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Impact of Competition and Client Size on Big Data Analytics Adoption: A TAM Study of Auditors

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ABSTRACT: The increasing complexity of audit engagements, particularly with large clients, and growing competition within the auditing field necessitate the adoption of advanced technologies such as Big Data Analytics (BDA). However, little is known about the factors influencing auditors' behavioral intention (BI) to adopt BDA tools. This study aims to investigate how audit client size and competition affect auditors' intention to adopt BDA in auditing processes, using the Technology Acceptance Model (TAM) as the theoretical framework. A census survey was conducted among 94 auditors from Big Four accounting firms in Palestine, achieving an 86% response rate. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that audit client size positively influences both perceived usefulness (PU) ($\beta = 0.366$, $p < 0.001$) and perceived ease of use (PEU) ($\beta = 0.490$, $p < 0.000$) of BDA tools. Similarly, competition positively affects PU ($\beta = 0.512$, $p < 0.000$) and PEU ($\beta = 0.333$, $p < 0.001$). Furthermore, PU significantly predicts auditors' BI to adopt BDA ($\beta = 0.532$, $p < 0.000$), while PEU does not. BI, in turn, positively influences the actual use of BDA tools ($\beta = 0.481$, $p < 0.001$). These findings spotlight the importance of leveraging client size and competitive pressures to enhance PU and PEU, thereby fostering the adoption of BDA technologies. By adopting these tools, auditing firms can improve efficiency, enhance fraud detection, and provide more comprehensive assurances, ultimately achieving a competitive edge in the market.

Keywords: audit transformation, behavioral intention, big data analytics, client size, competition, Palestine, perceived ease of use, perceived usefulness, technology acceptance model.

I. INTRODUCTION

The rapid technological advancement in the world, along with the increase in business size and complexity, has led most companies across the globe to increasingly use their data in more sophisticated ways. As a result, auditors are now dealing with a greater volume of data from various sources and types, thus facing a higher number of transactions [1, 2]. These challenges have prompted audit firms to develop and adopt new technological tools and techniques to provide companies with greater levels of assurance and valuable insights.

Auditing firms continue to invest heavily in BDA while they develop their audit methodologies to include the necessary guidance and instructions for their auditors to learn and use the new BDA techniques and tools [3, 4, 5, 6]. Examples of outputs from these tools include prepared working papers, smart forms, templates, and checklists, which enhance the efficiency and quality of the audit process [7]. Digital audit transformation in major audit firms continues to evolve and widen the spectrum of their automation journey. However, for these firms to achieve maximum benefits, it is essential not only to develop BDA technological tools but also to ensure their auditors adopt and effectively use these tools [8, 9, 10, 11].

TAM is designed to analyze information technology adoption behavior. It is based on two types of individual beliefs: perceived usefulness (PU) and perceived ease of use (PEU) [12]. Study [13] defined PU as "the degree to which an individual believes that using a particular system would enhance his or her job performance," and he defined PEU as "the degree to which an individual believes that using a particular system would be free of physical and mental effort". Therefore, PU and PEU affect the user's intention and attitude toward the acceptance and usage of any new technology.

While the TAM provides a robust framework for analyzing the adoption of information technologies, limited studies have investigated its application to BDA adoption in auditing, particularly with regard to PU and PEU. Furthermore, critical factors such as competition among audit firms and the size of audit clients—which may influence PU and PEU—have received little attention in prior research. There is also a lack of empirical evidence on how BI to adopt BDA tools translates into their actual usage (AU) [7].

In addition, the topic of BDA adoption has been underexplored in the Middle East and North Africa (MENA) region, particularly in the Palestinian context. This gap highlights the need for research that examines the extent to which auditors in this region adopt BDA tools in auditing processes [7].

To address these gaps, the current study investigates the impact of competition and audit client size on auditors' PU and PEU of BDA tools. It further examines how PU and PEU influence auditors' BI to adopt these tools and how BI translates into AU. By filling these gaps, this study provides critical insights into the factors driving BDA adoption in auditing, particularly in the MENA region.

This paper aims to achieve the following objectives:

- To assess the role of competition and audit client size on auditors' PU and PEU of BDA tools.
- To investigate the relationship between the PU and PEU of BDA tools and auditors' BI to adopt these tools.
- To explain how auditors' BI to adopt BDA tools translates into AU in the audit process.

Based on these objectives, the following research questions are posed:

- How do competition and audit client size influence auditors' perceptions of the usefulness and ease of use of BDA tools?
- How do PU and PEU of BDA tools influence auditors' B) to adopt these tools?
- How does BI to adopt BDA tools translate into AU in the auditing process?

The key contributions of this study are fourfold. First, it enriches the limited body of research on the adoption of BDA tools in auditing by extending the application of the TAM to include external factors such as competition and audit client size. Second, it addresses a significant geographic gap by focusing on the MENA region, with an emphasis on the under-researched Palestinian context. Third, it provides practical recommendations for auditing firms to enhance the perceived usefulness and ease of use of BDA tools, ensuring their effective adoption. Finally, this study highlights how the adoption of BDA tools can help auditing firms improve efficiency, enhance fraud detection, and deliver more comprehensive assurances, thereby achieving a competitive edge in the market.

The structure of the rest of this paper is as follows: Section 2 reviews the literature on the role of competition and audit client size in adopting BDA, discusses TAM and BDA, develops the hypotheses, and the paper's framework. Section 3 explains the method used. Section 4 provides the data analysis and results. Section 5 discussed the results, and section 6 presents the conclusion.

II. LITERATURE REVIEW

The TAM model [14] was developed (Figure 1), assuming that specific external variables influence PU and PEU. Research by [15] highlight the significant role these external variables in impacting the PU and PEU of adopting or rejection a new technology. They concluded that external variables directly affect both PU and PEU. However, research into the role of external variables, such as competition and audit client size, in technology adoption within auditing has been limited, creating a gap this study aims to address.

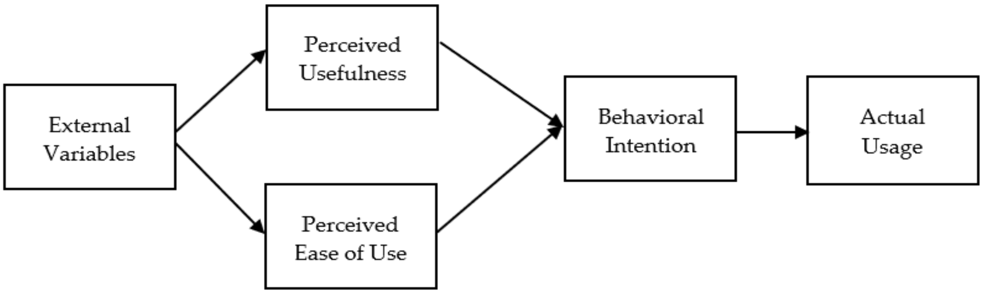

FIGURE 1. Technology Acceptance Model (TAM) [14] (1996) p. 20)

This study uses the TAM to explore auditors' intentions to adopt BDA tools developed by their firms for auditing processes. We also focus on external factors related to the characteristics of auditing firms, such as the size of the audit client and competition. The investigation aims to understand how client size and competition influence auditors' perceptions of the usefulness and ease of use of BDA technology.

1. EXTERNAL VARIABLES

External variables are particularly important in adapting TAM to industry-specific contexts, as they provide insight into factors that indirectly affect technology adoption by shaping perceptions of usefulness and ease of use [15].

1.1 Size Of Organization (Audit Clients)

Larger clients typically produce greater volumes of data and have more complex operations, creating a need for advanced tools to process data efficiently. This aligns with TAM's emphasis on PU and PEU as key factors influencing adoption, as auditors perceive BDA tools to be more useful and easier to use when auditing large clients with robust control environments and data quality [16].

The size of an entity significantly influences its capability to adopt and effectively utilize new technology, impacting both PU and PEU. For example, [17] highlighted those larger entities, with their advanced infrastructure and resources, are more likely to successfully integrate BDA into auditing processes. Similarly, recent studies such as [18] emphasize that larger firms often adopt BDA to analyze vast datasets, improving audit efficiency and fraud detection. Larger organizations usually have more resources, experiences, and skills; therefore, it's expected to adopt the most advanced and latest updated technologies that fit their business [16]. Auditors also realize that applying new technologies like BDA tools through their auditing of large entities would be useful and easy to use compared with auditing of small entities. In this opinion, since bigger companies create more data, they need fast audit methods, which is why auditors use BDA more often. Conversely, smaller entities, constrained by fewer resources, may be more conservative toward technology adoption, potentially viewing new technologies such as BDA as less beneficial or more challenging to use [19, 16, 14].

To better understand the effect of organizations' size on the adoption of new technologies, additional factors could be further explained, such as the organization's internal culture and degree of technical proficiency. Large companies are expected to have a strong innovation culture and high levels of technical proficiency; thus, they are more likely to see new technology favorably and make it easier to use, thereby making it easier for auditors to use BDA in their audits. Conversely, small companies with lower technical knowledge or a greater risk aversion may find it difficult to adopt and use new technologies, which ultimately affects auditors' perceptions of the simplicity and benefit of using BDA in auditing these companies [20].

Based on the above, the organizations' perceptions and then the actual adoption of new technology will reflect on auditors' perceptions about the usefulness and ease of use of applying new technologies to audit these companies. In addition, companies with a large number of employees would have an output of more than companies with fewer ones [21], and accordingly, more output denotes a greater volume of data produced, which makes multinational and large-size companies (audit clients) with big data volumes drive their auditors to find efficient techniques to audit them [16]. Many researchers found that strategic orientation influences audit companies to use BDA in audits to explore new trends in technology and organizational strategy since the extent of use of BDA depends on the size of the organization [19, 22, 23, 24, 16].

1.2 Competition

Competition has been identified as a critical driver of technological innovation, as firms operating in competitive environments must adopt advanced tools like BDA to maintain their market position and improve efficiency [25]. In the context of TAM, competition can influence PU by highlighting the strategic benefits of BDA and PEU by encouraging investments in usability enhancements and training for auditors.

Companies seek a competitive edge by using new technologies to make their goods and services better [25]. This leads to more technological innovation and usage. Companies want to stay competitive, so they use technologies that make their operations more efficient and improve the quality of their goods and services. The theory of spread of innovation says that companies are likely to accept new technologies that will give them a competitive edge, either by bringing about new ideas or by making them more efficient and cutting costs [26, 27]. Adopting technology to gain a competitive edge also means carefully thinking about how easy it is to use and how much training is needed, as these factors can affect the amount of uptake [28].

The level of competition is assumed to impact the rate of technological change in an industry, as well as the features of the technology itself, such as how well it works with other technologies and how complicated it is. Therefore, increasing the level of competition between companies, generates competitive pressure, which plays an important role in determining how quickly and widely a technology is adopted [29, 30, 26].

Recent studies have further highlighted the role of competition in driving BDA adoption. [31] argued that competitive pressures encourage audit firms to invest in BDA technologies, as clients increasingly demand faster and more insightful audits. Similarly, [32] observed that competition accelerates the adoption of advanced data analytics tools, as firms seek to differentiate themselves by offering improved audit quality and innovative services.

When we address the competition between audit firms specifically, rivalry makes it even more important to use new technologies like BDA to stay ahead of the competition. Auditing firms are increasingly expected to use advanced data analysis techniques, which is in line with the overall trend of audit firms shifting towards digital audit transformation. The competition among audit firms, particularly among the big four, motivates the use of advanced technology like BDA that may improve audit efficiency, quality, and client satisfaction, thereby improving operational efficiency and influencing the competitive environment. Subsequently, auditors perceive the usefulness and ease of use of BDA tools positively following the increasing competition in the auditing market [33, 16, 34, 35].

2. BDA AND TAM

Recently, many studies have focused on the adoption of BDA. These studies highlighted both the benefits and challenges of adopting BDA and sought to identify the best theories for examining BDA adoption and use. Despite various barriers, the importance of BDA adoption across different industries and economies has been emphasized [36, 37, 38].

A conceptual model based on the TAM was developed to explore factors influencing internet users' adoption of social commerce, as discussed in [39]. Brock and Khan [37] Also highlighted that using TAM is crucial for studying BDA adoption, as it explains people's motivations. However, they noted that TAM does not consider the practical aspects of system adoption. According to [40], technology adoption extends beyond BI and technical knowledge, as factors like trust, social influence, and various facilitating conditions also play a crucial role. Similarly, [36] argues that TAM does not account for aspects such as technology cost, management support, and the broader organizational environment and culture.

Some scholars have explored user experience with big data to understand its impact on technology adoption. For instance, a study in [41] investigated the application of big data among Danish SMEs by examining companies with prior experience. Similarly, [42] found that experienced users exhibit greater confidence in the technology's ease of use compared to inexperienced users, suggesting that experience serves as an external factor influencing technology adoption behavior.

Overall, most scholars agree that external variables affect PU and PEU, which are key factors in TAM that influence users' intentions to accept and adopt new technology, including BDA [43, 37, 44, 45, 46].

3. BDA IN AUDITING

BDA helps professionals understand companies' perceptions of business expectations. The complexity of accounting standards increases the need to adopt new technologies in financial accounting and reporting. BDA enhances real-time process capture, prompting companies to develop new techniques and technologies in accounting. However, it is crucial to align BDA practices with publicly stated processes [1].

Recent research, such as [47, 48], highlights how BDA enhances fraud detection and audit efficiency. These studies also underline that integrating BDA into the audit process requires substantial investment in training, infrastructure, and regulatory alignment. For example, [49] found that firms using BDA report higher client satisfaction due to improved audit insights, but challenges remain in adapting BDA to smaller datasets and resource-limited environments.

Big data facilitates the analysis of large data volumes, organizes information, and generates new insights, as highlighted in [50]. Auditing benefits from big data by enhancing financial analysis efficiency and fraud detection, complying with standards that encourage big data techniques even for smaller datasets. BDA in external auditing involves inspecting and transforming big data to improve auditing efficiency and decision-making [16]. Auditors handle complex business data, requiring continuous analysis of non-financial data from internal and external sources, necessitating BDA tools and process changes [16].

According to [51], regulatory bodies have raised concerns about the use of data analytics in evaluating audit evidence. Auditing through data analytics is limited as supplementary evidence, despite global strategies and positive auditor attitudes. Its scope is restricted until client incorporation, regulatory support, and efficiency in gathering audit evidence are proven. Guidelines for substantive tests of details [52] and fraud detection [2, 53] are being developed. Various data analytics approaches help auditors perform substantive tests and detect fraud more effectively [52].

The benefits of data analytics outweigh the challenges and costs, driving companies and audit firms towards effective execution. This allows analyzing 100% of journal entries, potentially improving audit quality. Data analytics is transformative for audit efficiency, especially for the Big Four firms, where audits differ significantly in BDA use for financial reporting and audit processes [2]. Audit firms aim for efficient, low-cost audits. While companies expect BDA in audits, there is disagreement about its impact on audit fees. Audit firms, having invested heavily in BDA technologies, advocate for adjusting audit fees to reflect BDA implementation in audits [2].

4. HYPOTHESES DEVELOPMNET

Auditors at leading firms, such as the "Big Four," benefit significantly from extensive experience with BDA technologies. This experience enhances their proficiency with BDA tools, contributing in better understanding of BDA applications. Such an environment reduces resistance to using BDA in their work, driven by factors like the high profile of audit clients and competitive pressures.

Discussion in literature review section revealed that the organizations' perceptions and then the actual adoption of new technology will reflect on auditors' perceptions about the usefulness and ease of use of applying new technologies to audit these companies. In addition, companies with a large number of employees would have an output of more than companies with fewer [21], and accordingly, more output denotes a greater volume of data produced, which makes multinational and large-size companies (audit clients) with big data volumes drive their auditors to find efficient techniques to audit them [16]. [16] Found that strategic orientation influences audit companies to use BDA in audits to explore new trends in technology and organizational strategy since the extent of use of BDA depends on the size of the organization.

Reviewing the literature also showed that the adoption of new technology normally varies according to the business sector, but many environmental factors are relevant to auditing firms' environment. The competitive pressure from other auditing firms to adopt computer-assisted audit techniques is one of them [34, 35]. This pressure may impact a firm's decision to adopt new technology, especially if the competitors' adopted technology results in improved audit efficiency and quality, pressuring the firm to adopt similar technology to maintain its competitive advantage by allowing them to reduce audit fees while maintaining client satisfaction [54, 55, 35]. Based on the above discussions, we formulate the following hypotheses:

H1a: The larger the audit client, the more positively it will perceive the usefulness of BDA tools.

H1b: The larger the audit client, the more positively it will perceive the ease of use of BDA tools.

H1c: Increased competition among auditing firms will positively affect the PU of BDA tools.

H1d: Increased competition among auditing firms will positively affect 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 [14]. This intention leads to the AU and adoption of technology [56]. PU and PEU are considered the most significant TAM variables that affect the BI of users to adopt actual technology [14]. Some of the previous studies emphasized the importance of understating the PU and PEU that affect the technology adoption behavior [57, 58, 36]. [59] 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. [60] 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 AU [61]. Based on the discussion regarding the impact of PEU and PU on the BI to use BDA and its AU and the related findings from the literature review section, the following hypotheses are proposed:

H 2a: PU of BDA tools have a positive effect on the BI to adopt these tools in the audit process.

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

H 2c: BI to adopt BDA tools in the audit process positively influences their AU.

5. *FRAMEWORK DEVELOPMNET*

The study model was initially developed from Davis's TAM (Figure 1). Study [14] develop their TAM model on the assumption of the existence of specific external variables that would impact the PU and PEU. The literature review section of this paper addressed some of the external variables that might impact the PU and PEU. Based on the discussion of the previous literature, these variables have been selected based on their expected impact on BDA adoption.

Figure 2 shows the interaction between the audit firm factors and the PU and PEU. The audit firm factors (competition and size of client) also would have an impact on auditors' perceptions of the usefulness and ease of use of BDA technological tools. The conceptual study model places the adoption and utilization of data analytics tools and technologies at the forefront. In today's competitive environment, where data has become important because it helps businesses in developing their strategies and optimizing their performances, Companies strive to make data-driven decisions and strategies, making the implementation of data analytics mission-critical [29, 30]. In addition, the increase in business size and complexity of companies across the world increase reliance on developing technological tools to process the huge volume of data [37], accordingly, big audit firms develop and adopt new technological tools and techniques to deal efficiently with a greater volume of data from different sources [8-11].

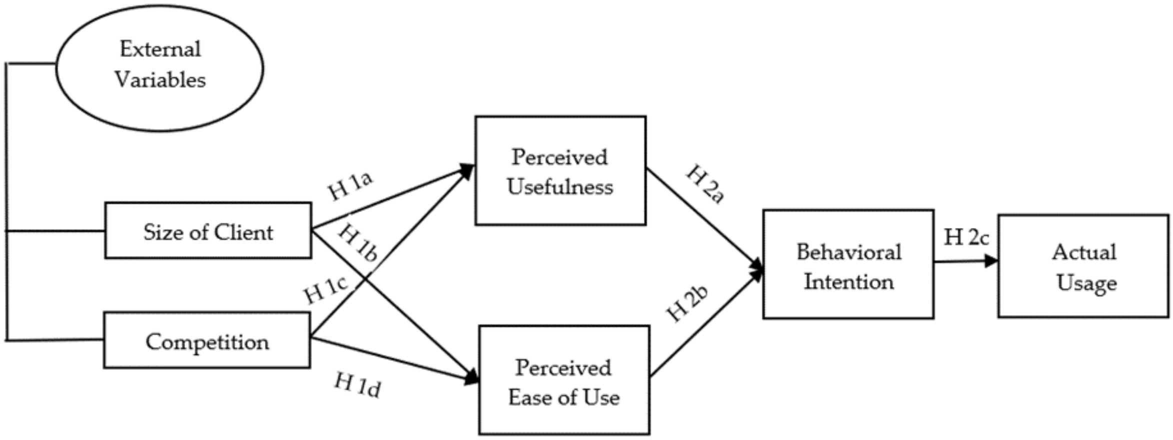

FIGURE 2. Conceptual study model.

III. METHOD

This study uses a quantitative research method by developing a questionnaire to examine the relationships between variables through statistical analysis [62, 63]. A survey was selected as the research instrument to systematically collect data, given its effectiveness in exploring subjective beliefs and behavioral intentions in TAM-based studies. The study focuses on identifying patterns and relationships between variables without influencing participants' behavior, allowing for reliable and objective insights. The survey instrument was developed based on established literature on the TAM and BDA adoption to ensure validity and relevance. The variables were chosen specifically to address the research questions and hypotheses, with the goal of testing their interactions and finding key connections [64]. Data were collected from auditors employed by the Big Four audit firms operating in Palestine, where BDA adoption is an organizational priority due to the global shift toward data-driven auditing practices.

1. SAMPLING METHODLOGY

The study population consists of external auditors working at the Big Four auditing firms in Palestine. These firms prioritize BDA in their agenda, therefore they investing heavily in it and developing various techniques and tools to guide their auditors, especially in light of the global data transformation [8-11]. Large companies, which have significant data volumes, drive their auditors to find efficient auditing techniques and are often audited by the Big Four firms [16].

The study uses a census sampling method, targeting the entire population of auditors [65, 66]. This method is suitable for smaller populations, specifically those under 100 units, and eliminates sampling errors, which helps gain better understanding [67]. While this method ensures comprehensive data collection, the precision depends on measurement accuracy [65]. The initial population was 105 auditors, reduced to 94 after excluding those with less than one year of experience. This selection focuses on auditors with more advanced expertise and reliable judgment [68, 69]. Questionnaires were distributed to these 94 auditors, achieving an 86% response rate. Excluding less experienced auditors aligns with literature indicating that the first year of employment typically focuses on training with lower performance expectations [70-72].

2. DEVELOPMENT OF MEASUREMENT MODEL

The survey instrument was designed to collect data relevant to the study objectives and was divided into four main parts, comprising a total of 43 items, along with a section on participant demographics.

- Part 1 (14 items): Investigates external variables related to the size of audit clients and competition.
- Part 2 (14 items): Examines the influence of PU and PEU on the BI to adopt BDA in auditing tasks.

- Part 3 (8 items): Measures the AU of BDA tools in auditing tasks.

All survey items, except for demographic questions, used a 7-point Likert scale ranging from 1 ("strongly disagree") to 7 ("strongly agree"). This scale was selected for its ability to accurately capture subjective beliefs, attitudes, and opinions, as supported by prior research [73]. The survey items were adapted from validated instruments in prior TAM and BDA studies, ensuring content validity.

Before data collection, the survey was pre-tested with a small sample of auditors (not included in the final analysis) to confirm clarity, reliability, and validity of the items. The results of the pre-test indicated high internal consistency across survey items.

IV. DATA ANALYSIS AND RESULTS

1. QUESTIONNAIRE ANALYSIS

To meet the objectives of this study and validate the proposed hypotheses, we used SMARTPLS 4 software for data analysis. The main statistical method employed was path analysis, a subset of Structural Equation Modeling (SEM). SEM is effective at evaluating multiple structural equations simultaneously, accounting for potential measurement errors [74]. This approach is ideal for analyses where a dependent variable in one equation might act as an independent variable in another, allowing for a detailed examina tion of variable relationships [76]. Path analysis is integral to SEM. It employs a series of multiple regression equations to investigate both direct and mediated relationships between observed variables [75]. This method aligns with the research goals, aiming to clarify the causal relationships and interactions among measurable variables. The study focused on seven main constructs: size of audit client, competition, PU, PEU, BI, and AU.

2. ASSESSMENT OF THE MEASUREMENT MODEL

The measurement model was evaluated to ensure the constructs' reliability and validity (Table 1). First, all the items in the model had factor loadings above the minimum acceptable value of 0.50 [76]. While factor loadings over 0.70 are ideal [65], social science studies often have lower loadings. Instead of automatically removing items with lower loadings, we examined their impact on composite reliability, content, and convergent validity.

Generally, items with loadings between 0.40 and 0.70 are considered for removal only if doing so improves composite reliability or average variance extracted (AVE) above the recommended value [77]. In this study, removing item SO5 (loading = 0.633) wouldn't significantly improve composite reliability or AVE, as these values were already above the required threshold. Additionally, none of the items' outer loadings included zero within their confidence intervals. Therefore, no items were removed from further analysis.

Table 1. Reflective constructs measurement properties

Reflective constructs	Construct items	Items loading	CR	AVE	Reference
Size of organization	SO1	0.733	0.905	0.578	[14]
	SO2	0.801			
	SO3	0.823			
	SO4	0.774			
	SO5	0.633			
	SO6	0.729			
	SO7	0.813			
Competition	CP1	0.825	0.927	0.646	[28]
	CP2	0.712			
	CP3	0.738			

	CP4	0.888			
	CP5	0.778			
	CP6	0.853			
	CP7	0.818			
Perceived Usefulness	PU1	0.929	0.977	0.874	[43]
	PU2	0.963			
	PU3	0.949			
	PU4	0.947			
	PU5	0.900			
	PU6	0.921			
Perceived ease of use	PEU1	0.865	0.961	0.804	[43]
	PEU2	0.901			
	PEU3	0.944			
	PEU4	0.923			
	PEU5	0.901			
	PEU6	0.842			
Behavioral intention	BI1	0.976	0.976	0.954	[14]
	BI2	0.977			
Actual use	AU1	0.857	0.958	0.742	[78]
	AU2	0.858			
	AU3	0.908			
	AU4	0.806			
	AU5	0.845			
	AU6	0.881			
	AU7	0.839			
	AU8	0.895			

Reliability was measured using Cronbach's alpha, rho-a, and composite reliability. All these statistics were above the recommended value of 0.700 [79]. The rho-a value, which falls between Cronbach's alpha and composite reliability [80], was also over 0.70, indicating good reliability [81].

Convergent validity was confirmed since the average variance extracted (AVE) was higher than 0.500. Checking discriminant validity is crucial to ensure that the measurement tools for different factors are unique. This involves verifying that the square root of the AVE for each construct is greater than the inter-construct correlations, as suggested by [82]. Table 2 shows that our model meets the Fornell-Larcker criterion, demonstrating compliance with this validation standard.

Table 2. The measurement model discriminant validity- Fornell-Larcker criterion

Constructs	Actual Use	Behavioral Intention	Competition	Perceived Ease of Use	Perceived Usefulness	Size of Organization
Actual Use	**0.862**					
Behavioral Intention	0.481	**0.977**				
Competition	0.581	0.682	**0.804**			
Perceived Ease of Use	0.614	0.632	0.649	**0.897**		
Perceived Usefulness	0.650	0.713	0.748	0.710	**0.935**	

Size of Organization	0.722	0.551	0.644	0.705	0.695	**0.760**

Additionally, the model's discriminant validity was evaluated using the heterotrait-monotrait ratio (HTMT) of correlations, a method recommended by [83]. An HTMT value less than 0.90 is considered satisfactory, signifying adequate discriminant validity between the constructs. On the other hand, HTMT values exceeding this limit suggest an absence of discriminant validity among the variables. The outcomes derived from the HTMT assessment are documented in Table 3, where each recorded value is below the 0.90 criterion, thereby confirming the discriminant validity of the model. Following the compilation of results from the study's measurement model evaluation, Figure 3 depicts the finalized research model that was explored.

Table 3. Heterotrait-Monotrait Ratio (HTMT)

Constructs	Actual Use	Behavioral Intention	Competition	Perceived Ease of Use	Perceived Usefulness	Size of organization
Actual Use	-					
Behavioral Intention	0.493	-				
Competition	0.605	0.722	-			
Perceived Ease of Use	0.646	0.661	0.686	-		
Perceived Usefulness	0.673	0.739	0.781	0.738	-	
Size of organization	0.794	0.601	0.699	0.753	0.752	-

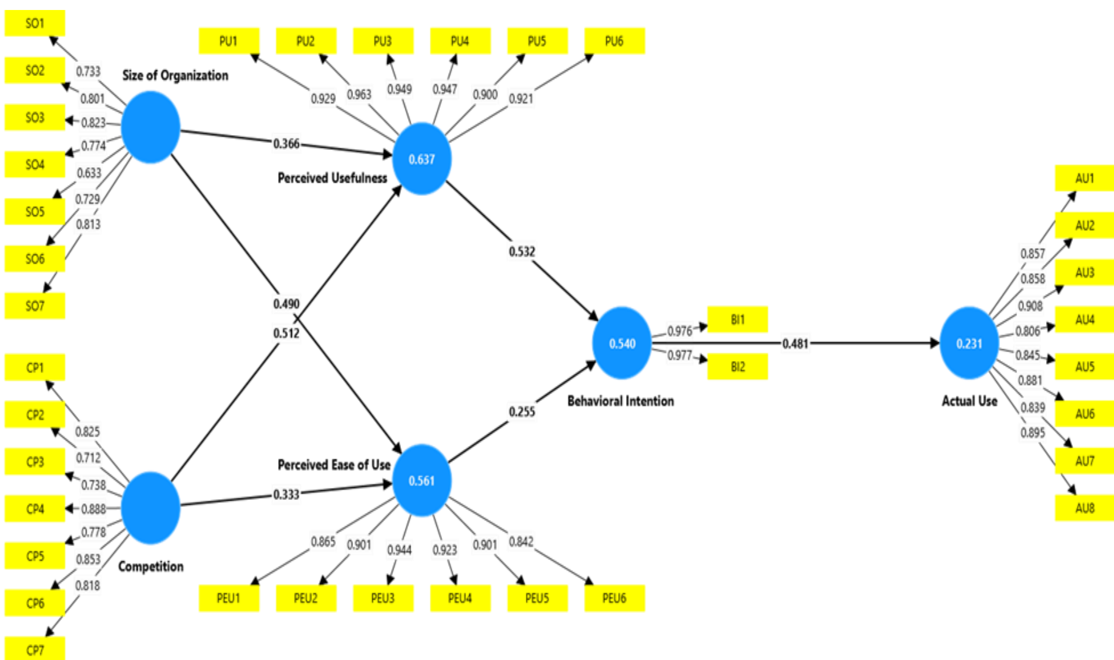

FIGURE 3. The measurement model.

3. ASSESSMENT OF THE STRUCTURAL MODEL

Next, we thoroughly examined the structural model to assess its predictive accuracy and understand the interactions among the constructs, as well as to evaluate the model's robustness and coherence. This step was crucial for verifying our hypotheses. The analysis focused on key indicators: the coefficient of determination (R^2), path coefficients (β values), T-statistics, effect size (f^2), and predictive relevance (Q^2). We used a bootstrapping procedure for this detailed evaluation.

According to [76], R^2 values are considered high at 0.75, moderate at 0.50, and low at 0.25. In our study, the R^2 values were moderate. The Q^2 values indicate the model's predictive capacity, with values above zero confirming the model's effectiveness in forecasting outcomes.

To demonstrate sufficient predictive relevance, Q^2 values must be greater than zero, showing that the external constructs can predict the internal constructs [76]. Table 4 shows the cross-validated redundancy values for AU, BI, PEU, and PU, which are 0.297, 0.438, 0.537, and 0.600, respectively. The effect size (f^2) measures the impact of each external latent variable on an internal latent variable, helping us understand how well the model explains the variance in internal latent variables.

Using [84] framework, f^2 values of 0.02, 0.15, and 0.35 are considered small, medium, and large impacts, respectively. Table 4 shows that the f^2 effect sizes range from a minimal impact of 0.070 for PEU's effect on PEU to a significant impact of 0.423 for competition's effect on PU. Additionally, the Q^2 values for the internal constructs all exceeded zero, confirming the structural model's predictive relevance.

Table 4. R^2 Values, 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
Competition	-	-	0.148	0.423	-	-
Size of organization	-	-	0.321	0.216	-	-
Actual Use	0.222	0.297	-	-	-	-
Behavioral Intention	0.528	0.438	-	-	-	0.301
Perceived Ease of Use	0.556	0.537	-	-	0.070	-
Perceived Usefulness	0.641	0.600	-	-	0.305	-

The study also used Path Coefficients to examine the proposed relationships among variables. As shown in Table 5, we followed the approach recommended by [77], using the bootstrapping method. This process provided important statistical figures, including beta coefficients, standard errors, t-values, and p-values.

Table 5. 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
H1d Competition -> Perceived Ease of Use	0.333	0.097	3.418	0.001	Supported
H1c Competition -> Perceived Usefulness	0.512	0.116	4.428	0.000	Supported
H 2b Perceived Ease of Use -> Behavioral Intention	0.255	0.150	1.693	0.091	Rejected
H 2a Perceived Usefulness -> Behavioral Intention	0.532	0.142	3.754	0.000	Supported
H1b Size of Organization -> Perceived Ease of Use	0.490	0.089	5.503	0.000	Supported
H1a Size of Organization -> Perceived Usefulness	0.366	0.113	3.243	0.001	Supported

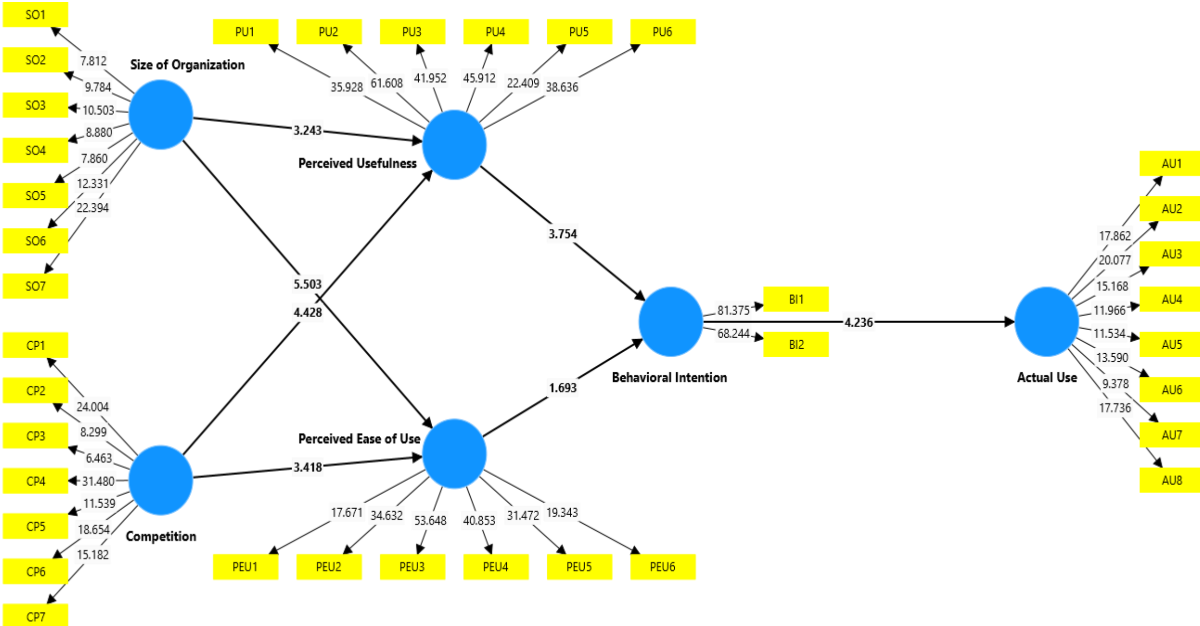

FIGURE 4. Bootstrapping (t-values) for the study model

Table 5 provides a detailed look at the relationships among various constructs, with each hypothesis clearly numbered for clarity. The analysis begins by validating the impact of BI on AU (hypothesis 2c), shown by a strong beta coefficient of 0.481, a T statistic of 4.236, and a p-value of 0.000. This significant result highlights the critical influence of BI on AU.

Next, the impact of competition on PEU (hypothesis 1d) is supported by a beta coefficient of 0.333, a T statistic of 3.418, and a p-value of 0.001, confirming the significant role of competition in enhancing PEU. Similarly, the effect of competition on PU (hypothesis 1c) is confirmed, with a beta coefficient of 0.512, a T statistic of 4.428, and a p-value of 0.000, showing competition's strong influence on PU.

On the other hand, the hypothesis about the impact of PEU on BI (hypothesis 2b) was not statistically significant (beta coefficient: 0.255, T statistic: 1.693, and p-value: 0.091), leading to its rejection. However, the impact of PU on BI (hypothesis 2a) is supported, with a beta coefficient of 0.532, a T statistic of 3.754, and a p-value of 0.000, indicating PU's significant influence on BI.

The study also shows the significant influence of organization size (audit clients) on PEU (hypothesis 1b) and PU (hypothesis 1a), with beta coefficients of 0.490 and 0.366, T statistics of 5.503 and 3.243, and p-values of 0.000 and 0.001, respectively. These findings highlight the importance of organizational size in shaping PU and PEU.

Overall, these results detail the relationships between constructs like BI, competition, PEU, and organization size. They offer insights for future research and practical applications, particularly regarding how external factors related to audit firm attributes, such as client size and competition, affect technology adoption behaviors

V. DISCUSSION

The conclusion of this research highlights how the factors of the size of audit clients, and competition influence auditors' PU and PEU of BDA, significantly affecting their BI and AU of these tools.

Auditors face specific challenges when working with BDA, particularly in terms of integrating these tools into their workflows, overcoming resistance to change, and ensuring the tools are easy to use while offering clear benefits. For example, larger audit clients produce vast amounts of data that need to be processed and analyzed efficiently, placing significant demands on auditors to adopt and master advanced BDA technologies. Smaller firms or less-experienced auditors may struggle with the steep learning curve associated with these tools, as well as a lack of adequate training or resources to facilitate adoption. In addition, auditors working in highly competitive environments must contend with the pressure to adopt new technologies to maintain their firm's market position while ensuring these tools deliver value-added outcomes, such as improved risk detection and audit quality.

The size of companies (audit clients) is an important determinant that was identified in this research. The data analysis results show that audit client size significantly influences both PU ($\beta = 0.366$, $p < 0.001$) and PEU ($\beta = 0.490$, $p < 0.001$). Larger companies typically have a solid control environment to process data. Consequently, auditors' perception of the quality of this data will improve, as they can process it more easily using their tools and generate the required output for their audits. This also achieves the desired benefit, as the quality of data processing helps auditors generate better outputs from BDA tools, which in turn improves their ability to identify risks and gain a better understanding of the business, thus providing more insights. These findings are aligned with the studies by [16], [17], and [19], which highlighted that larger organizations are more likely to rely on advanced technologies and have the appropriate resources and highly skilled technological professionals who facilitate data processing and, in turn, enhance auditors' PU and PEU. Additionally, [18] and [20] support this view, finding that larger entities, with their robust innovation culture and higher technical proficiency, perceive new technologies more favorably, thereby making it easier for auditors to use BDA in their audits.

Competition between auditors or auditing firms also plays a significant role in impacting PU and PEU. The findings reveal that competition has a strong influence on PU ($\beta = 0.512$, $p < 0.001$) and PEU ($\beta = 0.333$, $p < 0.001$). In highly competitive environments, auditors are more likely to view BDA as an important strategy due to the desire to maintain or improve their competitive standing. This result highlights the significance of using the competitive advantages provided by BDA tools, such as increased productivity and cost reduction, in order to maintain their clients and attract new business; thereby, auditors see that their firms will make the proper efforts and extra investments in these tools to make them user-friendly, along with higher value for them, thus increasing their PU and PEU. These results are agreed with [25], [29], and [31] findings that the existence of competitive pressure drive technological innovation. Additionally, the findings that auditors in competitive environments are more likely to see BDA as beneficial are supported by [28] and [32], who noted that competitive environments necessitate technological advancements to maintain or improve market standing. Furthermore, the study by [34] emphasizes the role of competition in driving the adoption of advanced data analysis techniques among audit firms.

This study addresses a critical research gap by examining the specific external factors (competition and audit client size) that influence the PU and PEU of BDA tools, particularly within the context of auditing. Existing research on BDA adoption in auditing primarily focuses on general factors, such as organizational readiness or perceived benefits, but fails to explore how external competitive pressures or client characteristics shape auditors' behavioral intention to adopt BDA tools. By addressing this gap, the study provides new insights into how auditors in Palestine's Big Four firms adopt these tools and how these findings can inform strategies for broader adoption in other regions and contexts.

Finally, the study confirms that PEU and PU are significant predictors of auditors' BI to adopt BDA. PU shows a stronger influence on BI ($\beta = 0.532$, $p < 0.001$), while PEU's influence on BI is insignificant ($p > 0.05$). This finding is particularly pertinent in the context of the Palestinian Big Four auditing firms, highlighting the need to emphasize the benefits of BDA in enhancing audit efficiency and effectiveness. Furthermore, this finding may be due to auditors prioritizing perceived usefulness over ease of use when considering the adoption of complex technologies like BDA tools. This could result from the high-pressure, performance-driven nature of their work environment. This research enriches the understanding of technology adoption within the auditing field and within the context of developing countries, offering valuable insights for both auditors and scholars. This finding is consistent with the findings of [12] and [59], who established that PU has a stronger impact on the BI to use new technology. This finding is particularly pertinent in the context of the Palestinian Big Four auditing firms, where the emphasis on the benefits of BDA in enhancing audit efficiency and effectiveness mirrors the insights provided by [60].

VI. CONCLUSION

This study examines the impact of auditing firms' attributes related to their efforts to incorporate BDA tools into their auditing process on BDA adoption. The selected attributes are the size of audit clients, and the competition. This examination was extended to TAM as a suitable framework to test the adoption of such technologies. The paper indicates that optimizing these attributes can significantly improve BDA auditors PU and PEU of BDA technological tools. Understanding the impact of these characteristics on auditing firms not only aids in the employing of BDA tools, but it also ensures that they achieve the required benefits from utilizing them. By clarifying the functionalities of BDA tools and clearly communicating their advantages to their employees from auditors, firms can elevate them towards these technologies, thus contributing to the enhancement of the quality and efficiency of auditing processes.

This study provides practical implications for audit firms seeking to enhance the adoption of BDA. Audit firms should prioritize emphasizing the usefulness of BDA tools in improving audit efficiency, risk identification, and client understanding, as these benefits are likely to encourage adoption among auditors. Addressing competitive pressures is also critical, and firms can achieve this by investing in advanced BDA technologies that provide a competitive advantage through cost reduction and increased productivity. Furthermore, larger audit clients should be leveraged as a catalyst for BDA adoption, as their robust control environments and high-quality data positively influence auditors' perceptions of these tools. Finally, to ensure widespread adoption, firms should implement comprehensive training programs that highlight the benefits of BDA tools, making them easier to use and understand for auditors, thereby fostering greater confidence and engagement with these technologies.

Despite its insightful contributions to the adoption of BDA within auditing, this study recognizes certain limitations. First, the study focuses on external factors (audit client size and competition), and other potential factors influencing BDA adoption (e.g., organizational culture or individual auditor traits) were not considered. Second, the research is geographically limited to auditors working in the Big Four firms in Palestine, which may restrict the generalizability of the findings. Third, the demographic profile of participants is limited to experienced auditors (those with more than one year of experience), excluding entry-level auditors who may have different perspectives on BDA adoption. Finally, this study is limited by its cross-sectional design, which prevents causal inferences.

Future research is invited to investigate a broader array of external factors that could influence the perceived value and usability of BDA tools. Broadening the participant base to include auditors from smaller, local firms and solo practitioners, as well as expanding the study's geographical reach beyond Palestine, could widen the relevance and applicability of the research findings. Applying alternative theoretical models, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), might uncover fresh insights into auditors' intentions towards embracing BDA technologies. Finaly, future research could also employ longitudinal designs to better establish causality in the relationships examined.

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Authors Contribution

All authors contributed equally to the development, design, and execution of this study.

Conflict Of Interest

The authors have no potential conflicts of interest, or such divergences linked to this research study.

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