of understanding about the audit process, which is likely to influence their attitudes towards the use of new audit techniques like BDA.

Respondents ranged in educational level from diploma to PhD, but the majority (71.5% — 93 out of 130) possessed a Bachelor's degree as shown in Figure 3.

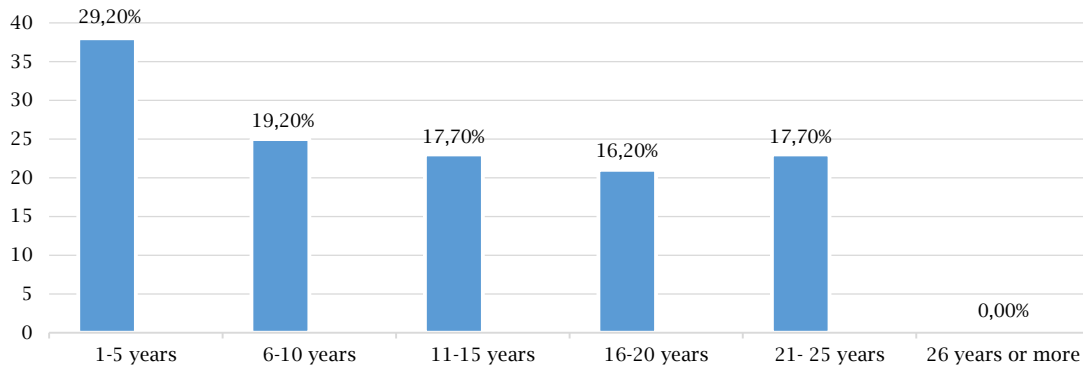
Figure 3. Educational level



It is clear from Figure 3 that external auditors in Jordan are knowledgeable since only a very tiny minority (2.3%) do not have a degree or higher degree. Consequently, there is a high level of understanding among external auditors of the audit process, which reflects on their perceptions about the use of new audit techniques like BDA. Additionally, there is also sufficient appreciation of the usefulness of these techniques and their positive impact on audit quality.

Almost half of the respondents fell into the experience range of between 1 and 5 years (29%) and between 6 and 10 years (19%). Those with experience of between 11 and 15 years comprised nearly 18% of the population, and those having between 16 and 20 years of experience accounted for just over 16% of the population. Almost 18% of respondents reported over 21 years of experience. Figure 4 shows the bar chart.

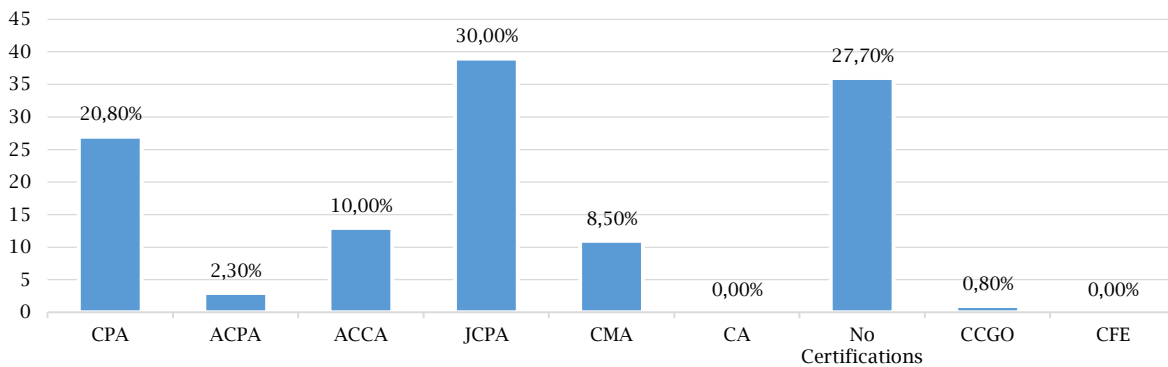
Figure 4. Experience



The range of experience possessed by auditors in Jordan is, therefore, seen to be substantial, thereby ensuring that auditors are used to detecting errors in financial statements and to reporting these in accordance with rules and regulations, and their professional duty.

In respect of their professionalism, as seen in Figure 5, external auditors possess various certifications as follows: 30% JCPA certificates, 21% CPA certificates, 28% have no professional certificates, and the remainder has certification from the ACPA, CMA, ACCA, and CCGO.

Figure 5. Professional certifications



4. ANALYSIS AND FINDINGS

4.1. Use of big data analytics by auditors in Jordan

While the data analytics usage was proposed to be mediating variable between perceive usefulness ease of use and audit quality; the research participants were asked to indicate whether they are using big data analytics or not. The results revealed that the majority (57%) of respondents do use big data analytics, and the remaining 43% do not.

4.2. Data analysis: SEM

Partial least square structural equation modelling (PLS-SEM) was used to diagnose the measurement model and the structure of the variables. SEM allows

a researcher to express a theory in terms of relationships among measured variables and latent constructs (variates), and to assess how well the theory fits reality as represented by the data (Hair, William, Babin, & Anderson, 2014). It is, therefore, very useful in uncovering important relationships and evaluating complicated models, especially when there is a mediating or moderating effect. In this study, it is initially theorised that data analytics usage has a mediating effect between the relationships of perceived usefulness and ease of use, and audit quality (Raykov & Traynor, 2016).

4.3. Model testing

Testing the model for reliability, convergent validity and discriminant validity showed the composite reliability to be more than 0.7 and the average variance extracted

(AVE) to be greater than 0.5 (Hair et al., 2014). Table 1 shows the AVE for each variable to range from 0.61 to 0.70, and CR values to range from 0.96 to 0.97. These values are higher than the benchmarks of 0.70 and 0.50. Hence, good construct reliability is assured.

Moreover, the statistical test of the reliability of the structured items from the questionnaire achieved Cronbach's alphas ranging from 0.95 to 0.96, thereby making them sufficiently reliable for further analysis (Sekaran & Bougie, 2016).

Convergent validity, to determine theoretical relationships between scale items, was examined by checking whether loadings were significant and exceeded the minimum recommended level of 0.5 (Steenkamp & van Trijp, 1991). All item loadings were larger than 0.6 and t-values indicate all loadings as significant at 0.001 level, except for two items (Q27 and Q42) with less than

acceptable values that were subsequently discarded. Low loadings of these variables might be due to the irrelevance of these variables to the hypothesised factors or to less understanding of these questions by respondents. Thus, the scale has good convergent validity. Additionally, all indicators and items have a VIF value < 5 as shown in Table 1. Hence, there is no collinearity issue present between the indicators. The present outcome delineates evidence of convergent and discriminant validity for the proposed model constructs, confirming the data's suitability for further analysis. Furthermore, evidence of discriminant validity noted by the low correlation coefficients in the square root of VIF values among the research variables (i.e., less than 0.80), as displayed in Table 2.

Table 1. Results of construct assessment

Constructs	Items	VIF	Factor loading	Mean	SD	Cronbach's α	CR	AVE
Perceived usefulness	Q1	1.06	0.727	4.718	0.45	0.955	0.960	0.615
	Q2	1.07	0.730	4.695	0.461			
	Q3	1.12	0.736	4.626	0.484			
	Q4	1.12	0.723	4.641	0.48			
	Q5	1.11	0.739	4.634	0.482			
	Q6	1.09	0.817	4.725	0.446			
	Q7	1.32	0.772	4.687	0.464			
	Q8	1.44	0.817	4.679	0.467			
	Q9	1.10	0.809	4.664	0.472			
	Q10	1.09	0.805	4.672	0.47			
	Q11	1.08	0.838	4.672	0.47			
	Q12	1.16	0.827	4.695	0.461			
	Q13	1.15	0.805	4.695	0.461			
	Q14	1.12	0.810	4.695	0.461			
	Q15	1.23	0.793	4.71	0.454			
Perceived ease of use	Q16	1.32	0.837	4.702	0.457	0.957	0.963	0.701
	Q17	1.22	0.892	4.664	0.472			
	Q18	1.21	0.823	4.649	0.538			
	Q19	1.08	0.888	4.656	0.475			
	Q20	1.09	0.828	4.649	0.538			
	Q21	1.11	0.879	4.58	0.605			
	Q22	1.31	0.854	4.618	0.598			
	Q23	1.13	0.861	4.626	0.571			
	Q24	1.18	0.881	4.634	0.569			
	Q25	1.20	0.732	4.542	0.691			
	Q26	1.21	0.715	4.595	0.577			
Audit quality	Q28	1.09	0.789	4.603	0.548	0.968	0.971	0.705
	Q29	1.06	0.815	4.588	0.537			
	Q30	1.04	0.807	4.466	0.646			
	Q31	1.22	0.844	4.55	0.527			
	Q32	1.22	0.822	4.557	0.527			
	Q33	1.32	0.812	4.58	0.524			
	Q34	1.23	0.890	4.534	0.529			
	Q35	1.22	0.860	4.565	0.511			
	Q36	1.11	0.898	4.534	0.499			
	Q37	1.10	0.840	4.405	0.674			
	Q38	1.23	0.855	4.489	0.584			
	Q39	1.28	0.861	4.443	0.632			
	Q40	1.44	0.842	4.534	0.557			
	Q41	1.34	0.808	4.611	0.488			

Table 2. Correlations matrix and the square root of AVE

Variables	Audit quality	Perceived ease of use	Perceived usefulness
Audit quality	1.00		
Perceived ease of use	0.303	1.00	
Perceived usefulness	0.555	0.785	1.00

Table 3 shows the result of the KMO test for sampling adequacy. The value of KMO should be greater than 0.5 for the sample to be adequate. The KMO value is 0.941 which is greater than the accepted value.

In addition, the p-value of Bartlett's test of sphericity is considered and this value should be smaller than 0.05; the p-value is 0.000 for this study which is consistent with the required value.

Table 3. KMO and Bartlett's tests

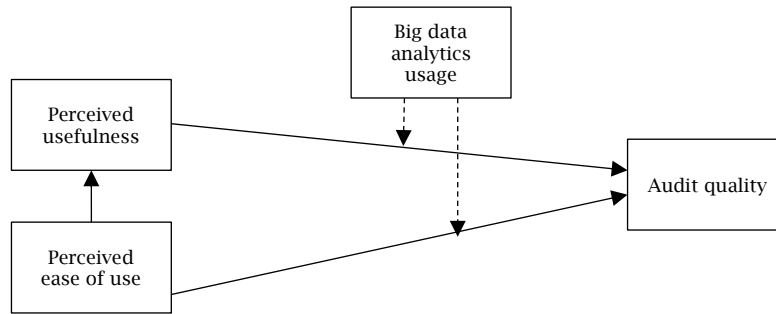
<i>Kaiser-Meyer-Olkin measure of sampling adequacy</i>	0.941
<i>Bartlett's test of sphericity approx. — Chi-square</i>	4576.936
<i>Df</i>	130
<i>Sig.</i>	0.000

Furthermore, a global fit model (GOF) assessment was conducted to test the global validation of the PLS model. The GOF value was 0.548, indicating the GOF was adequate to support the validation of the PLS model globally (Wetzels, Odekerken-Schröder, & van Oppen, 2009).

4.4. Analysis of the suggested model and hypotheses

After considering these findings, a change to the conceptual framework to provide more detail was made as illustrated in Figure 6.

Figure 6. Post-analysis research model



In Figure 6, the new relationships between the research variables is depicted, suggesting a moderating effect of big data analytics usage on the relationship between perceived usefulness and perceived ease of use, and audit quality. These relationships suggest exploring the following hypotheses:

- H1: *Perceived usefulness has a statistically significant impact on audit quality.*
- H2: *Perceived ease of use has a statistically significant impact on audit quality.*
- H3: *Actual use of big data analytics moderates the relationship between perceived usefulness and audit quality.*
- H4: *Actual use of big data analytics moderates the relationship between perceived ease of use and audit quality.*

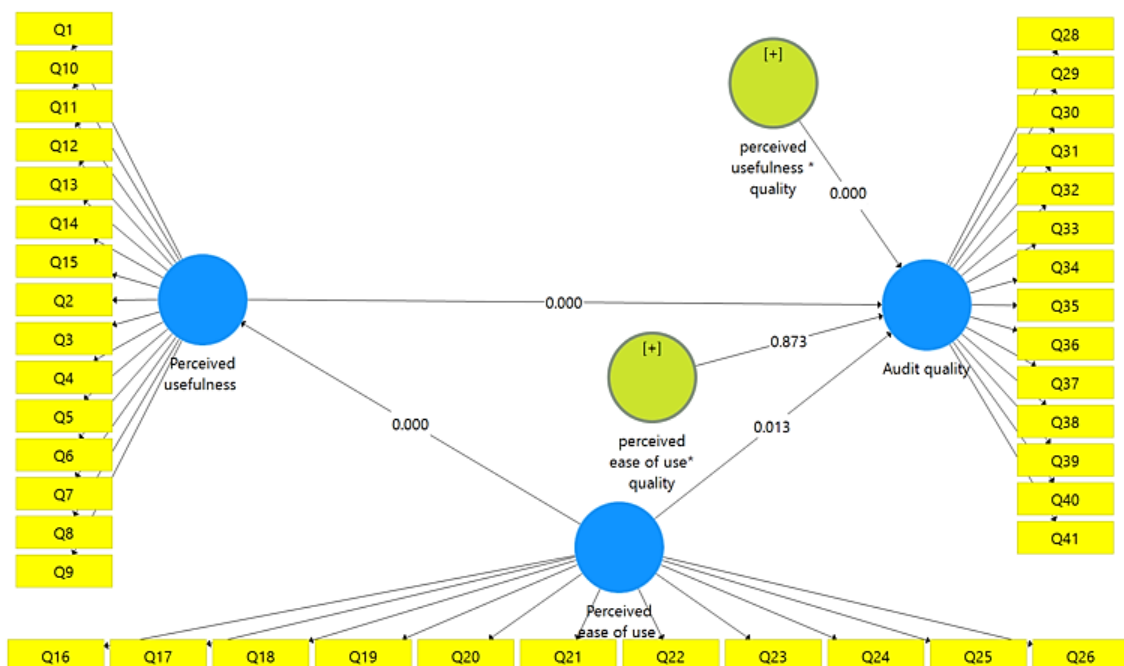
H5: *Perceived ease of use has a statistically significant impact on perceived usefulness.*

Testing the above hypotheses will be done using the results of the structural model that follows further.

4.5. Testing the structural model

Following Chin (1998), the bootstrapping method (based on 5000 replications) was performed in SmartPLS software to test the statistical significance of path coefficients (β). Figure 7 provides the path analysis for all the research hypotheses.

Figure 7. Structural research model



The outcome presented in Figure 7 provides support for four of the research hypotheses.

Specifically, audit quality was positively affected by perceived usefulness ($t = 4.92, \rho < 0.05$), thereby supporting *H1*. The results also showed that audit quality was significantly and positively affected by perceived ease of use ($t = 2.35, \rho < 0.05$). However, 69.2% of audit quality variance was explained by perceived usefulness and perceived ease of use. *H2* was, therefore, upheld. The study proves that the actual use of big data analytics moderates the relationship between perceived usefulness and audit quality. The interaction term (*perceived usefulness* \times *BDA usage*) ($t = 4.87, \rho < 0.05$) had a significant and positive effect on the audit

quality. Thus, a higher BDA usage strengthened the relationship between the perceived usefulness of the BDA system and audit quality, thereby supporting *H3*. However, contrary to expectation, actual use of big data analytics does not moderate the relationship between perceived ease of use and audit quality ($t = 0.892, \rho > 0.05$), and consequently, *H4* was not upheld. In respect of *H5*, the prediction was that perceived ease of use positively affected perceived usefulness ($t = 29.31, \rho < 0.05$), and the outcome conforms to this prediction, perceived ease of use explaining 73% of perceived usefulness variance. Hence, *H5* was supported. Table 4 summarises the results of path coefficient analysis for the five hypotheses.

Table 4. Results from hypotheses testing

<i>Path (hypothesis)</i>	<i>Standard deviation</i>	<i>T-statistics</i>	<i>P-values</i>	<i>Result</i>
<i>H1: Perceived usefulness</i> \rightarrow <i>Audit quality</i>	0.113	4.920	0.000	Supported
<i>H2: Perceived ease of use</i> \rightarrow <i>Audit quality</i>	0.128	2.350	0.019	Supported
<i>H3: Perceived usefulness</i> \times <i>Usage</i> \rightarrow <i>Audit quality</i>	0.159	4.871	0.000	Supported
<i>H4: Perceived ease of use</i> \times <i>Usage</i> \rightarrow <i>Audit quality</i>	0.136	0.892	0.119	Not supported
<i>H5: Perceived ease of use</i> \rightarrow <i>Perceived usefulness</i>	0.162	29.317	0.000	Supported

5. DISCUSSION

Given the absence of research into the acceptance of big data analytics and the impact of IT on audit quality, this study aimed to understand the influence of the TAM on using big data analytics and its consequences for audit quality. Its findings are now discussed in relation to the literature on accounting, auditing, information systems, and big data analytics.

5.1. Perceived usefulness and audit quality

In this study, the suggested relationship between perceived usefulness and the actual use of the information system (Kim et al., 2009) was adopted. It was shown in the model testing that perceived usefulness positively influenced audit quality, thereby indicating the external auditors' belief that if the information system they are using for auditing work, including the systems that use big data analytics, is useful this will reflect on their performance and improve audit quality.

This outcome supported the findings of Kim et al. (2009) who noticed a significant influence from perceived usefulness on the acceptance of technology by the internal auditors, and it further supports findings by Janvrin et al. (2008) and Mansour (2016) who reported a link between performance expectancy (similar to perceived usefulness), and the intention to use CAATs in auditing. Additional support for this result is seen in the literature relating to the influence of IT on audit quality (Mustapha & Lai, 2017), although Ada and Yardimcioglu (2016) did not find IT use to significantly influence independent audit quality.

5.2. Perceived ease of use and audit quality

In this study, the suggested relationship between perceived ease of use and audit quality found in the literature was adopted. It was shown in the model testing that perceived ease of use positively influences audit quality, thereby confirming external auditors' belief that if the information systems they are using for auditing work, including those concerned with big data analytics, are easy to use and free of effort, they will tend to use them more, and thus improve the audit quality. This result aligns with that of Kim et al. (2009) who noticed a significant influence from perceived ease of use on the acceptance of technology by the internal

auditors, and that of Janvrin et al. (2008) who noticed a significant influence from effort expectancy (similar to perceived ease of use) and the use of IT and CAATs. Further support for this result is seen in the literature relating to the influence of IT on audit quality (Mustapha & Lai, 2017), although Ada and Yardimcioglu (2016) did not find a significant influence in this respect.

5.3. The moderating effect of the big data analytics usage

Big data analytics usage in accounting and auditing work is widely discussed in the literature review in the context of the large and growing volume of data that necessitates such systems in order to enhance auditors' performance and the decision-making that depends upon the results of that performance. Support for the use of big data analytics in auditing comes particularly from Deloitte (n.d.) and Janssen et al. (2017). It is shown that using big data analytics systems in auditing enables auditors to cover the data better, quickly identify the risks, and complete auditing with a higher level of quality that subsequently delivers a greater level of insight to the clients (Deloitte, n.d.). It also enhances the ability to detect fraud and prevent mistakes during an auditing (Janssen et al., 2017).

In examining the influence of big data analytics usage on audit quality, this study explored the moderation effect suggested by the literature, finding the existence of such an effect from big data analytics usage on the relationship between perceived usefulness and audit quality. This result implies that audit quality is expected to increase for external auditors who use big data analytics systems in their work in the belief that their use is beneficial to them in enhancing their performance and productivity.

However, there is no support in the research for a moderating effect of big data analytics usage on the influence of perceived ease of use on audit quality. This result that external do not believe that the degree of ease associated with big data analytics systems is influential upon audit quality.

5.4. Perceived ease of use and perceived usefulness

The results of the analysis show that perceived ease of use had a significant positive influence on perceived usefulness. This result indicates that when external auditors believe big data analytics systems do not

require much effort to use, they are encouraged to use them more, and subsequently, their performance and productivity are improved, as also are their beliefs about the usefulness of big data analytics systems.

This finding supports other researchers' outcomes, i.e., the work by Kim et al. (2009) that adopts the TAM model and its theorisations of the direct influence from perceived ease of use on perceived performance (Davis, 1986; Davis et al., 1989).

6. CONCLUSION

The study finds that perceived usefulness and perceived ease of use have a direct effect on audit quality, without mediating the actual use of data analytics. However, the use of big data analytics is shown to moderate the relationship between perceived usefulness and audit quality, but not between the perceived ease of use and audit quality.

The study findings indicate that the Jordanian audit profession has adapted to the international auditing environment in implementing technological advancements, namely big data analytics, in order to manage the high volume of data, and help to detect mistakes, risks, and fraud. It, therefore, makes a contribution to the literature in demonstrating the Jordanian response in this respect, thus providing information about the Middle Eastern context. Additionally, it makes an academic contribution in its use of the TAM to explore this context, and in its development of a conceptual framework that supports the exploration of some of its dimensions on the use of big data analytics and subsequent effect upon audit quality in Jordan. In this respect, both perceived usefulness and perceived ease of use were seen as significant. Moreover, the study contributes by supporting the moderating effect of big data analytics usage on the influence of perceived usefulness on audit quality; and by demonstrating the influence of perceived ease of use on perceived usefulness. The conceptual model developed can arguably be used for other developing countries where auditing operates in a similar environment.

To the researcher's best knowledge, this study is one of the first to employ TAM factors and use the moderation effect of big data analytics usage in the auditing sector. Moreover, it integrates two different aspects of the literature: big data in auditing, and the use of using information technologies and

systems in accounting and auditing. It confirms the applicability of the TAM in this context.

The study also makes a contribution to practice by highlighting the managerial implications for auditing companies and offices in Jordan related to the use and development of the latest technologies and systems in their work. Moreover, based on the findings of the current study, the perceptions of external auditors regarding ease of use and usefulness enable auditing firms' managers to evaluate their training needs in the interests of optimum skill enhancement. Additionally, the attention of the audit environment is drawn to the need to integrate IT advancements in auditing, particularly in terms of managing large volumes of data, in the interest of improving the quality of their work.

The sample of 130 questionnaires is a limitation when using SEM, but the sampling adequacy test is believed to mitigate the effects of this on the validity of the findings and its generalisability. However, in future research, larger sample size is desirable.

Given that the Jordanian accounting and audit environment is relatively advanced in the Middle Eastern context, the applicability of its results to other countries needs careful consideration. The theoretical model may/may not have relevance for other Middle Eastern countries and therefore it is suggested that it could be used with caution in an effort to determine how generalisable it is in its current form, and what amendments might be necessary to increase its generalisability for the region (this might include the inclusion of other technology acceptance theories, such as the UTAUT (Venkatesh et al., 2003), diffusion of innovation (DIO) (Rogers, 2003) and the technology-organization-environment (TOE) framework (Tornatzky & Fleisher 1990), and/or the inclusion of more variables, such as the influence of facilitating conditions and social influence.

Comparison studies might also be useful to establish differences between auditor perceptions towards using big data analytics systems in the private and public sectors. Finally, more research addressing the challenges of the use of big data analytics in the field of accounting and auditing is desired to determine whether the promised benefits can be realised more substantially in the audit process.

REFERENCES

1. Ada, Ş., & Yardımcıoğlu, M. (2016). An empirical investigation of the antecedents of independent audit quality. In *Proceedings of the MT International Conference on Business Research* (pp. 10-19).
2. Al-Hajaya, K. (2019). The impact of audit committee effectiveness on audit quality: Evidence from the Middle East. *International Review of Management and Marketing*, 9(5), 1-8. <https://doi.org/10.32479/irmm.8341>
3. Alqatanani, K. M., & Hezabr, A. A. (2015). To what extent the auditors in the Kingdom of Bahrain recognize auditing strategies in the light information technology and what is impact on the audit? A field study. *International Journal of Economics, Commerce and Management*, 3(5), 698-711. Retrieved from <http://ijecm.co.uk/wp-content/uploads/2015/05/3541.pdf>
4. Appelbaum, D., Kogan, A., & Vasarhelyi, M. A. (2018). Analytical procedures in external auditing: A comprehensive literature survey and framework for external audit analytics. *Journal of Accounting Literature*, 40(2), 83-101. <https://doi.org/10.1016/j.acclit.2018.01.001>
5. Arnold, V. (2018). The changing technological environment and the future of behavioural research in accounting. *Accounting and Finance*, 58(3), 315-339. <https://doi.org/10.1111/acfi.12218>
6. Austin, A. A., Carpenter, T. D., Christ, M. H., & Nielson, C. (2018). *The data analytics transformation: Evidence from auditors, CFOs, and standard-setters*. <http://dx.doi.org/10.2139/ssrn.3214140>
7. Bedard, J. C., Johnstone, K. M., & Smith, E. F. (2010). Audit quality indicators: A status update on possible public disclosures and insights from audit practice. *Current Issues in Auditing*, 4(1), C12-C19. <https://doi.org/10.2308/ciia.2010.4.1.C12>
8. Bender, T. H. (2017). *The effect of data analytics on audit efficiency*. Retrieved from <https://thesis.eur.nl/pub/38929>

9. Brown-Liburd, H., Issa, H., & Lombardi, D. (2015). Behavioural implications of big data's impact on audit judgment and decision making and future research directions. *Accounting Horizons*, 29(2), 451-468. <https://doi.org/10.2308/acch-51023>
10. Cao, M., Chychyla, R., & Stewart, T. (2015). Big data analytics in financial statement audits. *Accounting Horizons*, 29(2), 423-429. <https://doi.org/10.2308/acch-51068>
11. Carson, E., Fargher, N., Geiger, M., Lennox, C., Raghunandan, K., & Willekens, M. (2013). Auditor reporting for going-concern uncertainty: A research synthesis. *Auditing: A Journal of Practice & Theory*, 32(supplement 1), 353-384. <https://doi.org/10.2308/ajpt-50324>
12. Chin, W. (1998). The partial least squares approach for structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295-336). Mahwah, NJ: Lawrence Erlbaum Associates Publishers.
13. Christensen, B. E., Glover, S. M., Omer, T. C., & Shelley, M. K. (2016). Understanding audit quality: Insights from audit professionals and investors. *Contemporary Accounting Research*, 33(4), 1648-1684. <https://doi.org/10.1111/1911-3846.12212>
14. Chung, J., Farrar, J., Puri, P., & Thorne, L. (2010). Auditor liability to third parties after Sarbanes-Oxley: An international comparison of regulatory and legal reforms. *Journal of International Accounting, Auditing and Taxation*, 19(1), 66-78. <https://doi.org/10.1016/j.intaccudtax.2009.12.005>
15. Dai, J., & Vasarhelyi, M. A. (2016). Imagineering audit 4.0. *Journal of Emerging Technologies in Accounting*, 13(1), 1-15. <https://doi.org/10.2308/jeta-10494>
16. Davis, F. (1986). *A technology acceptance model for empirically testing new end-user information systems: Theory and results* (Unpublished PhD thesis, Massachusetts Institute of Technology). Retrieved from <http://hdl.handle.net/1721.1/15192>
17. Davis, F., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, 35(8), 982-1003. <https://doi.org/10.1287/mnsc.35.8.982>
18. De Santis, F., & D'Onza, G. (2021). Big data and data analytics in auditing: In search of legitimacy. *Meditari Accountancy Research*, 29(5), 1088-1112. <https://doi.org/10.1108/MEDAR-03-2020-0838>
19. DeFond, M. L., & Zhang, J. (2014). A review of archival auditing research. *Journal of Accounting and Economics*, 58(2-3), 275-326. <https://doi.org/10.1016/j.jacceco.2014.09.002>
20. Deloitte. (n.d.). *Deloitte prepares firm for 'Audit of the Future': An interview with Joe Ucuzoglu*. Retrieved from <https://www2.deloitte.com/us/en/pages/audit/articles/deloitte-prepares-firm-for-audit-of-the-future-accounting-today-article.html>
21. Earley, C. E. (2015). Data analytics in auditing: Opportunities and challenges. *Business Horizons*, 58(5), 493-500. <https://doi.org/10.1016/j.bushor.2015.05.002>
22. EY. (2013). *Audit committee bulletin* (Issue 5). Retrieved from <https://www.iaa.nl/SiteFiles/EY%20-%20Audit%20Committee%20Bulletin%20-%20Issue%205%20-%202013.pdf>
23. Francis, J. R. (2004). What do we know about audit quality? *The British Accounting Review*, 36(4), 345-368. <https://doi.org/10.1016/j.bar.2004.09.003>
24. Francis, J. R. (2011). A framework for understanding and researching audit quality. *Auditing*, 30(2) 125-152. <https://doi.org/10.2308/ajpt-50006>
25. Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, 35(2), 137-144. <https://doi.org/10.1016/j.jinfomgt.2014.10.007>
26. Gepp, A., Linnenluecke, M. K., O'Neill, T. J. O., & Smith, T. (2018). Big data techniques in auditing research and practice: Current trends and future opportunities. *Journal of Accounting Literature*, 40, 102-115. <https://doi.org/10.1016/j.acclit.2017.05.003>
27. Gray, G. L., & Debreceeny, R. S. (2014). A taxonomy to guide research on the application of data mining to fraud detection in financial statement audits. *International Journal of Accounting Information Systems*, 15(4), 357-380. <https://doi.org/10.1016/j.accinf.2014.05.006>
28. Griffin, P. A., & Wright, A. M. (2015). Commentaries on big data's importance for accounting and auditing. *Accounting Horizons*, 29(2), 377-379. <https://doi.org/10.2308/acch-51066>
29. Hair, J. F., William, B. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate data analysis* (7th ed.). Upper Saddle River, NJ: Pearson Education.
30. Hosseiniakani, S. M., Inacio, H., & Mota, R. (2014). A review on audit quality factors. *International Journal of Academic Research in Accounting, Finance and Management Sciences*, 4(2), 243-254. Retrieved from <https://core.ac.uk/download/pdf/32243217.pdf>
31. Jans, M., Alles, M., & Vasarhelyi, M. (2013). The case for process mining in auditing: Sources of value added and areas of application. *International Journal of Accounting Information Systems*, 14(1) 1-20. <https://doi.org/10.1016/j.accinf.2012.06.015>
32. Janssen, M., van der Voort, H., & Wahyudi, A. (2017). Factors influencing big data decision-making quality. *Journal of Business Research*, 70, 338-345. <https://doi.org/10.1016/j.jbusres.2016.08.007>
33. Janvrin, D. J., & Watson, M. W. (2017). "Big data": A new twist to accounting. *Journal of Accounting Education*, 38, 3-8. <https://doi.org/10.1016/j.jaccedu.2016.12.009>
34. Janvrin, D. J., Lowe, D. J., & Bierstaker, J. (2008). *Auditor acceptance of computer-assisted audit techniques*. Retrieved from http://www.mtc.gov/uploadedFiles/Multistate_Tax_Commission/Audit_Program/Resource/AuditorAcceptance.pdf
35. Kilgore, A., & Martinov-Bennie, N. (2014). *The drivers of audit quality: Auditors' perceptions*. The Association of Chartered Certified Accountants (ACCA). Retrieved from [https://www.accaglobal.com/content/dam/acca/global/PDF-technical/audit-publications/pol-tp-daq2\(auditors\).pdf](https://www.accaglobal.com/content/dam/acca/global/PDF-technical/audit-publications/pol-tp-daq2(auditors).pdf)
36. Kim, H.-J., Mannino, M., & Nieschwietz, R. J. (2009). Information technology acceptance in the internal audit profession: Impact of technology features and complexity. *International Journal of Accounting Information Systems*, 10(4), 214-228. <https://doi.org/10.1016/j.accinf.2009.09.001>
37. Knechel, W. R. (2013). Do auditing standards matter? *Current Issues in Auditing*, 7(2), A1-A16. <https://doi.org/10.2308/ciia-50499>
38. Knechel, W. R., Krishnan, G. V., Pevzner, M., Shefchik, L. B., & Velury, U. K. (2013). Audit quality: Insights from the academic literature. *Auditing: A Journal of Practice & Theory*, 32(Supplement 1), 385-421. <https://doi.org/10.2308/ajpt-50350>

39. Krahel, J. P., & Titera, W. R. (2015). Consequences of big data and formalization on accounting and auditing standards. *Accounting Horizons*, 29(2), 409–422. <https://doi.org/10.2308/acch-51065>
40. Lai, P. C. (2017). The literature review of technology adoption models and theories for the novelty technology. *JISTEM-Journal of Information Systems and Technology Management*, 14(1), 21–38. Retrieved from <https://ssrn.com/abstract=3005897>
41. Lee, I. (2017). Big data: Dimensions, evolution, impacts, and challenges. *Business Horizons*, 60(3), 293–303. <https://doi.org/10.1016/j.bushor.2017.01.004>
42. Manita, R., & Elommal, N. (2010). The quality of audit process: An empirical study with audit committees. *International Journal of Business*, 15(1), 87–99. Retrieved from <http://www.craig.csufresno.edu/ijb/Volumes/Volume%2015/V151-6.pdf>
43. Mansour, E. M. (2016). Factors affecting the adoption of computer assisted audit techniques in audit process: Findings from Jordan. *Business and Economic Research*, 6(1), 248–271. <https://doi.org/10.5296/ber.v6i1.8996>
44. Masmoudi, S. M. (2021). The effect of audit committee characteristics on financial reporting quality: The moderating role of audit quality in the Netherlands. *Corporate Ownership & Control*, 18(3), 19–30. <https://doi.org/10.22495/cocv18i3art2>
45. Moffitt, K. C., & Vasarhelyi, M. A. (2013). AIS in an age of big data. *Journal of Information Systems*, 27(2) 1–19. <https://doi.org/10.2308/isys-10372>
46. Momani, A. M., & Jamous, M. (2017). The evolution of technology acceptance theories. *International Journal of Contemporary Computer Research*, 1(1), 51–58. Retrieved from <http://ojs.mediu.edu.my/index.php/IJCCR/article/view/479>
47. Mustapha, M., & Lai, S. J. (2017). Information technology in audit processes: An empirical evidence from Malaysian audit firms. *International Review of Management and Marketing*, 7(2), 53–59. Retrieved from <https://econjournals.com/index.php/irmm/article/view/4077>
48. Public Company Accounting Oversight Board (PCAOB). (2010). *Auditing standard (AS) No. 1105: Audit evidence*. Retrieved from <https://pcaobus.org/Standards/Auditing/Pages/AS1105.aspx>
49. PwC. (2015). *Data driven: What students need to succeed in a rapidly changing business world*. Retrieved from <https://cpb-us-w2.wpmucdn.com/sites.gsu.edu/dist/1/1670/files/2015/08/pwc-data-driven-paper-1wdb00u.pdf>
50. Rajgopal, S., Srinivasan, S., & Zheng, X. (2018). Measuring audit quality. *Review of Accounting Studies*. Retrieved from https://pdfs.semanticscholar.org/d653/1fbd558e794b3d150d11a2e7d71536c3f3a0.pdf?_ga=2.262247500.1575418794.1579084511-1506203731.1575892903
51. Raykov, T., & Traynor, A. (2016). Evaluation of multicomponent measuring instrument reliability in complex design studies. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(2), 270–277. <https://doi.org/10.1080/10705511.2014.938219>
52. Rezaee, Z., & Wang, J. (2017). Big data, big impact on accounting. *A Plus*. Retrieved from <https://aplusmag.goodbarber.com/topics/c/0/i/17867251/big-data-big-impact-accounting>
53. Rodríguez-Mazahua, L., Rodríguez-Enríquez, C. A., Sánchez-Cervantes, J. L., Cervantes, J., García-Alcaraz, J. L., & Alor-Hernández, G. (2016). A general perspective of Big Data: Applications, tools, challenges and trends. *The Journal of Supercomputing*, 72(8), 3073–3113. <https://doi.org/10.1007/s11227-015-1501-1>
54. Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). New York, NY: Free Press.
55. Rose, A. M., Rose, J. M., Sanderson, K.-A., & Thibodeau, J. C. (2017). When should audit firms introduce analyses of big data into the audit process? *Journal of Information Systems*, 31(3), 81–99. <https://doi.org/10.2308/isys-51837>
56. Russom, P. (2011). *Big data analytics* (TDWI Best Practices Report). Retrieved from https://tdwi.org/research/2011/09/~media/TDWI/TDWI/Research/BPR/2011/TDWI_BPReport_Q411_Big_Data_Analytics_Web/TDWI_BP_Report_Q411_Big%20Data_ExecSummary.ashx
57. Schneider, G. P., Dai, J., Diane, J., Ajayi, K., & Raschke, R. L. (2015). Infer, predict, and assure: Accounting opportunities in data analytics. *Accounting Horizons*, 29(3), 719–742. <https://doi.org/10.2308/acch-51140>
58. Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill building approach*. Oxford, the UK: John Wiley & Sons.
59. Sidek, Z. M., & Meng, F. J. (1996). Statistical sampling techniques for auditors. *Journal of Information Technology*, 8(2), 35–41. Retrieved from http://eprints.utm.my/id/eprint/32731/1/ZailaniMohamedSidek1996_StatisticalSamplingTechniquesforAuditors.pdf
60. Steenkamp, J.-B. E. M., & van Trijp, H. C. M. (1991). The use of LISREL in validating marketing constructs. *International Journal of Research in Marketing*, 8(4), 283–299. [https://doi.org/10.1016/0167-8116\(91\)90027-5](https://doi.org/10.1016/0167-8116(91)90027-5)
61. Stewart, T. R. (2015). Data analytics for financial statement audits. In *Audit analytics and continuous audit: Looking toward the future* (Essay 5, pp. 105–128). American Institute of Certified Public Accountants, Inc. Retrieved from https://us.aicpa.org/content/dam/aicpa/interestareas/frc/assuranceadvisoryservices/downloadabledocuments/auditanalytics_lookingtowardfuture.pdf
62. Surendran, P. (2012). Technology acceptance model: A survey of literature. *International Journal of Business and Social Research*, 2(4), 175–178. Retrieved from <https://thejournalofbusiness.org/index.php/site/article/view/161>
63. Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington, MA: Lexington Books.
64. United States Government Accountability Office (GAO). (2003). *Public accounting firms: Required study on the potential effects of mandatory audit firm rotation*. Retrieved from <https://www.gao.gov/new.items/d04216.pdf>
65. Uyar, M., Alnipak, S., & Guner, M. F. (2015). An evaluation on factors effecting auditors' information technologies in the accounting audit. *International Journal of Academic Research in Business and Social Sciences*, 5(9), 322–337. <https://doi.org/10.6007/IJARBS/v5-i9/1853>
66. Vasarhelyi, M. A., & Romero, S. (2014). Technology in audit engagements: A case study. *Managerial Auditing Journal*, 29(4), 350–365. <https://doi.org/10.1108/MAJ-06-2013-0881>
67. Vasarhelyi, M. A., Kogan, A., & Tuttle, B. M. (2015). Big data in accounting: An overview. *Accounting Horizons*, 29(2), 381–396. <https://doi.org/10.2308/acch-51071>
68. Velte, P., & Loy, T. (2018). The impact of auditor rotation, audit firm rotation and non-audit services on earnings quality, audit quality and investor perceptions: A literature review. *Journal of Governance & Regulation*, 7(2), 74–90. https://doi.org/10.22495/jgr_v7_i2_p7

69. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>

70. Wetzels, M., Odekerken-Schröder, G., & van Oppen, C. (2009). Using PLS path modeling for assessing hierarchical construct models: Guidelines and empirical illustration. *MIS Quarterly*, 33(1), 177–195. <https://doi.org/10.2307/20650284>

71. Yoon, K., Hoogduin, L., & Zhang, L. (2015). Big data as complementary audit evidence. *Accounting Horizons*, 29(2), 431–438. <https://doi.org/10.2308/acch-51076>

72. Zhang, J., Yang, X., & Appelbaum, D. (2015). Toward effective big data analysis in continuous auditing. *Accounting Horizons*, 29(2), 469–476. <https://doi.org/10.2308/acch-51070>

APPENDIX: QUESTIONNAIRE

Part A: Big data analytics usage

Are you using the big data analytics available on your audit program?

1. Yes 2. No

Part B: Perceived usefulness

No.	Perceived usefulness	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
Q1	Using big data analytics in my job would enable me to accomplish tasks more quickly					
Q2	Using big data analytics would improve my job performance					
Q3	Using big data analytics in my job would increase my productivity					
Q4	Using big data analytics enhances my effectiveness on the job					
Q5	Using big data analytics makes it easier to do my job					
Q6	I find big data analytics useful in my job					
Q7	I often use big data analytics to serve my clients					
Q8	I frequently use big data analytics to find information regarding particular issues in the audit process					
Q9	Advanced techniques are required to collect, manage and analyse data					
Q10	The use of big data analytics helps the auditor to obtain the evidence in a timely manner					
Q11	Using big data analytics helps the auditor to obtain more relevant evidence of the item to be audited					
Q12	The use of big data analytics leads to an improved ability of the auditor to prepare evidence with a strong argument					
Q13	Using big data analytics reduces the costs of completing the audit process					
Q14	Using big data analytics helps in better distribution of tasks between the audit team					
Q15	Using big data analytics improves the ability to audit the largest amount of data and the possibility of increasing the size of test samples					

Part C: Perceived ease of use

No.	Perceived ease of use	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
Q16	I know what the term “Big data” means					
Q17	“Big data” is collected in my workplace					
Q18	Big data analytics are available on the audit program used					
Q19	Learning to work with big data analytics would be easy for me					
Q20	I find it easy to get big data analytics to do what I want to do					
Q21	I find big data analytics flexible to interact with					
Q22	It is easy for me to become skilful at using big data analytics					
Q23	I find big data analytics easy to use					
Q24	I deal with large amounts of variable and complex data					
Q25	Increased transaction volume leads to the possibility of error in its analysis and handling					
Q26	Increasing the volume of information leads to the possibility of not detecting errors					
Q27	Data storage creates great challenges for data analysis					

Part D: Audit quality

No.	Audit quality	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
Q28	Good experience and specialisation in the company sector is required when performing audit tasks					
Q29	To perform the audit task, I need to understand the company's accounting information system					
Q30	It is not necessary to know the company's environment when conducting the audit?					
Q31	I identify all important and sensitive processes in the company when I start the audit task					
Q32	The internal reports of the company are reviewed to assess the expected risks					
Q33	The audit task begins with making a plan and ensuring it is complied with					
Q34	Some financial statements are discussed with the Audit Committee					
Q35	Some financial statements are discussed with the company's managers					
Q36	I do not care about the weaknesses and risks identified in previous years					
Q37	Audit programs used by customers are often inappropriate and interlinked with identified weaknesses					
Q38	I provide some non-audit services to clients					
Q39	It is not necessary to contact the company's internal auditors when I perform the audit					
Q40	Specialisation is taken into consideration when distributing tasks between auditors					
Q41	I usually spend a long time with the clients I have been auditing					
Q42	Each process in the audit work is reviewed to ensure quality control					