The Role of Training in Big Data Analytics Adoption: An Empirical Study of Auditors Using the Technology Acceptance Model

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Abstract: This study investigates the impact of training on auditors' intention to adopt Big Data Analytics (BDA) in auditing processes, using the Technology Acceptance Model (TAM) as a theoretical framework. This study seeks to fill the gap in research on the impact of training in the adoption of BDA in audit procedures. While most existing studies have concentrated on the general benefits and challenges of BDA in auditing and other business sectors, they have largely overlooked the specific influence of training as an external factor on the use of BDA in auditing processes. Moreover, there is a significant research gap concerning the application of BDA in developing countries, including Palestine. A census survey of 94 auditors from Big Four accounting firms in Palestine was conducted, with an 86% response rate. Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis revealed that training positively influences perceived usefulness ($\beta = 0.658$, $p < 0.001$) and perceived ease of use ($\beta = 0.616$, $p < 0.001$) of BDA tools. Perceived usefulness significantly affects behavioral intention to adopt BDA ($\beta = 0.532$, $p < 0.001$), while perceived ease of use does not. Behavioral intention positively impacts actual use of BDA tools ($\beta = 0.481$, $p < 0.001$). Based on these findings, audit firms should focus on strategies to translate positive intentions into actual usage. This can be accomplished through ongoing support and resources, such as regular training programs and showcasing success stories that highlight the practical advantages of BDA tools. By fostering an environment that actively supports and encourages the use of BDA, audit firms can ensure that their auditors not only intend to use these tools but also integrate them into their daily auditing practices. This paper contributes to understanding BDA adoption in auditing, particularly in developing countries, and provide insights for audit firms in designing effective training programs to enhance BDA adoption.

Keywords: Big data analytics, Behavioral intention, Perceived ease of use, Perceived usefulness, Technology acceptance model, Training

1. Introduction

Utilization of Big Data Analytics (BDA) in the financial reporting and accounting field is increasing across various sectors; thereby, professionals in these fields are increasing their interest in such tools to enhance their analytical capabilities to be up to date with the latest technologies (İdil and Akbulut, 2018; Austin et al., 2018). BDA is found to be an effective technique in enhancing the understanding of business operations and the complexities of accounting treatments, in addition to offering opportunities for real-time process analysis, which reinforces the adoption of new technologies in financial accounting and reporting (İdil and Akbulut, 2018).

Audit firms, mainly the Big 4, are investing heavily in BDA, integrating it into their audit methodologies to provide auditors with the knowledge required for applying the BDA tools in their auditing processes (Kapoor, 2020). Examples of these BDA tools that are continually updated and developed by these firms include digital working papers, smart forms, templates, and checklists (Pedrosa, Costa, & Aparicio, 2020). However, the adoption of these tools by auditors varies from one to another although they are available and accessible to them; thus, the journey towards digital audit transformation represents a major challenge for these audit firms. This paper focuses on clarifying the influence of one of the audit firms' characteristics, represented by the level of provided training, that may motivate auditors to use BDA.

Despite the availability and accessibility of BDA tools, their adoption levels in auditing remain inconsistent. Some auditors use BDA tools extensively, while others use them minimally or not at all. This inconsistency can be attributed to various factors, including the size of the audit firm, the strategic orientation, and the technological capabilities of the organization. Large audit firms are more likely to adopt BDA due to their ability to invest in the necessary tools and resources. However, the adoption is generally limited by the quality and comparability of data, as well as the availability of qualified data analysts. Additionally, the extent of BDA usage is often influenced by the engagement partner or manager, and many audit firms have not made it mandatory to use or

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test advanced BDA tools. The application of BDA in auditing is still in its early stages, with many firms exploring its potential benefits and challenges. This inconsistency highlights the need for research to identify the barriers to adoption and the factors that can enhance the uptake of BDA tools (Krieger, Drews, & Velte, 2021; Eilifsen et al., 2020).

This study aims to address the gap in the impact of training in adopting BDA in audit procedures, as most existing research has focused on the general benefits and challenges of BDA applications in the auditing field and across various other business sectors. The specific effect of external factor represented by training on the use of BDA in performing audit procedures has been ignored. Additionally, there is a significant gap regarding the lack of focus on BDA applications in developing countries including Palestine.

Adopting the Technology Acceptance Model (TAM), as developed by Davis, Bagozzi, & Warshaw (1989), as a framework would help in understanding auditors' attitudes and interactions towards such technologies. This model is specifically designed to examine the behavior associated with the adoption of information technology. It revolves around two key beliefs: perceived usefulness (PU) and perceived ease of use (PEU) (Davis, Bagozzi, & Warshaw, 1989). According to Davis (1986, p.26), PU is defined as “the degree to which an individual believes that using a particular system would enhance his or her job performance,” while PEU is defined as “the degree to which an individual believes that using a particular system would be free of physical and mental effort”. Consequently, PU and PEU influence the user's intention and attitude towards the acceptance and utilization of new technology. Venkatesh, Davis, & Morris (2007) highlight that numerous researchers have examined the reliability and validity of the TAM by applying it to various technologies with different methodologies and at different times. Despite the existence of several models, such as Innovation Diffusion Theory and Theory of Planned Behavior which were used to study technology acceptance behavior (Oliveira and Martins, 2011), TAM is widely regarded as the most significant and effective model for interpreting technology acceptance behaviors and attitudes (Marangunić & Granić, 2015). This research makes two significant contributions. Firstly, it addresses the topic of BDA in auditing within a developing countries context, as this paper is one of the few in Palestine examining BDA in the auditing field. Secondly, it extends the scope of research on how external factors affect PU and PEU in auditing by adding a specific external variable related to audit firms (training) and assessing their effect on auditors' perceptions regarding BDA tools.

The paper aims to achieve the following objectives:

- To assess the degree of impact of training on auditors’ PEU and PU of BDA tool.
- To examine the relationship between the PU and PEU of BDA tools on auditors' BI to adopt these tools.
- To explain how auditors' BI to adopt BDA tools translate into actual use (AU) in the audit process.

The structure of the remaining parts of this paper is as follows: Section 2 reviews the literature on firms’ specific attribute (training), TAM, and BDA, in addition to hypothesis development. Section 3 introduces the paper’s framework. Section 4 addresses the methodology adopted in the paper. Section 5 covers the data analysis and results. The last sections (Sections 6 & 7) present the discussion and conclusion, summarizing the results, limitations, and the recommendations for future studies.

2. Literature Review

TAM provides a theoretical framework for analyzing technology adoption tendencies, focusing on two main factors: PU and PEU. These variables influence the attitudes of users, especially professionals like auditors, towards the acceptance or rejection of new technology (Davis, Bagozzi, & Warshaw, 1989). In their study, (Hwa, Hwei, & Peck, 2015) examined how users' BI to adopt web-based e-learning systems are influenced by their PU and PEU. The researchers found that the users' perception of the user-friendly and the expected benefits of these systems directly influenced their desire to use them, resulting in an increase in AU. Grimaldo and Uy (2020) found a strong and direct correlation between people' favorable attitude towards using job search sites and online recruitment tools, and their desire to use and then AU.

Davis and Venkatesh (1996) developed their TAM model (Figure 1 (a)) on the assumption of the existence of specific external variables that would impact the PU and PEU. Tarabasz and Poddar (2019) noted that external variables have a significant role in interpreting why PU and PEU impact the decision regarding the adoption or rejection of new technology, thus, they concluded that external variables would directly impact the PU and PEU of new technology. Although limited research was conducted on the impact of external variables on PU and PEU, some scholars like Davis, Bagozzi, & Warshaw (1989); Sharma and Mishra (2014); Grimaldo and Uy (2020) addressed some examples of external variables that might impact the PU and PEU, such as trust, support and documentation. In our study, we will focus on the training as one of the key variables to assess its impacts on PU and PEU.

This study employs the TAM to examine auditors' intentions to adopt BDA tools developed by their companies for use in auditing processes. Furthermore, we focus on external factor that have been previously identified in the literature as being directly related to the characteristics of auditing firms. Among these is training. The potential influence of training on auditors' assessments of the usefulness and ease of BDA technology use is what drives the investigation of this variable.

2.1 Impact of Training on PU and PEU

The acceptance of new technologies and the efficient use of such technologies inside businesses are both significantly impacted by training. It acts as a way to equip users with the essential skills and knowledge for the exploitation of technology, hence increasing the PU and PEU of the technology (Valenstein-Mah et al., 2020). In-person, online, and self-guided training can help professionals clarify questions and integrate technology into daily operations by building confidence and understanding (Valenstein-Mah et al., 2020; Shatri, 2020). Organizations struggle to develop successful training programs despite the advantages. Developing training programs involves creating ones that fit individual learning styles and encourage involvement. The complexity of the technology and training approach impacts training effectiveness, which may require customized programs to meet individual needs (Schröder et al., 2022; Al-Rahmi et al., 2019).

In order to get a better understanding of the role of training in increasing the perception of new technology adoption, other factors may be considered such as e-learning, training duration, learning style, and the use of interactive tools. These factors supposed to positively increase the benefits of training programs and then increase their adoption (Šumak et al., 2011; Al-Azawei, Parslow, & Lundqvist, 2017). Recognizing these matters raises the need to customize training programs to learners' needs and the specific requirements of the technology (Buchanan, Sainter, & Saunders, 2013; Al-Azawei, Parslow, & Lundqvist, 2017).

Major auditing firms acknowledge the significance of training in supporting their efforts toward a complete shift to digital audit transformation. Since this shift is essential for these firms' strategy to maintain a competitive advantage in the market, they are motivated to use advanced technology like BDA to enhance audit efficiency and quality. Consequently, these firms develop related training programs to prepare their auditors to utilize these newly developed technologies. Auditors perceive the usefulness and ease of use of BDA tools positively, following the increasing their knowledge and skills resulted from these training programs (Eilifsen et al., 2020; Buchanan, Sainter, & Saunders, 2013; Adrianto, 2018).

2.2 BDA and TAM

Recently, there has been a significant increase in studies dealing with the adoption of BDA. These studies addressed the benefits and issues related to the adoption of BDA, and focused on identifying the best theory that can be adopted to examine BDA adoption and use. Although many barriers could impact the adoption of BDA, such studies on big data adoption emphasized the importance of adopting BDA in organizations across different industries and economies (Olufemi, 2018; Brock and Khan, 2017; Verma, Bhattacharyya, & Kumar, 2018).

Biucky et al., (2017) provided a conceptual model based on TAM to explore factors impacting internet users' adoption of new technology represented by social commerce. They found that using TAM helps in interpreting the end users' intention to adopt a new IT system. Brock and Khan (2017) noted that the adoption of TAM was a critical factor in the study of the adoption of BDA. In addition, they also noted that TAM explains people's motivations for adopting the system. However, they also found that TAM does not consider the practical side of system adoption. Sharma and Mishra (2014) noted that technology adoption may require more than behavioral intention and technical knowledge; thus, they identified various factors such as trust, social influence, and numerous facilitating conditions. Meanwhile, Olufemi (2018) found that TAM does not consider technology cost, management support, and entities' environment and culture in the intention to adopt new technology. The user experience of big data was also addressed by some scholars to assess its impact on technology adoption. Müller and Jensen (2017) selected companies with previous experiences and knowledge in big data to investigate the application of big data among Danish SMEs. Li and Lai (2011) noted that experienced users feel more confident regarding the technology's ease of use than inexperienced users, recommending that experience is an external factor that impacts technology adoption behavior.

The common conclusion among most scholars is that the external variables have an effect on PU and PEU, and the PU and PEU themselves are considered the main TAM factors that can influence users' behavioral intentions to accept and adopt new technology, including BDA (Davis, 1989; Brock & Khan, 2017; Razmak & Bélanger, 2018; Bayraktaroglu et al., 2019).

2.3 BDA in Auditing

BDA helps professionals to understand companies' perceptions of business expectations. The need for understanding complex accounting standards increases the motivation to adopt new technologies in financial accounting and reporting, and the emergence of BDA helps to gain better chances of capturing real-time processes. This has led companies to invent new techniques and technologies to understand the role of BDA in accounting, but they should ensure that actual practices of BDA are aligned with the formally and publicly pronounced processes (İdil & Akbulut, 2018).

Gepp et al. (2018) found that big data offers an opportunity to analyze large volumes of data, sort information, and provide new insights. Auditing would benefit from adopting such big data approaches to enhance the efficiency of financial analysis and detect fraud. This complies with auditing standards that encourage the use of big data techniques, even for smaller data sets, to provide additional insights. BDA in external auditing is the process of inspecting and transforming big data to seek the efficiency and effectiveness of auditing and enhance the decision-making process (Dagilienė & Klovienė, 2019). Though auditors work with financial data, the volume and complexity of business require continuous analysis of non-financial data from both internal and external sources, demanding the use of BDA tools and changes in the audit processes (Dagilienė & Klovienė, 2019).

Eilifsen et al. (2020) identified some limitations and concerns represented by the evaluation of audit evidence collected through data analytics by regulatory bodies. Furthermore, auditing through data analytics is limited as supplementary evidence despite a global strategy concerning data analytics usage and the auditors' positive attitude towards its use. Its scope of use shall be limited until it is incorporated by clients, supported by regulators, and proves efficient and effective to gather evidence in the audit process. Auditing through BDA is extended by developing instructions and guidelines for substantive tests of details (No et al., 2019), and for fraud detection (Austin et al., 2018; Tang & Karim 2019). Several data analytics approaches were identified for auditors to effectively perform substantive tests of details (No et al., 2019) and for better fraud detection (Austin et al., 2018). The extent of applying BDA is determined by assessing the audit risk and materiality, also by the degree of understanding gained by the audit team about the nature, time, and extent of audit procedures designed to test accounts through BDA (No et al., 2019).

The benefits of using data analytics exceed challenges and costs, driving companies and audit firms towards the effective execution of data analytics, making it possible to analyze 100% of the journal entries, and potentially improving audit quality. Thus, data analytics is a transformative tool driving audit efficiency, adopted by various audit firms, especially Big Four firms, knowing that audits conducted by larger audit firms differ significantly in terms of BDA used in the financial reporting and audit process (Austin et al., 2018). An efficient audit with fewer expenses is the main purpose that audit firms are currently seeking. While companies expect their auditors to use BDA in the audit, disagreement about whether and how it affects audit fees is a concern among auditors, who have made a large investment in new BDA technologies. Therefore, many audit firms have called for the necessity of changing the audit fees in response to the implementation of BDA in the audit process (Austin et al., 2018).

2.4 Hypotheses Development

Auditors at top audit companies, like the "Big Four," gain from learning a lot about BDA technologies. This experience makes them much better at using BDA tools, which makes the move easier and helps them understand how BDA apps work. This kind of setting makes it less likely that auditors won't want to use BDA in their work.

Training turns out to be a key factor in how useful and easy to use new tools are seen to be. It is very important to give people full training when new technology is introduced so that it can be used and integrated well. This training help not only makes professionals more comfortable using the technology, but it also makes it more likely that it will be adopted (Valenstein-Mah, et al., 2020). Training also helps people understand the technology better, which can help clear up any misunderstandings or doubts that might stop people from using it (Shatri, 2020). Major auditing firms acknowledge the significance of training, instituting programs to equip their teams with the skills necessary for data analysis (Eilifsen et al., 2020). Buchanan, Sainter, and Saunders (2013) advice for concentrated training programs to enhance the supposed benefits and simplicity of use of new technologies, therefore promoting their adoption. Based on these discussions, we formulate the following hypotheses to investigate the impact of training on the PU and PEU:

***H1a:** Training has positive effect on the PU of BDA tools.*

***H1b:** Training has positive effect on the PEU of BDA tools.*

The finding as presented in the literature review section provides support that the PU and PEU affect the user's intention toward the acceptance and usage of a particular technology (Davis and Venkatesh, 1996). This intention leads to the actual use and adoption of technology (Diop, Zhao, & Duy, 2019). PU and PEU are considered the most significant TAM variables that affect the BI of users to adopt actual technology (Davis & Venkatesh, 1996). Some of the previous studies emphasized the importance of understating the PU and PEU that affect the technology adoption behavior (Al Amin et al., 2020; Cabrera-Sánchez & Villarejo-Ramos, 2019; Olufemi, 2018). Hwa, Hwei, & Peck (2015) investigated the role of PU and PEU on BI to adopt web-based e-learning systems, and they found that PU and PEU, have a significant relationship to predicting users' BI to adopt web-based e-learning systems. Grimaldo and Uy (2020) concluded that the perception of usefulness and ease of use of technology has a positive and direct relationship with the intention to use them. BI is the tendency to implement certain behaviors in the future and is also a predictor of the adoption of new technology; thus, the intent and need to use new technology ultimately led to its actual use (Shahbaz et al., 2019).

Based on the discussion regarding the impact of PU and PEU on the BI to use BDA and its actual use, we propose the following hypothesis:

***H 2a**: PU has a positive effect on the BI to adopt BDA technological tools in the audit process.*

***H 2b**: PEU has a positive effect on the BI to adopt BDA technological tools in the audit process.*

***H 2c**: BI to adopt BDA technological tools in the audit process has a positive effect on the actual use of these tools.*

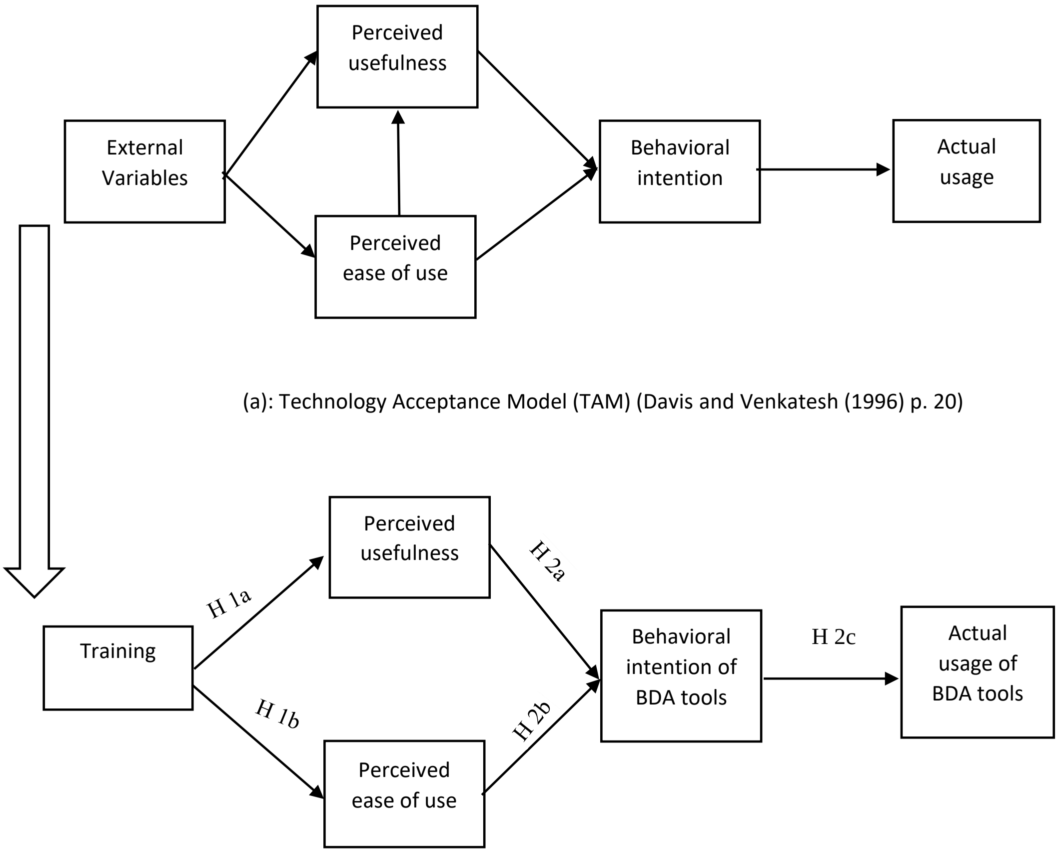
3. Model Development

The study model is based on an examination of the impact of training on the PU, PEU, and consequent adoption of technology. The TAM serves as the theoretical foundation for this analysis. This framework visually represents the interconnections among the variables and factors of the study, expanding upon the foundational principles of Davis's TAM (as shown in Figure 1 (a)). It accepts the proposition put forth by Davis and Venkatesh (1996) that perceived utility and simplicity of use are substantially influenced by specific external factors. This paper elucidates a certain external factor—specifically, training—that may influence auditors' perspectives on the utility and navigability of BDA technological tools, as revealed through a review of the relevant literature.

PU and PEU stand as cornerstone variables within TAM, critically influencing the BI of users towards embracing new technologies (Davis and Venkatesh, 1996). The significance of these variables in determining technology adoption behaviors has been addressed in previous studies (Al Amin et al., 2020; Cabrera-Sánchez & Villarejo-Ramos, 2020; Olufemi, 2018), in which the researchers highlighted their connections in predicting the intention towards new technology adoption (Grimaldo & Uy, 2020).

Furthermore, the developed research model suggests a direct pathway started from the external variables, then the auditor's perception of the usefulness and ease of use of BDA, which further linked to their intention to employ BDA tools in their work and ultimately resulted in their practical and actual application (Davis and Venkatesh, 1996; Shahbaz et al., 2019). Many scholars have given some examples of the output of this practical utilization of BDA by auditors, such as templates, checklists, and digital working papers (Pedrosa, Costa, & Aparicio, 2020; Knechel, 2007; Hurtt et al., 2013). Figure 1 (b) presents the conceptual framework that was built based on the literature review of the main research topics along with the related theoretical discussion. The model translated the above-mentioned linkage between the main areas of this study (external variables, PU, PEU, BI, and AU of BDA tools). This framework summarizes the decision-making process by auditors to adopt or reject BDA in their work to balance the pressure from their firm to apply it, discontinuing the traditional audit methods, and their perception of the ease and usefulness of these tools.

The research model presented in figure 1 (b) has two essential features: it integrates and elaborates on training as one of the external factors identified in the literature as influencing PU and PEU, thereby offering a comprehensive view of the elements affecting the adoption of data analytics. Furthermore, it investigates whether the training provided by audit firms might enhance auditors' perceptions of BDA tools and whether this enhanced perception could lead to a broader adoption of BDA tools in auditing practices.



(a): Technology Acceptance Model (TAM) (Davis and Venkatesh (1996) p. 20)

(b): Conceptual Study Model

Figure 1: Models Contributing to the Development of the Study Framework

4. Method

4.1 Research Design

The purpose of this study is to determine whether relationships exist between the study's independent and dependent variables across its three stages. In the first stage, the external variable, represented by the training, will serve as independent variables, while PEU and PU will be the dependent variables. In the second stage, PEU and PU will function as independent variables, with the practicing auditors' BI to adopt BDA in auditing as the dependent variable. This is followed by the third stage, in which BI is treated as the independent variable and AU as the dependent variable.

The study adopts quantitative research method by relying on the survey technique for data collection, as this method is effective for interpreting correlations and predicting the value of a specific variable based on another's value (Khaldi, 2017; Reio, 2016). The data gathered from the questionnaire were analyzed using SMARTPLS4.

Path analysis was utilized to investigate the connections between the research's independent and dependent variables (Loehlin, 2004).

4.2 Population and Sample

The study population consisted of practicing auditors working at the big four auditing firms in Palestine at the time of data collection. The sample selection method for this research was the census approach, where the entire population also represented the sample (Levy & Lemeshow, 2013; Gibbins, Salterio, & Webb, 2001). This method is effective when dealing with smaller population, such as when the total population is fewer than 100 units (Levy & Lemeshow, 2013; Vinzi et al., 2010). Out of 105 auditors in the Big Four firms in Palestine, 11 with less than one year of experience were excluded, reducing the survey population to 94. The survey received 81 responses, yielding an 86% response rate. Less experienced auditors were excluded to ensure the reliability of audit judgments, as research indicates that experience enhances auditors' ability to identify risks and inconsistencies (Sayed Hussin et al., 2017; Pagalung & Habbe, 2017).

4.3 Questionnaire Design

The questionnaire was designed to collect the main demographic information about the participants. Additionally, the questionnaire includes three main sections with a total of 29 statements as follows: The first section contains 7 statements related to the training factor. The second section contains 14 statements to determine whether PEU and PU impact auditors' BI to adopt BDA. The last section, consisting of 8 statements to measure the AU of BDA technological tools. The questionnaire items in all sections (except for the demographic part) were measured using a 7-point Likert scale, ranging from 1 ('strongly disagree') to 7 ('strongly agree'). This scale is commonly used to examine participants' perceptions, attitudes, and opinions when a questionnaire is employed to assess specific subjective matters (Schrum et al., 2020).

The Training factor is based on the research of Al-Azawei, Parslow, and Lundqvist (2017) which includes question from TG1 to TG7. In TAM section, Davis's (1989) TAM questionnaire was employed to measure the independent variables of PEU and PU, encompassing questions from PU.1 to PU.6 and PEU.1 to PEU.6. Davis developed a measurement scale for these variables to assess user acceptance of new technology. However, since Davis's 1989 model did not include the dependent variable of BI to use, the work of Davis and Venkatesh (1996) will also be referenced, as they incorporated this aspect into the TAM framework (questions BI.1 and BI.2). Finally, AU section of the questionnaire is designed to assess the AU of BDA technological tools, addressing questions from AU.1 to AU. 8. The focus here is on measuring the independent variable of the AU of these tools. This part is adopted from Janvrin, Bierstaker, & Lowe (2009), who explored auditors' use of computer-assisted audit techniques (CAATs) within the audit process. Some modifications Janvrin, Bierstaker, & Lowe (2009)' instrument was made to better align with the focus of this questionnaire section.

5. Data Analysis and Results

5.1 Questionnaire Analysis

To achieve the study' objectives and test the related hypotheses, SmartPLS 4 software was used. Two vital methodological elements were considered: the measurement model and the structural model. Currently, Path analysis and PLS-SEM techniques are broadly used as the primary statistical approach in various research fields. (Hair et al., 2010, 2016; Kline, 2023).

Table 1 presents the means and standard deviations for each of the constructs. We grouped the responses collected on the seven-point Likert scale into three categories: 'low' for ratings from 1 to less than 3,'medium' for ratings from 3 to less than 5, and 'high' for ratings from 5 to 7. This division was intended to yield uniform and dependable feedback from the auditor participants. The analysis indicated that all the constructs scored within the 'high' category. This suggests a positive reception towards the technology among the auditors. Furthermore, training influences the implementation of the technology, underscoring the significance of this external factor in facilitating the adoption and effective utilization of the technology in audit firms.

Table 1: Level of implementation of the external variables, TAM, and AU

	Mean	Standard Deviation	Level of Implementation
Training	5.50	0.95	High
Perceived usefulness	5.42	1.02	High
Perceived ease of use	5.16	0.94	High
Behavioral intention	5.44	1.07	High
Total for TAM	5.31	0.89	High
Actual use	5.14	1.07	High

5.2 Assessment of the Measurement Model

The measurement model was assessed to establish the reliability and validity of the constructs (Table 2). First, the factor loading of all the items in the model exceeded the minimum acceptable value of 0.50 (Hair et al., 2010). Although factor loading over 0.70 is recommended (Vinzi et al., 2010), researchers in social science studies often encounter lower loading (less than 0.70). Instead of immediately deleting these indicators, their effects on composite reliability, content validity, and convergent validity shall be examined. Items with outer loadings from 0.40 to 0.70 should be considered for removal only if their deletion increases of composite reliability or average variance extracted (AVE) above the recommended value (Hair et al., 2016). In this paper, removing the item (TG5, loading = 0.639) would not have significantly increased the composite reliability and AVE, as the values were already above the threshold. Additionally, evaluating the confidence interval of the loading revealed that none included zero. Hence, no items were removed from the study for further analysis.

Table 2: Reflective constructs measurement properties

Reflective constructs	Construct items	Items loading	CR	AVE	Reference
Training	TG1	0.789	0.930	0.657	Al-Azawei, Parslow, & Lundqvist (2017)
	TG2	0.830			
	TG3	0.850			
	TG4	0.803			
	TG5	0.639			
	TG6	0.886			
	TG7	0.852			
Perceived Usefulness	PU1	0.930	0.977	0.874	Davis (1989)
	PU2	0.964			
	PU3	0.949			
	PU4	0.947			
	PU5	0.899			
	PU6	0.920			
Perceived ease of use	PEU1	0.868	0.961	0.804	Davis (1989)
	PEU2	0.903			
	PEU3	0.944			
	PEU4	0.922			
	PEU5	0.898			
	PEU6	0.841			
Behavioral intention	BI1	0.976	0.976	0.954	Davis & Venkatesh (1996)
	BI2	0.977			

Reflective constructs	Construct items	Items loading	CR	AVE	Reference
Actual use	AU1	0.857	0.958	0.742	Janvrin, Bierstaker, & Lowe (2009)
	AU2	0.858			
	AU3	0.908			
	AU4	0.806			
	AU5	0.845			
	AU6	0.881			
	AU7	0.839			
	AU8	0.895			

Reliability was assessed using Cronbach's alpha, rho-a, and composite reliability; statistics for both were greater than the recommended value of 0.700 (Wasko & Faraj, 2005). The rho-a value returned was between the Cronbach's alpha and composite reliability (Sarstedt, Ringle, & Hair, 2017), it was also more than 0.70, thereby indicating high reliability (Henseler et al., 2016). Additionally, convergent validity was acceptable since the AVE was more than 0.500. Moreover, the verification of discriminant validity is essential for confirming the uniqueness of the measurement tools associated with different factors. This process checks that the square root of the AVE for each construct is greater than the inter-construct correlations, as proposed by Fornell and Larcker (1981). Table 3 presents the results of applying the Fornell-Larcker criterion to our study's model, which indicating compliance with this validation standard.

Table 3: The measurement model discriminant validity- Fornell-Larcker criterion.

Constructs	Actual Use	Behavioral Intention	Perceived Ease of Use	Perceived Usefulness	Training
Actual Use	**0.862**				
Behavioral Intention	0.481	**0.977**			
Perceived Ease of Use	0.615	0.631	**0.897**		
Perceived Usefulness	0.650	0.712	0.710	**0.935**	
Training	0.728	0.481	0.616	0.658	**0.810**

Additionally, the model's discriminant validity was evaluated using the heterotrait-monotrait ratio (HTMT) of correlations (Ab Hamid, Sami, & Sidek, 2017). An HTMT ratio should be less than 0.90 to achieve adequate discriminant validity between the constructs. We presented all of results from HTMT assessment in Table 4, where each recorded value is below the 0.90 threshold, thereby confirming the discriminant validity of the model.

Following the compilation of results from the study's measurement model evaluation, Figure 2 depicts the finalized research model that was explored.

Table 4: Heterotrait-Monotrait Ratio (HTMT)

Constructs	Actual Use	Behavioral Intention	Perceived Ease of Use	Perceived Usefulness	Training
Actual Use	-				
Behavioral Intention	0.493	-			
Perceived Ease of Use	0.646	0.661	-		
Perceived Usefulness	0.673	0.739	0.738	-	
Training	0.781	0.511	0.648	0.695	-

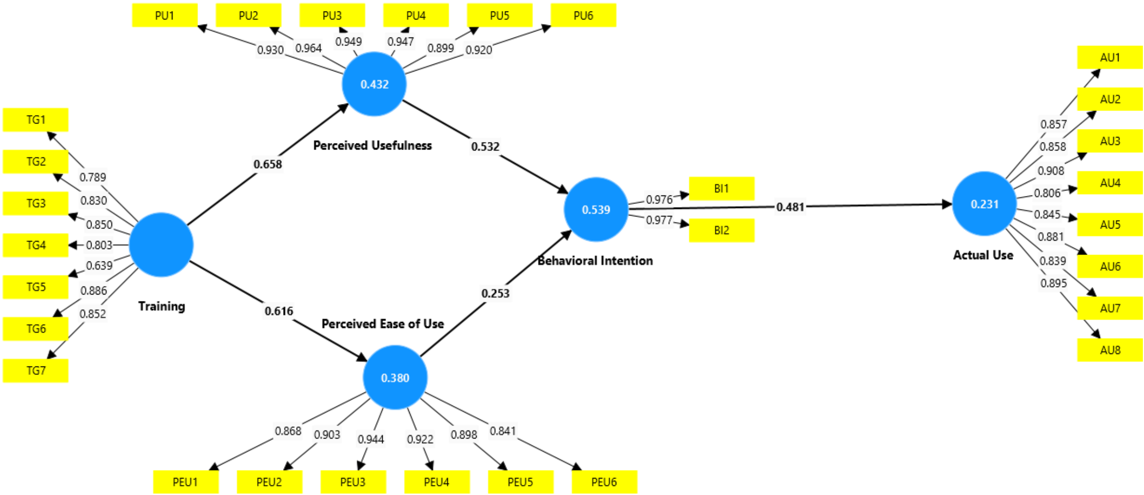


Figure 2: The measurement model

5.3 Assessment of the Structural Model

The next step in the study was to examine the structural model to determine its predictive accuracy and explore the interactions among the constructs, as well as the model's robustness and coherence. This phase was important for verifying the study's hypotheses. The analysis used a bootstrapping procedure and focused on several key indicators: the coefficient of determination (R^2), path coefficients (β values), T-statistics, the effect size (f^2), and the model's predictive relevance (Q^2). R^2 values are considered high at 0.75, moderate at 0.50, and low at 0.25 (Hair et al., 2010). In this paper, the R^2 values are considered moderate. The Q^2 values act as markers of the model's predictive capacity, with the results affirming the model's effectiveness in forecasting outcomes.

Crucially, for a model to demonstrate sufficient predictive relevance, the Q^2 values must surpass zero, confirming that the external constructs possess predictive utility for the internal constructs, following the guidance of Hair et al. (2010). Table 5 outlines the cross-validated redundancy values for AU, BI, PEU, and PU, documented at 0.264, 0.214, 0.369, and 0.415, respectively. The effect size (f^2) measures the influence of each external latent variable on an internal latent variable, enabling an assessment of how well the structural model accounts for the variance in internal latent variables.

Adhering to Cohen's (1988) framework, f^2 values of 0.02, 0.15, and 0.35 are categorized as indicative of small, medium, and large impacts, respectively. The data presented in Table 5 indicate that the f^2 effect sizes range from a minimal impact, with a value of 0.069 for PEU on BI, to a significant impact, with a value of 0.762 for training's effect on PU. In addition, the Q^2 values for the internal constructs all exceeded 0, thus confirming the structural model's predictive relevance.

Table 5: R^2, communality, and redundancy

Construct	R^2 adj	Q^2	f^2 Perceived Ease of Use	f^2 Perceived Usefulness	f^2 Behavioral Intention	f^2 Actual Use
Training	-	-	0.613	0.762	-	-
Actual Use	0.222	0.264	-	-	-	-
Behavioral Intention	0.527	0.214	-	-	-	0.301
Perceived Ease of Use	0.372	0.369	-	-	0.069	-
Perceived Usefulness	0.425	0.415	-	-	0.305	-

Moreover, the study engaged in the use of Path Coefficients to scrutinize the proposed relationships among variables. The findings, elaborated in Table 6, adhere to the approach recommended by Hair et al. (2016), which involves the application of the bootstrapping method. This procedure produced key statistical figures such as beta coefficients, standard errors, t-values, and p-values.

Table 6: Hypothesis testing results

Hypothesis	Beta coefficients	Standard deviation	T statistics	P values	Decision
H 2c Behavioral Intention -> Actual Use	0.481	0.114	4.236	0.000	Supported
H 2b Perceived Ease of Use -> Behavioral Intention	0.253	0.150	1.688	0.091	Rejected
H 2a Perceived Usefulness -> Behavioral Intention	0.532	0.142	3.760	0.000	Supported
H1b Training -> Perceived Ease of Use	0.616	0.080	7.680	0.000	Supported
H1a Training -> Perceived Usefulness	0.658	0.080	8.219	0.000	Supported

Table (6) and figure (3) provided offers a detailed examination of the relationships among various constructs, with each hypothesis clearly numbered for enhanced clarity. The analysis begins with a compelling validation of the impact of BI on AU (hypothesis 2c), as evidenced by a robust beta coefficient of 0.481, a T statistic of 4.236, and a p-value of 0.000. This significant finding highlights the critical influence of BI on AU.

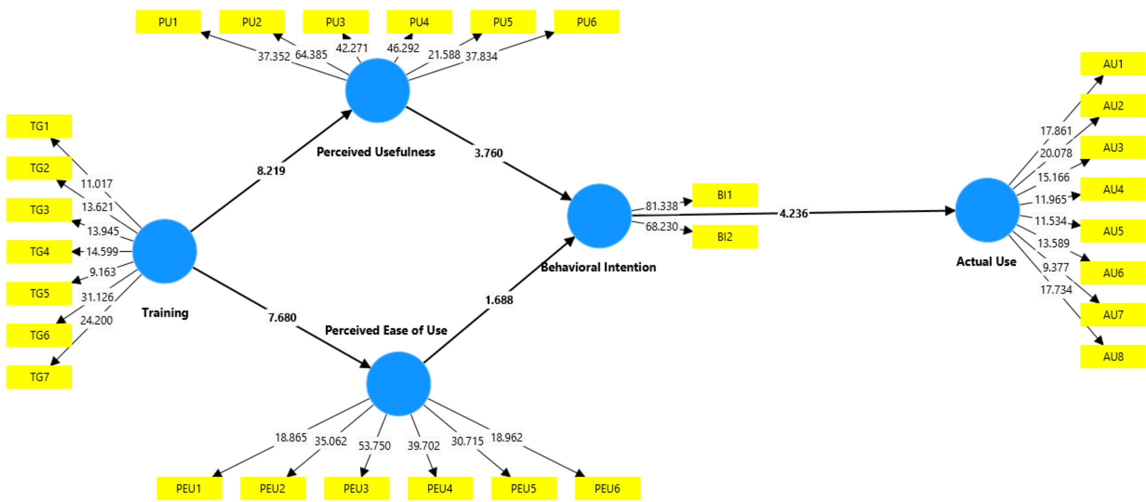


Figure 3: PLS Bootstrapping (t-values) for the study model

The study also demonstrates the significant influence of the PU on BI (hypothesis 2a), with beta coefficients of 0.532, T statistics of 3.760, and p-values of 0.000. This finding emphasizes the important role of PEU in influencing BI. Conversely, the hypothesis regarding PEU's impact on BI (hypothesis 2b) did not achieve statistical significance (beta coefficient: 0.253, T statistic: 1.688, and p-value: 0.091), resulting in its rejection.

The study also demonstrates the significant influence of the training on PEU (hypothesis 1b) and PU (hypothesis 1a), with beta coefficients of 0.616 and 0.658, T statistics of 7.680 and 8.219, and p-values of 0.000 and 0.000, respectively. These findings highlight the importance of training in shaping PU and PEU.

Collectively, these refined results detail the relationship between constructs such as BI, PU, PEU, and training. These findings offer insights for future research and practical applications, particularly on the effect of one of the external factors related to audit firm attributes represented by training on technology adoption behaviors.

6. Discussion

The Findings of this study provide insights into the influence of training on PU and PEU, and their collective impact on BI to adopt BDA tools, and how these intentions translate into actual usage. Training was found to have a positive effect on PU and PEU of BDA tools (H1a and H1b). These findings are similar with finding of some of previous studies, such as Valenstein-Mah et al. (2020) who emphasized that detailed training programs enhance users' understanding and confidence in new technologies. Shatri (2020) also found that training help professionals integrate technology into daily operations by building confidence and understanding. Other studies, like Buchanan, Sainter, & Saunders (2013), and Adrianto (2018), also highlight the importance of training in technology adoption; they found that effective training programs customized to the users or learners' need significantly enhance the PU and PEU of new technologies, motivating their adoption. These findings indicates that Auditing firms should invest in good training programs specified to the needs of their auditors. Such programs should be designed to address the different learning styles and ensure that auditors are comfortable and confident in using BDA tools. This approach not only facilitate the adoption of new technologies but also enhance the overall quality and efficiency of the audit process.

Regarding Hypothesis (H2a), the results showed that PU has a positive effect on the BI to adopt BDA tools, which aligns with the findings of Davis and Venkatesh (1996) and Hwa, Hwei, & Peck (2015). Grimalso and Uy (2020) also concluded that the perception of usefulness has a positive relationship with the intention to use technology. Furthermore, Cabrera-Sánchez and Villarejo-Ramos (2019) and Al Amin et al. (2020) emphasized the importance of PU in expecting users' behavioral intention to adopt new technologies. Their studies indicate the importance role of PU in driving technology adoption behaviors and attitudes. Accordingly, auditing firms should focus on highlighting the benefits of BDA tools to their auditors. Conducting training courses including on the job training on BDA applications would help these firm to demonstrate how these tools can enhance audit efficiency and quality. This can reinforce a positive perception of their usefulness and ultimately encouraging adoption.

On the other hand, while the study found that PEU has a positive impact on BI, this was not statistically significant (H2b). This suggest that while ease of use is important, the PU of the new technology play a more critical role in shaping auditors' intentions to use BDA. This finding is opposite to the conclusion of Davis and Venkatesh (1996), who empathized on the significant role of PEU in technology adoption. However, Sharma and Mishra (2014) noted that technology adoption may require more than just ease of use to include other factors such as trust and social influence, which may also play a role. This may explain the lack of a significant impact of PEU on BI in our study. Although simplifying the user interface and ensuring that BDA tools are easy to use is important, audit firms should primarily focus on proving the benefits of these tools. Emphasizing the practical advantages of BDA tools in improving audit efficiency and quality can more effectively increase adoption.

Furthermore, BI to adopt BDA tools was found to have a positive effect on the actual use of these tools (H2c). The study validates that BI significantly influences AU, supporting the framework proposed by Davis and Venkatesh (1996). External auditors who intend to use BDA tools are more likely to use them in performing their audit procedures. This finding is consistent with the TAM model and emphasizes the importance of increasing willingness towards new technologies to ensure their practical application. Previous studies, such as Diop, Zhao, & Duy (2019) and Shahbaz et al. (2019), also support the significant relationship between BI and AU. These studies highlight that a BI is a predictor of actual technology use. Based on these findings, audit firms should implement strategies to convert positive intentions into actual usage. This can be achieved through continuous support and resources, such as regular training programs, and success stories cases that present the practical benefits of BDA tools. By creating an environment that supports and encourages the use of BDA, Audit firms can ensure that their auditors not only intend to use BDA tools but also integrate them into their daily audit practices.

The above findings provide insights particularly relevant for audit firms in developing countries, where the adoption of advanced technologies like BDA is still in early stages. By addressing one of the critical external factors, represented by training, that is expected to influence technology adoption, firms can better navigate the challenges associated with digital transformation and improve their overall audit quality and efficiency.

7. Conclusion

7.1 Implications for Practice

This study demonstrates the significant role of training in shaping auditors' perceptions and adoption of BDA tools in Palestine. Our findings reveal that training positively influences both PU and PEU of BDA tools, with PU being a key driver of BI to adopt BDA. The strong link between BI and AU underscores the importance of fostering positive attitudes towards BDA among auditors.

These results have important implications for audit firms, particularly in developing countries. They suggest that investing in comprehensive BDA training programs can significantly enhance auditors' willingness to adopt these tools, potentially leading to improved audit quality and efficiency. However, the lack of significant impact of PEU on BI indicates that firms should focus on demonstrating the utility of BDA tools rather than just their user-friendliness. This finding is particularly relevant in the context of training, as it suggests that training programs should not only make BDA tools easier to use but also emphasize their practical benefits and how they can improve audit processes.

The conclusions of this study specifically address the three objectives laid out at the end of the introduction:

1. To examine the effect of training on PU and PEU of BDA tools: The study found that training has a positive effect on both PU and PEU, highlighting the importance of comprehensive training programs tailored to the needs of auditors.
2. To investigate the relationship between PU, PEU, and BI to adopt BDA tools: The results indicated that PU has a significant positive impact on BI, while PEU, although important, was not statistically significant. This underscores the need for training programs to focus on demonstrating the practical utility of BDA tools.
3. To explore the impact of BI on the actual use of BDA tools: The study confirmed that BI significantly influences AU, supporting the importance of fostering positive behavioral intentions through targeted training and support.

In summary, while ease of use is a critical factor, the perceived usefulness of BDA tools plays a more decisive role in their adoption. Therefore, audit firms should design their training programs to not only simplify the user experience but also highlight the tangible benefits of BDA tools in enhancing audit efficiency and quality. By doing so, they can more effectively drive the adoption and integration of these tools into daily audit practices, ultimately improving the overall audit process. Furthermore, while this study was based on a specific sample of external auditors in Palestine, the implications for practice can be generalized to other developing countries facing similar challenges in adopting advanced technologies. The insights gained from this research suggest that investing in training programs tailored to the unique needs of auditors can support the adoption of BDA tools and improve audit quality and efficiency.

7.2 Limitations

Despite its practical implications, this study has two main limitations. The first limitation arises from the study's focus on external auditors employed by the Big four auditing firms in Palestine. Excluding the remaining auditors from small firms may limit the generalizability of the findings to other regions or auditors from local firms. Second, adopting the TAM as a theoretical framework may not address all aspects related to impact of training on BDA utilization.

7.3 Future Research

Future research may consider expanding the geographical scope and auditing firm size by including auditors from different countries and firms of various sizes to enhance generalizability. Additionally, exploring other theoretical frameworks or models to assess the impact of training on BDA utilization could offer new perspectives.

References

Ab Hamid, M. R., Sami, W., & Sidek, M. M. (2017, September). Discriminant validity assessment: Use of Fornell & Larcker criterion versus HTMT criterion. In *Journal of Physics: Conference Series* (Vol. 890, No. 1, p. 012163). IOP Publishing.

Adrianto, Z. (2018). Auditing in the era of big data: a literature review. *Jurnal Akuntansi dan Keuangan, 17*(1), 1-6.

Al Amin, M., Nowsin, N., Hossain, I., & Bala, T. (2020). Impact of social media on consumer buying behaviour through online value proposition: A study on e-commerce business in Bangladesh. *Academy of Strategic Management Journal*, *19*(5), 1-18.

Al-Azawei, A., Parslow, P., & Lundqvist, K. (2017). Investigating the effect of learning styles in a blended e-learning system: An extension of the technology acceptance model (TAM). *Australasian Journal of Educational Technology*, 33(2).

Al-Rahmi, W. M., Yahaya, N., Aldraiweesh, A. A., Alamri, M. M., Aljarboa, N. A., Alturki, U., & Aljeraiwi, A. A. (2019). Integrating technology acceptance model with innovation diffusion theory: An empirical investigation on students' intention to use E-learning systems. *Ieee Access*, 7, 26797-26809.

Austin, A., Carpenter, T., Christ, M., & Nielson, C. (2018). The data analytics transformation: Evidence from auditors, CFOs, and standard-setters*, vorläufiger Entwurf, vorgestellt an der ISAR-Konferenz*.

Bayraktaroglu, S., Kahya, V., Atay, E., & Ilhan, H. (2019). Application of expanded technology acceptance model for enhancing the HRIS usage in SMEs. *International Journal of Applied Management and Technology*, *18*(1), 7.

Biucky, T. S., Abdolvand, N., & Rajaee Harandi, S. (2017). The effects of perceived risk on social commerce adoption based on tam model. *International Journal of Electronic Commerce Studies.*

Brock, V., & Khan, H. U. (2017). Big data analytics: does organizational factor matters impact technology acceptance?. *Journal of Big Data*, *4*(1), 1-28.

Buchanan, T., Sainter, P., & Saunders, G. (2013). Factors affecting faculty use of learning technologies: Implications for models of technology adoption. *Journal of Computing in Higher education*, 25(1), 1-11.

Cabrera-Sánchez, J. P., & Villarejo-Ramos, A. F. (2020). Factors affecting the adoption of big data analytics in companies. *Revista de Administração de Empresas*, *59*, 415-429.

Cohen, S. (1988). Perceived stress in a probability sample of the United States.

Dagilienė, L., & Klovienė, L. (2019). Motivation to use big data and big data analytics in external auditing. *Managerial Auditing Journal*.

Davis, F. D. (1986). A technology acceptance model for empirically testing new end-user information systems: Theory and results (Doctoral dissertation, Massachusetts Institute of Technology).

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management science*, *35*(8), 982-1003.

Davis, F. D., & Venkatesh, V. (1996). A critical assessment of potential measurement biases in the technology acceptance model: three experiments. *International journal of human-computer studies*, *45*(1), 19-45.

Diop, E. B., Zhao, S., & Duy, T. V. (2019). An extension of the technology acceptance model for understanding travelers' adoption of variable message signs. *PLoS one*, *14*(4), e0216007.

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.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, *18*(1), 39-50.

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*.

Gibbins, M., Salterio, S., & Webb, A. (2001). Evidence about auditor–client management negotiation concerning client's financial reporting. *Journal of Accounting Research*, 39(3), 535-563.

Grimaldo, J. R., & Uy, C. (2020). Factors Affecting Recruitment Officers' Intention to Use Online Tools. *Review of Integrative Business and Economics Research*, *9*, 194-208.

Hair Jr, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). Multivariate data analysis (7 ed). *London; Prentice Hall*.

Hair, Jr, J. F., Sarstedt, M., Matthews, L. M., & Ringle, C. M. (2016). Identifying and treating unobserved heterogeneity with FIMIX-PLS: part I–method. *European business review*, *28*(1), 63-76.

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: updated guidelines. *Industrial management & data systems*, *116*(1), 2-20.

Hurtt, R. K., Brown-Liburd, H., Earley, C. E., & Krishnamoorthy, G. (2013). Research on auditor professional skepticism: Literature synthesis and opportunities for future research. *Auditing: A Journal of Practice & Theory*, *32*(Supplement 1), 45-97.

Hwa, S. P., Hwei, O. S., & Peck, W. K. (2015). Perceived usefulness, perceived ease of use and behavioural intention to use a learning management system among students in a Malaysian university. *International Journal of Conceptions on Management and Social Sciences*, *3*(4), 29-35.

İdil, K. A. Y. A., & Akbulut, D. H. (2018). Big data analytics in financial reporting and accounting. *PressAcademia Procedia*, *7*(1), 256-259.

Janvrin, D., Bierstaker, J., & Lowe, D. J. (2009). An investigation of factors influencing the use of computer-related audit procedures. Journal of Information Systems, 23(1), 97-118.

Kapoor, M. (2020, June 2). Big Four Invest Billions in Tech, Reshaping Their Identities. Retrieved from Bloomberg Tax https://news.bloombergtax.com/financial-accounting/big-four-invest-billions-in-tech-reshaping-their-identities

Kline, R. B. (2023). *Principles and practice of structural equation modeling*. Guilford publications.

Knechel, W. R. (2007). The business risk audit: Origins, obstacles and opportunities. *Accounting, Organizations and Society*, *32*(4-5), 383-408.

Khaldi, K. (2017). Quantitative, qualitative or mixed research: which research paradigm to use?. *Journal of Educational and Social Research*, *7*(2), 15-15.

Krieger, F., Drews, P., & Velte, P. (2021). Explaining the (non-) adoption of advanced data analytics in auditing: A process theory. *International Journal of Accounting Information Systems*, *41*, 100511.

Levy, P. S., & Lemeshow, S. (2013). *Sampling of populations: methods and applications*. John Wiley & Sons.

Li, H. L., & Lai, M. M. (2011). Demographic differences and internet banking acceptance. *MIS REVIEW: An International Journal*, *16*(2), 55-92.

Loehlin, J. C. (2004). *Latent variable models: An introduction to factor, path, and structural equation analysis*. Psychology Press.

Müller, S. D., & Jensen, P. (2017). Big data in the Danish industry: application and value creation. *Business process management journal*.

No, W. G., Lee, K., Huang, F., & Li, Q. (2019). Multidimensional audit data selection (MADS): A framework for using data analytics in the audit data selection process. *Accounting Horizons*, *33*(3), 127-140.

Olufemi, J. (2018). Considerations for the Adoption of Cloud-based Big Data Analytics in Small Business Enterprises. *Electronic Journal of Information Systems Evaluation*, *21*(2), pp63-79.

Pagalung, G., & Habbe, A. H. (2017). The Effects of Audit Experience, Trust and Information Technology on the Professional Skepticism and Ability in Detecting Fraud by Internal Bank Auditors in Jakarta, Indonesia.

Pedrosa, I., Costa, C. J., & Aparicio, M. (2020). Determinants adoption of computer-assisted auditing tools (CAATs). *Cognition, Technology & Work*, *22*(3), 565-583.

Razmak, J., & Bélanger, C. (2018). Using the technology acceptance model to predict patient attitude toward personal health records in regional communities. *Information Technology & People*, *31*(2), 306-326.

Reio, T. G. (2016). Nonexperimental research: Strengths, weaknesses and issues of precision. *European Journal of Training and Development*.
Sarstedt, M., Ringle, C. M., & Hair, J. F. (2017). Treating unobserved heterogeneity in PLS-SEM: A multi-method approach. *Partial least squares path modeling: Basic concepts, methodological issues and applications*, 197-217.
Sayed Hussin, S. A. H., Iskandar, T. M., Saleh, N. M., Jaffar, R. (2017). Professional skepticism and auditors' assessment of misstatement risks: the moderating effect of experience and time budget pressure. *Economics and Sociology, 10*(4), 225-250
Schröder, S., Wiek, A., Farny, S., & Luthardt, P. (2022). Toward holistic corporate sustainability—Developing employees' action competence for sustainability in small and medium-sized enterprises through training. *Business Strategy and the Environment*.
Schrum, M. L., Johnson, M., Ghuy, M., & Gombolay, M. C. (2020, March). Four years in review: Statistical practices of likert scales in human-robot interaction studies. In *Companion of the 2020 ACM/IEEE International Conference on Human-Robot Interaction* (pp. 43-52).
Shahbaz, M., Gao, C., Zhai, L., Shahzad, F., & Hu, Y. (2019). Investigating the adoption of big data analytics in healthcare: the moderating role of resistance to change. *Journal of Big Data*, *6*(1), 1-20.
Sharma, R., & Mishra, R. (2014). A review of evolution of theories and models of technology adoption. *Indore Management Journal*, *6*(2), 17-29.
Shatri, Z. G. (2020). Advantages and disadvantages of using information technology in learning process of students. *Journal of Turkish Science Education*, 17(3), 420-428.
Šumak, B., Heričko, M., Pušnik, M., & Polančič, G. (2011). Factors affecting acceptance and use of Moodle: An empirical study based on TAM. *Informatica*, *35*(1).
Tang, J., & Karim, K. E. (2018). Financial fraud detection and big data analytics–implications on auditors' use of fraud brainstorming session. *Managerial Auditing Journal*.
Tarabasz, A., & Poddar, G. (2019). Factors influencing adoption of wearable devices in Dubai. *Journal of Economics and Management*, *36*(2), 123-143.
Valenstein-Mah, H., Greer, N., McKenzie, L., Hansen, L., Strom, T. Q., Wiltsey Stirman, S., ... & Kehle-Forbes, S. M. (2020). Effectiveness of training methods for delivery of evidence-based psychotherapies: A systematic review. *Implementation Science*, 15(1), 1-17.
Venkatesh, V., Davis, F., & Morris, M. G. (2007). Dead or alive? The development, trajectory and future of technology adoption research. Journal of the association for information systems, 8(4), 267-286.
Verma, S., Bhattacharyya, S. S., & Kumar, S. (2018). An extension of the technology acceptance model in the big data analytics system implementation environment. *Information Processing & Management*, *54*(5), 791-806.
Vinzi, V. E., Chin, W. W., Henseler, J., & Wang, H. (2010). *Handbook of partial least squares* (Vol. 201, No. 0). Berlin: Springer.
Wasko, M. M., & Faraj, S. (2005). Why should I share? Examining social capital and knowledge contribution in electronic networks of practice. *MIS quarterly*, 35-57.

Appendix A: Details of Instrument Items

Variable	Instrument item
	A. Demographics Variables Section
Demographics Variables	• Age • Gender • Academic degree • Current job position • Years in the audit profession
	B. External Variable Section
Training	• Training on big data analytics tools improves my performance in using these tools. • Training on big data analytics tools increases my scientific performance in auditing. • Training on big data analytics tools enhances my learning effectiveness. • The training on using big data analytics tools is clear and understandable. • Interacting with the training programs on big data analytics tools is mentally easy. • I find that the training makes using big data analytics tools easy. • The types of training on big data analytics tools make them easy to use.
	C. Technology Acceptance Model (TAM) Section
PU	• Using big data analytics tools in my job would enable me to accomplish tasks more quickly. • Using big data analytics tools would improve my job performance. • Using big data analytics tools in my job would increase my productivity. • Using big data analytics tools would enhance my effectiveness on the job. • Using big data analytics tools would make it easier to do my job. • I would find big data analytics tools useful in my job.
PEU	• Learning to operate big data analytics tools would be easy for me.

	• I would find it easy to get big data analytics tools to do what I want them to do. • My interaction with big data analytics tools would be clear and understandable. • I would find big data analytics tools to be flexible to interact with. • It would be easy for me to become skillful at using big data analytics tools. • I would find big data analytics tools easy to use.
Intention to use	• Assuming I had access to big data analytics tools, I intend to use them. • Given that I had access to big data analytics tools, I predict that I would use them.
D. Actual Use Section	
Actual use of BDA tools	• While working on the audit of that assignment, I used the big data analytics tools when evaluating fraud risk. • While working on the audit of that assignment, I used the big data analytics tools for sample selection. • While working on the audit of that assignment, I used the big data analytics tools when identifying journal entries to be tested. • While working on the audit of that assignment, I used the big data analytics tools when evaluating and testing the control effectiveness. • While working on the audit of that assignment, I used the big data analytics tools for performing IPE (Information Produced by the Entity) test. • While working on the audit of that assignment, I used the big data analytics tools in the substantive testing of balance sheet accounts. • While working on the audit of that assignment, I used the big data analytics tools in the substantive testing of income sheet accounts. • While working on the audit of that assignment, I relied on big data analytics tools in performing overall analytical procedures.