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The Influence of Big Data Analytics Adoption on Auditors' Professional Skepticism in Risk Assessment: An Empirical Study Using the Technology Acceptance Model

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Abstract. This study investigates the impact of Big Data Analytics (BDA) on risk assessment procedures performed by auditors and its subsequent influence on their professional skepticism. Utilizing the Technology Acceptance Model (TAM) as a framework, the study examines the effects of perceived usefulness (PU) and perceived ease of use (PEOU) on auditors' intentions to adopt BDA and their actual usage in risk assessment processes. A mixed-method approach was employed, combining quantitative data from a census survey of 94 auditors from the Big Four accounting firms in Palestine (86% response rate) and qualitative data from semi-structured interviews with 9 auditors at the manager level or above. The findings revealed that PU directly influences auditors' intentions to adopt BDA and subsequently impacts the actual usage of BDA in risk assessment procedures. PEOU, while not directly affecting behavioral intentions, contributes to PU. The actual use of BDA was found to positively impact professional skepticism, potentially enhancing audit quality through improved identification of risks and better evaluation of audit evidence. This study contributes valuable empirical evidence to the existing literature on the impact of BDA in audit procedures, specifically in the risk assessment process, and highlights the importance of technology in advancing auditors' technical approach and maintaining professional skepticism.

Keywords: Actual Use, Behavioral Intention, BDA, PEOU, PU, Professional Skepticism, Risk Assessment Procedures, TAM

1. Introduction

In the modern era of data advancement, businesses across various sectors are facing new challenges and opportunities regarding the emergence of Big Data Analytics (BDA) in decision-making processes (IAASB 2016). BDA aims to provide analysis of data sets in the form of a story, presenting different forms like patterns, trends, and insights that are vital in shaping strategic decisions and enhancing organizational performance (Awan et al., 2021; Adrianto, 2018).

The application of BDA is expanding in various areas such as customer segmentation, marketing strategies, cost analysis, and optimization of supply chains (Seyedan and Mafakheri, 2020). Through the strategic application of BDA, companies can achieve a deeper comprehension of their operational processes, thereby facilitating more data-driven decision-making (Awan et al., 2021). In the auditing field, the adoption of BDA by auditors provides an enhanced way for improving the quality and efficiency of audit processes. It enables compliance with the requirements of International Standard on Auditing (ISA) 315, which outlines the auditor's responsibilities in identifying and evaluating the risks of material misstatements in financial statements (ISA 315, A.21). By incorporating BDA, auditors would be able to see the full picture and analyze an entity's business and its internal control process, identifying critical risk factors at the audit planning stage.

This research aims to address the gap in the use of BDA in specific audit procedures, such as risk assessment, 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 use of BDA in risk assessment procedures has been ignored. Additionally, there is a knowledge gap regarding the impact of BDA on auditors' professional skepticism.

Originally developed by Davis (1986), the Technology Acceptance Model (TAM) has been widely applied to understand technology adoption across various fields. TAM is designed to analyze information technology adoption behavior. It is based on two types of individual beliefs: perceived usefulness and perceived ease of use (Davis, 1989). Research has repeatedly validated TAM's reliability across different technologies, confirming its superiority over other models like the Innovation Diffusion Theory and the Theory of Planned Behavior. Additionally, while various models have been explored for their effectiveness in predicting technology acceptance, TAM remains the most important and powerful model that is used in interpreting technology acceptance behaviors and attitude (Davis, 1989; Verma et al., 2018; Demoulin & Coussement, 2020). In the context of our study, using the TAM as a study framework would help in explaining technology acceptance and usage behaviors for auditors while performing these specific audit procedures. Based on TAM, perceived usefulness and ease of use are critical factors impacting technology adoption decisions, as it provides a useful perspective through which the adoption and application of BDA by auditors can be analyzed. (Davis, 1989). In the context of BDA, PU refers to the extent to which auditors perceive BDA as valuable in understanding the business and identifying key risk factors, while PEOU refers to the extent to which auditors perceive BDA as easy to use (Davis and Venkatesh, 1996).

This paper makes four key contributions. First, it addresses the lack of empirical studies on BDA practices in the auditing field, particularly in developing countries. Notably, it stands as one of the papers of its kind in Palestine, exploring BDA within the auditing context. Second, it extends the limited body of research examining the impact of PU and PEOU on the utilization of BDA in performing specific audit procedures, such as identifying and assessing the risk of material misstatement during the planning phase of an audit. Third, through mixed methods research (combining quantitative and qualitative approaches), this paper investigates the ultimate impact of the actual use of BDA for risk assessment procedures on auditors' professional skepticism. It provides significant evidence from Palestine within the context of developing countries, thereby contributing to the existing literature on BDA practices and professional skepticism. Finally, the paper develops a conceptual framework by integrating BDA, TAM, and professional skepticism. This framework offers clear guidance and

valuable insights for auditors, facilitating the effective utilization of BDA tools to enhance professional skepticism.

The aim of this study is to investigate the impact of PU and PEOU on the utilization of BDA in risk assessment procedures and its subsequent effect on professional skepticism. This study sets forth several key objectives aimed at understanding the utilization of BDA within audit practices, specifically in performing risk assessment procedures:

- To analyze the impact of PU and PEOU on auditors' behavioral intentions to implement BDA in risk assessment procedures.
- To assess how these behavioral intentions are impact the actual usage of BDA in risk assessments.
- To examine the impact of the application of BDA in risk assessments on auditors' professional skepticism.

The paper is organized into eight sections as follows: Section Two reviews previous studies on TAM, BDA, and professional skepticism; Section Three addresses the hypotheses development for this study. Section Four covers the proposed study framework that forms the basis for TAM and BDA, and their linkage to auditors' professional skepticism. Section Five presents the methodology adopted for the study. Section Six discusses the data analysis and results. The final two sections, Section Seven, detail the discussion of the results, and Section Eight presents the study's conclusion.

2. Literature Review

2.1 Integration of BDA and TAM in Understanding Technology Adoption

The combination of BDA and the TAM forms an effective concentration in modern research, highlighting the interaction between these elements as they influence the adoption of new technologies across various sectors. Developing from the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB), the TAM framework is founded with the purpose of interpreting how technologies are adopted by analyzing users' behaviors and acceptance levels. TAM is based on two major concepts represented by perceived usefulness and ease of use, which significantly impact user attitudes toward new technologies (Davis et al., 1989; Koul & Eydgahi, 2017; Oliveira & Martins, 2011). These concepts have been frequently applied in diverse fields, ranging from the adoption of digital banking solutions (Hossain et al., 2020) to mobile learning in educational environments (Buabeng-Andoh, 2018), demonstrating TAM's wide applicability.

The mentioned combination between BDA and TAM has contributed to explaining BDA's ability to handle a large volume of data, which requires advanced technologies for effective processing and analysis (Brock & Khan, 2017; Adnan & Akbar, 2019). This was evidenced by previous research results in various sectors like healthcare, retail, and manufacturing, which have effectively contributed to interpreting how BDA can enhance customer satisfaction, operational efficiencies, and the adoption of artificial intelligence in the manufacturing industry (Félix et al., 2018; Tao et al., 2018; Shahbaz et al., 2019).

Furthermore, the application of the TAM within BDA adoption research has provided critical insights, particularly when the TAM is extended to include other variables such as trust and self-efficacy, in facilitating new technology adoption, thereby enhancing our understanding of how a new technology impacts organizational performance and the strategic uses of technology in business fields (Gangwar, 2020; Verma et al., 2018).

2.2 Integration of BDA in Audit practices

The adoption of BDA in the auditing field is increasing, presenting a critical shift from a traditional approach to a new advanced approach based on new technologies, which are increasingly recognized for their capacity to enhance business insights and decision-making capabilities (Adrianto, 2018;

Appelbaum et al., 2017). This transformation makes auditors motivated to adopt new technologies that can enhance their ability to analyze and solve complex audit issues (İdil & Akbulut, 2018; Austin et al., 2018).

Gepp et al. (2018) address the effectiveness of BDA methods in auditing, especially in using BDA to enhance fraud detection capabilities. Dagilienė & Klovienė (2019) also highlight the importance of BDA in external audits, where it is found as an important approach to enhance the efficiency and effectiveness of the audit process. Nonetheless, adopting BDA within auditing practices has various challenges, such as data quality issues, difficulties in data extraction, and the need for compliance with auditing standards.

An exploratory study conducted by Eilifsen et al. (2020) denotes that decisions to adopt BDA are often made by senior management, such as engagement partners or managers, within audit firms. While the adoption of data analytics tools is not yet mandatory, there is a clear trend towards their broader utilization. Another research conducted by No et al. (2019) recommends developing specific guidelines for performing substantive tests and detecting fraud through BDA.

Despite these advantages, the integration of BDA into auditing does face some challenges. Gepp et al. (2018) and Dagilienė & Klovienė (2019) emphasize that although BDA can significantly improve the efficiency of the auditing process and fraud detection, it requires developed data management systems. In addition, they express concern related to the lack of BDA guidance in current auditing methodologies. Furthermore, issues related to data quality and extraction challenges may limit the desired benefit from using BDA in external audits. Moreover, the literature indicates that one of the most important concerns is that utilizing BDA in audits could negatively influence the exercise of the required level of professional skepticism, thereby impacting auditors' capabilities in identifying fraud, which ultimately impacts audit quality (Li, 2022; Austin et al., 2018; Barr-Pulliam et al., 2020; Appelbaum et al., 2017).

2.3 BDA in Enhancing Risk Assessment Procedures

BDA could be used by organizations to make well-informed decisions by using a large volume of data to understand trends, patterns, and potential risks, and then they can proactively detect these risks, thus enabling strategic decision-making and risk mitigation actions (Dagiliene & Kloviene, 2019). However, the implementation of BDA in identifying the risk of material misstatements presents multiple challenges, such as long-term audit engagements, as well as the size of the audit client, and the technological structure of client businesses, which may impact the decision by audit firms to use BDA. To overcome these challenges, audit firms need to develop specific guidance and strategies that can be applied in their audit methodologies to ensure consistency in BDA utilization and effective adoption. Developing audit methodologies by audit firms to include the required guidance for utilizing BDA in performing audit procedures, including the risk assessment process, could enhance decision-making and ensure that their strategies are standardized on a specific platform related to BDA application (Dagiliene & Kloviene, 2019).

ISA 315 covers the procedures required by auditors to identify risks of material misstatements as part of the risk assessment process. BDA might significantly support auditors in complying with ISA 315 requirements. For example, using BDA during this process enables a deeper understanding of a client's business and its activities. In addition, BDA enhances audit quality by supporting conclusions with solid data evidence through the BDA capabilities in organizing and visualizing a large volume of data which aids auditors in interpreting audit evidence, thereby supporting their professional skepticism (Ruhnke, 2023; PWC, 2013). Furthermore, the usage of BDA in audit processes makes auditors possess advanced IT knowledge and skills, to be up to the developing requirements of modern audit tasks. Therefore, BDA is considered an important tool for auditors to fulfill the requirements of ISA 315 (Krieger et al., 2021).

Despite the increasing accessibility and potential advantages of BDA in audit practices, there is a noticeable gap in understanding how auditors effectively use BDA for risk assessments as required by ISA 315. This study tries to understand the challenges associated with the adoption and implementation of BDA by auditors in risk assessments, interpreting its implications on professional skepticism and subsequently on audit quality.

2.4 Influence of BDA on Professional Skepticism

As mentioned in section 2.2, utilizing BDA in audits could negatively influence the exercise of the required level of professional skepticism that ensures the reliability and quality of audits. Professional skepticism involves a questioning mind and a critical assessment of audit evidence, which is essential for identifying anomalies and potential fraud (Nelson, 2009; Hurtt et al., 2013; ISA 200, Para.13-I). Professional skepticism should be maintained throughout all phases of the auditing process, from the initial client acceptance to the final report issuance. A lack of exercising the required level of professional skepticism can lead to audit failures and expose the auditor to the risk of reputation loss (Septian & Astika, 2019; Grenier, 2017).

However, the utilization of BDA in auditing, while reinforcing analytical capabilities, introduces challenges related to maintaining professional skepticism. Auditors are required to balance between adapting new technologies such as BDA, which change traditional auditing methods, and maintaining the required level of professional skepticism (Al-Hiyari et al., 2019; Cristea, 2021). Previous literature highlight how technological tools and automation can transform audit practices including performing the risk assessment procedures, potentially reducing effort but affecting skepticism and audit quality. Li (2022) identifies several behavioral challenges, such as auditors' attitudes and data quality, which can influence skepticism. Cristea (2021) finds that Romanian auditors view technology as supportive in performing auditing tasks throughout the entire audit phases including risk assessment process. Therefore, auditors should combine their knowledge of technology with their skeptical behaviors. Training and experience in marinating the required level of professional skepticism while performing detailed audit procedures, such risk assessment, represent another challenge. Overall, while BDA offers benefits, it also presents challenges in maintaining appropriate professional skepticism, which is important for audit quality (Li, 2022; Austin et al., 2018; Barr-Pulliam et al., 2020; Appelbaum et al., 2017; Hurtt, 2013).

With rapid technological advancements, there is a core need for developing auditing tools and methodologies by auditors, which are the current tasks that global audit firms, mainly the Big four, are focusing on (Pedrosa, et al., 2020; Al-Hiyari et al., 2019; Barr-Pulliam et al., 2020). The implementation of advanced IT systems including BDA is expected to enhance audit effectiveness and efficiency by providing auditors with more time to exercise skepticism on the risky areas while saving their time on routine and non-risky tasks (Al-Hiyari et al., 2019; Tiron-Tudor & Deliu, 2022).

Janvrin et al. (2009) address the relationship between using advanced technology in audit and its influence on auditors' professional skepticism. He described using technological tools such as BDA as "structure" and auditors' skepticism as "judgment", suggesting that BDA supports rather than replaces auditor judgment.

Despite the potential role of BDA to facilitate auditors' work, particularly in executing audit procedures such as identifying and assessing risks of material misstatements as per ISA 315, there are ongoing concerns about exercising an adequate level of professional skepticism. Ensuring the right balance between technological advancements and maintaining skepticism is critical for maintaining the integrity of audit outcomes in an increasingly complex business world.

3. Hypothesis Development

3.1 Behavioral Intentions to adopt BDA in Risk Assessment

According to Davis and Venkatesh (1996), PU and PEOU significantly affect a user's intentions towards adopting and using a specific new technology. Existing literature has consistently emphasized the importance of understanding how PU and PEOU influence technology adoption behaviors (Al Amin et al., 2020; Cabrera-Sánchez and Villarejo-Ramos, 2020; Olufemi, 2018). Behavioral intention, which refers to the likelihood of following behaviors in the future, is a key factor in technology adoption (Shahbaz et al., 2019).

Reviews of existing literature also emphasize that PEOU directly enhances and increases PU since technologies that are user-friendly are considered more beneficial and they improve job performance (Davis, 1986; Sánchez-Mena et al., 2017). Based on this discussion on the influence of PEOU and PU on behavioral intentions, we propose the following hypotheses:

H1: PU positively affects auditors' behavioral intentions to use BDA in risk assessment procedures.

H2: PEOU positively affects auditors' behavioral intentions to use BDA in risk assessment procedures.

H3: The PEOU of BDA among auditors enhances their PU of BDA in risk assessment procedures.

3.2 Actual Usage of BDA in Risk Assessment Procedures

Davis and Venkatesh (1996) indicated that PU and PEOU influence a user's intention to adopt and use a specific technology. Diop et al. (2019) noted that this intention translates into the actual adoption and usage of the technology. The same conclusion was reached by Shahbaz et al. (2019), who revealed that behavioral intentions to use the new technology lead to its actual implementation. Grimaldo and Uy (2020) further supported this conclusion, emphasizing that there is a direct and positive correlation between PU and PEOU of technology and the intention to use it. Building on these findings, the following hypothesis is formulated to cover the practical application of BDA in risk assessment procedures:

H4: The auditors' behavioral intention to use BDA in risk assessment procedures positively affects the actual usage of the technology.

3.3 The Impact of Using BDA in Risk Assessment Procedures on Professional Skepticism

The utilization of BDA into audit processes, specifically in performing the risk assessment procedures significantly influences auditors' assessment of audit evidence. Anomalies detected through BDA contribute to auditors' application of professional skepticism, particularly in determining which anomalies may require further investigation. (Li, 2022). The implementation of BDA provides auditors with the technique to analyze large volume of data, thus improving the auditor performance specially their ability to identify and evaluate the risk of material misstatements, thereby enhance auditors' professional skepticism (Handoko and Rosita, 2022). Sari and Musyarofah, (2020), also found that the effective use of BDA is linked with enhanced professional skepticism, which in turn, enhances the auditors' capabilities to identify and assess risks of material misstatement due to fraud (Sari and Musyarofah, 2020). This study aims to explore how auditors maintain the required level of professional skepticism during risk assessment processes, particularly during the planning phase of the audit. The actual application of BDA during this process and its influence on professional skepticism are leading to formulate the following hypothesis:

H5: The use of BDA by auditors positively affects their professional skepticism.

4. Research Model

The research model for this study is based on the existing literature that addresses technology adoption and professional skepticism, with the TAM utilized as the theoretical framework. Figure 2 visually illustrates the causal relationships among the research factors and variables. Initially derived from

Davis's TAM (as depicted in Figure 1), the research model incorporates Davis and Venkatesh's (1996) model that PU and PEOU are key TAM variables influencing users' behavioral intention to adopt technology (Davis and Venkatesh, 1996).

The study model further set that the intention to use BDA tools leads to their actual utilization (Davis and Venkatesh, 1996; Shahbaz et al., 2019). Hurtt et al. (2013) recommended examining whether the outcome of audit procedures performed through BDA, including risk assessment procedures, might influence auditors, potentially reducing their motivation to perform their duties with due care. Therefore, the research model explores the extent to which reliance on data from the actual use of BDA in performing risk assessment procedures affects professional skepticism.

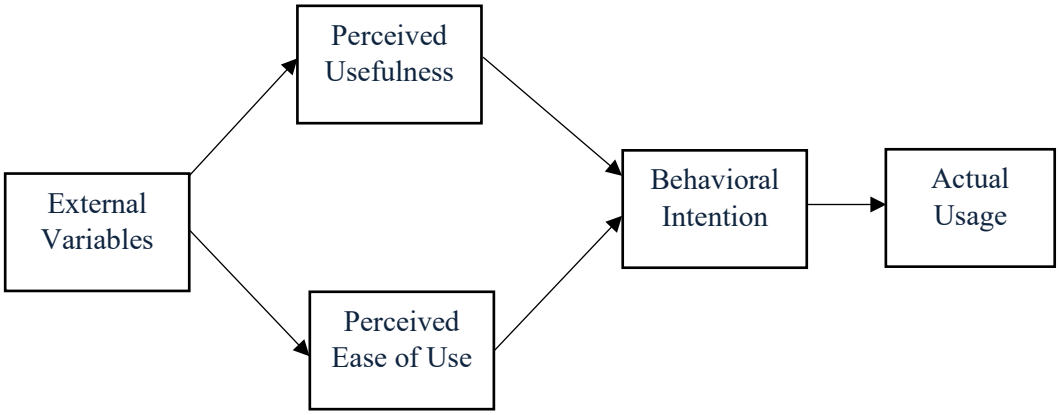

Fig1: Technology Acceptance Model (TAM) (Davis and Venkatesh (1996) p. 20).

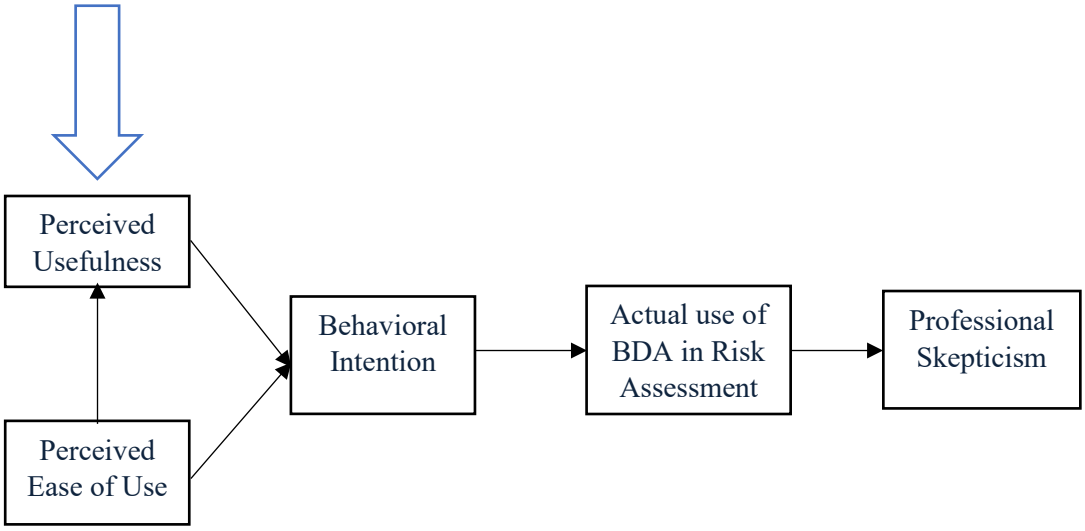

Fig 2: Conceptual framework.

5. Research Methodology

This study employs a mixed-method approach, integrating quantitative and qualitative research methodologies, as per Creswell's framework (2009), aiming for a comprehensive explanation of auditors' perspectives. Initially, quantitative methods, through questionnaires, are utilized to examine variable relationships statistically (Khaldi, 2017; Reio, 2016), drawing from TAM, BDA, and professional skepticism literature. The statistical data will be gathered from participants who are auditors at the big four auditing firms in Palestine to answer the study's questions. The quantitative

phase facilitates correlation analysis without influencing respondent behavior, even though not imply causation (Glasofer & Townsend, 2020).

Following the quantitative analysis, the study shifts to a qualitative phase, where semi-structured interviews are conducted with nine auditors who participated in the questionnaire. This method provides additional interpretations and insights on the results revealed from the quantitative phase through applying the thematic analysis (DiCicco-Bloom & Crabtree, 2006; Braun & Clarke, 2006).

5.1 Sampling techniques

The study population consists of auditors from the Big Four auditing firms in Palestine. The selection of solely the Big Four is due to their focus on data transformation and their strategic use in auditing, compared with small audit firms that are not progressing toward emerging BDA in their audit works (Li & Lai, 2011; Saadé & Kira, 2007; Dagiliene & Kloviene, 2019).

The study adopted a census approach, which means selecting the entire population as the sample. This approach is considered effective for smaller populations as it eliminates sampling errors and enhances the accuracy of the data collected (Levy & Lemeshow, 2013; Gibbins et al., 2001; Vinzi et al., 2010). Before initiating the study, to assess the reliability, validity, and consistency of the questionnaire, several copies were distributed to auditors, totaling 20 participants. Conducting a pilot study in this manner aids researchers in various ways, such as evaluating the questionnaire's feasibility and refining its design. The initial participants included 105 auditors from the Big Four auditing firms. However, to focus on those with sufficient professional experience, auditors with less than one year of experience were excluded, reducing the sample to 94 auditors. After distributing the questionnaires, a response rate of 86% was achieved from those auditors. For the qualitative phase, participants were selected from those who responded to the questionnaire among audit managers and above, to get their views on BDA adoption and its effects on professional skepticism. Out of the 26 managers and partners, 9 participated in the semi-structured interviews, significantly contributing to the depth of the qualitative analysis (Sayed Hussin et al., 2017; Pagalung & Habbe, 2017).

Although this study employs a mixed-method approach, it has limitations concerning sample size and generalizability, as it exclusively involves auditors from these firms, and only in Palestine, potentially limiting the applicability of the findings to other settings. In addition, by excluding auditors with less than one year of experience and achieving an 86% response rate, there is a risk response bias toward the views of more experienced auditors. Understanding these limitations is important for interpreting the findings and guiding future research to address these gaps.

5.2 Measurement development

The research questionnaire is divided into three sections, consisting of 31 items. In addition to these items, demographic information is also collected. The first section contains 14 items assessing the influence of PU and PEOU on auditors' behavioral intentions to adopt BDA for risk assessment procedures. This section is uses Davis (1989) measurement scales to measure PU and PEOU through specific questionnaire items (PU1 to PU6 and PEOU 1 to PEOU6). While Davis's original model did not cover the behavioral intention to use technology, this aspect is addressed by referring to Davis and Venkatesh's (1996) extension of TAM which include it (questions BI1 and BI2). The second section, with 5 items, focuses on measuring the actual implementation of BDA in the risk assessment process. The related questions (AU1 to AU5) are adopted from Janvrin et al.'s 2009 study, which investigated auditor's use of computer-assisted audit technique (CAATs) within audit process, particularly focusing the extent of CAATs' reliance in various audit tasks. For this study, we selected the audit tasks that are more relevant to performing risk assessment procedures and modified some procedural statements to better suit the current paper's objectives. The third section, consisting of 12 items, investigates how the actual usage of BDA influences professional skepticism in risk assessment procedures. This section assesses professional skepticism using a modified model by Robinson et al. (2018) which was assessed

through questions from PS1 to PS12. Responses for the main sections are gathered using a 7-point Likert scale, where 1 represents 'strongly disagree' and 7 stands for 'strongly agree'.

To provide additional interpretation of the quantitative phase results obtained through the questionnaires, the study adopted a semi-structured interview approach. This qualitative approach is important for obtaining a deeper understanding of complex issues, allowing for more insights into the core areas of the research topic (DiCicco-Bloom & Crabtree, 2006).

6. Data analysis and results

6.1 Analysis of questionnaires

In this study, SMARTPLS 4 software was employed to achieve the paper objectives and test the hypotheses. The researchers applied path analysis, which is a component of Structural Equation Modeling (SEM), as the principal statistical technique. SEM is a good tool for this kind of research as it allows for the simultaneous analysis of multiple structural relationships while accounting for measurement errors, which is essential for examining complex relationships between variables (Kline, 2023). Utilizing path analysis within the SEM framework enables a comprehensive interpretation of the hypotheses, providing a clear description of the direct and indirect effects among the studied constructs (Hair et al., 2010).

6.2 Measurement model assessment

The measurement model is important for estimating the relationships between latent variables and their indicators, primarily focusing on evaluating reliability, internal consistency, and validity. This is particularly true for reflective constructs such as the TAM factors dimension (PU, PEOU, and behavioral intention), the actual use dimension, and the professional skepticism dimension. Table 1 provides the results of the measurement model, which were assessed using three key metrics: item loading, convergent validity through Average Variance Extracted (AVE), and internal consistency via Composite Reliability (CR).

According to Hair et al. (2019), CR values that exceed 0.708 indicate sufficient reliability. Item loadings are also expected to exceed 0.708 to validate the constructs' validity. Furthermore, an AVE should exceed 0.50 to confirm the applicability of each factor (Fornell & Larcker, 1981).

Based on the measurement model results as shown in Table 1, the item loadings for the constructs ranged between 0.750 and 0.977. In addition, each construct exhibited a CR above 0.946, reflecting high reliability. Moreover, the AVE for all constructs exceeded the threshold of 0.5, thus confirming their convergent validity. Additionally, the assessment of discriminant validity, which is essential for distinguishing the uniqueness between measurement instruments of different factors, was conducted to ensure that the square root of the AVE for each construct was greater than the correlations among the constructs (Fornell & Larcker, 1981).

Table 2 provides the results of applying the Fornell-Larcker criterion within our model, confirming compliance with this criterion. The model's discriminant validity is evaluated using the heterotrait-monotrait ratio (HTMT) of correlations, as proposed by Ab Hamid et al. (2017). A value below 0.90 is considered acceptable, signifying adequate discriminant validity, while values above this threshold indicate otherwise. Table 3 displays all HTMT test results, demonstrating values below the 0.90 threshold and thus confirming the model's discriminant validity.

Table 1: Reflective constructs measurement properties

Reflective constructs	Construct items	Items loading	CR	AVE	Reference
Perceived Usefulness	PU1	0.929	0.977	0.874	Davis (1989)
	PU2	0.963			Davis (1989)
	PU3	0.948			Davis (1989)
	PU4	0.946			Davis (1989)
	PU5	0.901			Davis (1989)

	PU6	0.922			Davis (1989)
Perceived ease of use	PEOU1	0.866	0.961	0.804	Davis (1989)
	PEOU2	0.901			Davis (1989)
	PEOU3	0.944			Davis (1989)
	PEOU4	0.923			Davis (1989)
	PEOU5	0.901			Davis (1989)
	PEOU6	0.841			Davis (1989)
Behavioral intention	BI1	0.977	0.976	0.954	Davis & Venkatesh (1996)
	BI2	0.977			Davis & Venkatesh (1996)
Actual use	AU1	0.851	0.946	0.778	Janvrin et al. (2009)
	AU2	0.937			Janvrin et al. (2009)
	AU3	0.845			Janvrin et al. (2009)
	AU4	0.891			Janvrin et al. (2009)
	AU5	0.882			Janvrin et al. (2009)
Professional Skepticism	PS1	0.872	0.982	0.823	Robinson et al. (2018)
	PS2	0.931			Robinson et al. (2018)
	PS3	0.937			Robinson et al. (2018)
	PS4	0.956			Robinson et al. (2018)
	PS5	0.952			Robinson et al. (2018)
	PS6	0.750			Robinson et al. (2018)
	PS7	0.912			Robinson et al. (2018)
	PS8	0.929			Robinson et al. (2018)
	PS9	0.895			Robinson et al. (2018)
	PS10	0.920			Robinson et al. (2018)
	PS11	0.882			Robinson et al. (2018)
	PS12	0.932			Robinson et al. (2018)

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

Constructs	Actual Use	Behavioral Intention	Perceived Ease of Use	Professional Skepticism	Perceived Usefulness
Actual Use	**0.882**				
Behavioral Intention	0.415	**0.977**			
Perceived Ease of Use	0.597	0.633	**0.897**		
Professional Skepticism	0.640	0.481	0.401	**0.907**	
Perceived Usefulness	0.637	0.713	0.712	0.564	**0.935**

Table 3: Heterotrait-Monotrait Ratio (HTMT)

Constructs	Actual Use	Behavioral Intention	Perceived Ease of Use	Professional Skepticism	Perceived Usefulness
Actual Use	-				
Behavioral Intention	0.439	-			
Perceived Ease of Use	0.637	0.661	-		
Professional Skepticism	0.663	0.495	0.412	-	
Perceived Usefulness	0.667	0.739	0.738	0.573	-

After concluding the analysis of the study's measurement model, Figure 3 presents the research study model that was implemented.

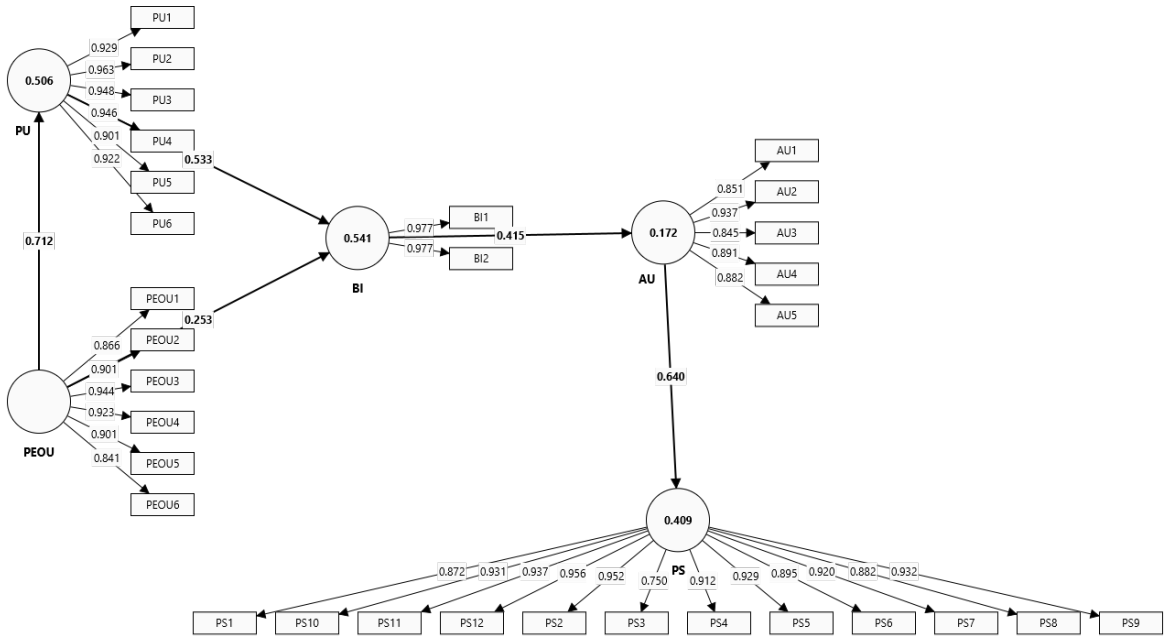

Fig 3: The measurement model.

6.3 Assessment of the structural model

The subsequent phase required evaluating the structural model to determine its predictive relevance and examine the relationships among constructs, thereby assessing the model's robustness and coherence. This step was pivotal for testing the hypotheses set in the study. The evaluation consists of four key metrics: the coefficient of determination (R^2), path coefficients (β values), T-statistics, effect size (f^2), and the predictive relevance (Q^2) of the model. A bootstrapping analysis was adopted to facilitate this assessment.

According to Hair et al. (2010), R^2 values of 0.75, 0.50, and 0.25 indicate high, moderate, and low predictive power, respectively. In this study, R^2 values indicate high predictive capability for all constructs. Additionally, Q^2 values, which are indicators of the model's predictive relevance, should exceed zero to confirm the predictive relevance of the constructs. Table 4 presents the Q^2 values for actual use, behavioral intention, professional skepticism, and perceived usefulness, recorded at 0.213, 0.372, 0.081, and 0.485, respectively. The Q^2 values for all constructs are above 0, affirming the model's predictive relevance and ability.

Table 4: 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	f^2 Professional Skepticism
Perceived Ease of Use	-	-	-	1.026	0.069	-	-
Actual Use	0.162	0.213	-	-	-	-	0.693
Behavioral Intention	0.529	0.372	-	-	-	0.208	-
Professional Skepticism	0.402	0.081	-	-	-	-	-
Perceived Usefulness	0.500	0.485	-	-	0.306	-	-

The effect size (f^2) serves as a key metric for assessing the impact of latent constructs on latent variables within the structural model. The resulting quantification allows researchers to understand the extent to which each construct contributes to interpreting the variance observed in the variables. According to Cohen's (1988) guidelines, f^2 values of 0.02, 0.15, and 0.35 are categorized as small, medium, and large effect sizes, respectively.

In Table 4, we present the f^2 values for each construct. The f^2 value with PU is 1.026, indicating a large effect size. This suggests that PEOU significantly influences PU. Additionally, the f^2 value with behavioral intention is 0.069, representing a small effect size. This indicates that PEOU has a relatively minor impact on behavioral intention. Moreover, the f^2 value with Behavioral Intention is 0.306, indicating a high effect size. This suggests that PU significantly impacts behavioral intention. The f^2 value with actual use is 0.208, indicating a medium effect size. This implies that behavioral intention moderately impacts actual use. Finally, the f^2 value with professional skepticism is 0.693, indicating a large effect size. This suggests that actual use strongly influences professional skepticism.

For hypothesis testing part, the analysis utilized path coefficients to examine the hypothesized relationships. The outcomes, detailed in Table 5 and figure 4, follow the methodology suggested by Hair et al. (2019), employing the bootstrapping technique. Notably, the numerical data related to beta coefficients, standard deviations, and p-values are based on a two-tailed test.

Table 5: Hypothesis testing results

Hypothesis	Beta coefficients	Standard deviation	T statistics	P values	Decision
H1: PU -> Behavioral intention	0.533	0.141	3.772	0.000	Supported
H2: PEOU -> Behavioral intention	0.253	0.150	1.686	0.092	Rejected
H3: PEOU -> PU	0.712	0.079	9.033	0.000	Supported
H4: Behavioral intention -> Actual use	0.415	0.143	2.898	0.004	Supported
H5: Actual use -> Professional skepticism	0.640	0.089	7.178	0.000	Supported

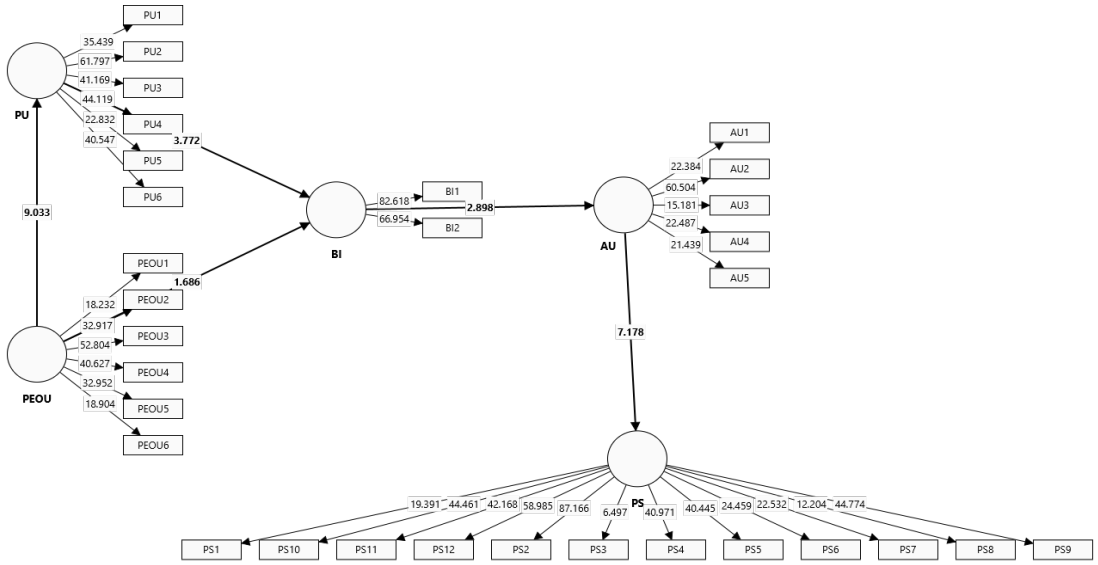

Fig: 4. PLS Bootstrapping (t-values) for the study model.

As shown in table (5), the results of hypothesis testing reveal significant insights into the relationships among the variables. Firstly, H1, which posits a relationship between PU and behavioral intention, is strongly supported with a beta coefficient of 0.533, a t-value of 3.772, and a p-value of 0.000. This indicates a statistically significant positive relationship between PU and behavioral intention. However, H2, proposing a link between PEOU and behavioral intention, is rejected due to its beta coefficient of 0.253, a t-value of 1.686, and a p-value of 0.092. These results suggest that there is insufficient evidence to support the proposed relationship between PEOU and behavioral intention.

In contrast, H3, which examines the relationship between PEOU and PU, demonstrates strong support with a beta coefficient of 0.712, a t-value of 9.033, and a p-value of 0.000. This indicates a significant positive relationship between PEOU and PU. Moreover, H4, suggesting a link between behavioral intention and actual use, receives support with a beta coefficient of 0.415, a t-value of 2.898, and a p-value of 0.004. This indicates a statistically significant impact of behavioral intention on actual use.

Hypothesis 5, which sets a relationship between the actual use of BDA and professional skepticism, is strongly supported with a beta coefficient of 0.640, a t-value of 7.178, and a p-value of 0.000. These results indicate a statistically significant positive impact of actual use on professional skepticism.

These results provide insights into the relationship between the variables studied, particularly in how auditors perceive the use of BDA in risk assessment procedures and its subsequent effect on professional skepticism. The analysis highlights the significant role that each construct plays within the structural model. Notably, the influence of PEOU on PU, along with the clear impact of actual use on professional skepticism, emphasizes the critical factors driving the model.

6.4 Interviews analysis

The second phase of this study involved semi-structured interviews with external auditors at the manager position or above (managers to partners), who had previously participated in the questionnaire phase. This qualitative phase aimed to gain a more understanding of the quantitative findings, particularly how perceived usefulness and ease of use impact the adoption of BDA in risk assessment procedures and its subsequent effects on professional skepticism.

The qualitative analysis revealed several key themes, highlighting the auditors' perceptions and views regarding the integration of BDA into risk assessment procedures, and providing further explanation of the outcomes resulting from the quantitative stage.

1. Enhanced identification of risk of material misstatements: BDA has been incorporated as a fit tool in modern audit practices, offering auditors an advanced means to better identify risks of material misstatements. Through interviews with external auditors from the Big Four auditing firms, it became evident that BDA plays a critical role in the risk assessment process, offering insights into the entity's business operations and financial performance. One auditor said,

   " Yes, big data analytics are utilized in my audit process for understanding of the entity's business as part of risk assessment procedures."

   Moreover, auditors highlighted how BDA contributes to enhanced auditors' ability in risk identification and obtain deeper understanding of the entity's business and operations. By analyzing the output generated from BDA tools related to financial statements captions represented with assets, liabilities, revenues, expenses, and other financial indicators, BDA provides auditors with a comprehensive view of the entity's financial position and performance, in addition to enhance their understanding of the business environment under audit. This deeper understanding aids auditors in evaluating the accuracy and completeness of financial statements, thus strengthening their capabilities to perform high quality audit. According to another auditor,

   "BDA inherently involve gaining an understanding of the entity's business activities, transactions, and financial reporting processes, which are essential components of understanding the business under audit throughout the audit period, providing real-time insights into potential risks."

2. Efficiency and effectiveness: while efficiency is mentioned as important, auditors prioritize maintaining audit quality over ease of use. However, they acknowledge that perceiving BDA as user-friendly can enhance its perceived usefulness, particularly in terms of efficiency and effectiveness in audit procedures. Some auditor emphasized:

   " While ease of use is important, my intention to use BDA is primarily driven by its utility in maintaining audit quality and professional skepticism."

"…While efficiency is important, it shouldn't compromise quality."

3. Better compliance with ISA 315 requirements: the utilization of BDA aligns with compliance requirements set forth in auditing standards like ISA 315. Auditors noted that relying on BDA for risk assessment procedures aids in automating testing procedures, refining selection criteria, and ensuring adherence to auditing standards. This alignment underscores BDA's role not only in improving audit efficiency but also in enhancing compliance with regulatory requirements. One auditor indicated,

   "Relying on BDA…..and ensuring that we comply with ISA 315 requirements."

4. From intention to actual usage: the transition from the intention to the actual usage of BDA in audit processes was highlighted as a key theme. Auditors expressed that their initial intentions to use BDA led to its practical implementation in their auditing tasks. As one auditor stated,

   "Intending to rely on BDA for risk assessment procedures will eventually result in its practical utilization in my audit processes."

5. Impact on professional skepticism and audit quality: the consensus among auditors is that BDA positively affects professional skepticism and audit quality. It helps focus on risky areas, refine selection criteria, and automate testing, all of which contribute to higher audit quality. There are some of their statements:

   "Relying on BDA can positively influence my professional skepticism by directing attention to risky areas…."

   "….the use of BDA for understanding of the entity's business as part of risk assessment procedures……while strengthening my professional skepticism ….."

   "BDA tools can help in identifying flag unusual or potentially fraudulent entries…….and then enhance our professional skepticism."

In summary, the interviews with auditors showed the significant role of BDA in modern audit practices. There was unanimous recognition of its value in enhancing risk identification, efficiency, compliance, and particularly in reinforcing professional skepticism, which ultimately contributes to an increase in the quality of the audit.

7. Discussion

This study investigates the integration of BDA into risk assessment procedures within the auditing field and evaluates its influence on auditors' professional skepticism. The results corroborate existing theoretical frameworks and contribute new empirical evidence, which enriches the literature by linking our findings with prior research.

The quantitative data showed a strong positive relationship between PU and auditors' behavioral intentions to utilize BDA in risk assessment procedures (H1). This suggests that auditors are more inclined to adopt BDA when they perceive these tools as increasing their performance in risk assessment procedures. The qualitative interviews further reinforced the value of BDA, with auditors noting its strategic benefits in obtaining a deeper understanding and providing valuable insights on entities under audit, which facilitate more informed decision-making in audit engagements. This connection is supported by previous studies, such as Davis et al. (1989), who identified that PU is a crucial determinant of technology adoption in the TAM. Subsequent studies, such as those by Cabrera-Sánchez and Villarejo-Ramos (2020) and Amin et al. (2020), found that PU in the context of BDA adoption in professional settings positively influences users' decisions to adopt BDA.

Unexpectedly, the analysis of H2 did not find a significant relationship between PEOU and behavioral intention, suggesting that while ease of use is important, it may not be a critical factor for auditors when considering the adoption of BDA in risk assessment procedures. Instead, the qualitative data revealed that auditors prioritize the effectiveness and strategic advantages of BDA over its user-

friendliness. This deviation from general TAM findings suggests that in certain professional practices like auditing, the output and effectiveness of technology may be considered more important than its usability concerns. This conclusion is supported by research like that of Sánchez-Mena et al. (2017), which indicates that users in complex professional fields may prioritize functionality over ease of use. Additionally, Buabeng-Andoh (2018) found that ease of use could be important in contexts where users face a steep learning curve or where technology directly interacts with less tech-savvy users, but this significance will be reduced if the adoption is related to complex professional practices.

The analysis revealed a strong positive correlation between PEOU and PU (H3) indicating, that the ease of use of BDA is perceived as more beneficial by auditors. This relationship was noted from the feedback of auditors who observed that the adoption of BDA in auditing, including the risk assessment process, reduces cognitive load and makes the technology more attractive for daily tasks. This connection between ease of use and perceived usefulness is fundamental in TAM research and remains consistent across various technologies and user demographics (Davis, 1989). A study conducted by Oliveira and Martins (2011), which addressed the adoption of banking technologies, noted that easily integrating new technology into existing workflows without major disruption is highly valued. Furthermore, the study by Gangwar (2020) emphasizes that in sectors like healthcare and retail, ease of use significantly enhances the perceived usefulness of BDA by reducing operational complexities and improving user interaction with technology. However, auditors see that their readiness to adopt new technologies could significantly influence their perception, meaning that those more comfortable with technology might rate BDA higher in terms of ease of use and usefulness. This aligns with findings by Olufemi (2018), who noted that the TAM does not account for factors such as technology cost, management support, and the entity's environment and culture in the intention to adopt new technology. Additionally, Grimaldo and Uy (2020) identified external variables like trust and support that might impact PU and PEOU. In the auditing context, large auditing firms have addressed some of these limitations by implementing extensive training programs to equip their teams with the necessary skills to analyze and understand new technologies (Eilifsen et al., 2020). Therefore, the relationship between PEOU and PU may also be influenced by the availability of training and support, as well as auditors' technology readiness and the broader organizational environment.

The analysis also confirmed a positive impact of behavioral intention on the actual use of BDA in risk assessment procedures (H4), highlighting that auditors' behavioral intentions to use BDA are a reliable predictor of their actual adoption and usage. This finding is aligned with the core principles of TAM and is supported by literature, including Davis and Venkatesh (1996). Diop et al. (2019) and Shahbaz et al. (2019) provide empirical evidence that intentions are predictors of technology usage, particularly when users recognize the benefits from technology adoption. This relationship is further evidenced in a professional context, as demonstrated by a study conducted by Grimaldo and Uy (2020), who found that behavioral intentions lead to the actual implementation of new technologies in audit practices.

A significant relationship was observed between the actual use of BDA and an enhancement in professional skepticism (H5), indicating that BDA enhances auditors' capacity to critically evaluate audit evidence and identify anomalies. This reinforcement in professional skepticism is important for maintaining a high level of audit quality. The positive impact of BDA on professional skepticism has been emphasized in several studies. For instance, Li (2022) and Austin et al. (2018) discuss how BDA can enhance auditors' ability to identify risks of material misstatements due to fraud, thus increasing the required level of professional skepticism. Moreover, the research by Robinson et al. (2018) explain how BDA supports auditors' judgment, suggesting that while technology automates many processes, it also provides auditors with tools to gain more understanding of the entity's financial statements through questioning the underlying data more effectively. This aligns with the existing auditing literature that emphasizes the need for a balance between technology use and the maintenance of skepticism to ensure audit quality (Pedrosa et al., 2020; Al-Hiyari et al., 2019).

8. Conclusion

This study provides empirical insights into the integration of BDA in risk assessment procedures within the auditing field and its influence on auditors' professional skepticism. The findings corroborate the TAM and contribute new evidence to the existing literature by linking the adoption of BDA to its impact on professional skepticism during risk assessment processes.

The quantitative data revealed that PU directly influences auditors' intentions to adopt BDA and subsequently impacts the actual usage of BDA in risk assessment procedures. While PEOU did not directly affect behavioral intentions, it contributed to PU, suggesting that user-friendly BDA tools are perceived as more beneficial by auditors. The qualitative interviews further reinforced the value of BDA in enhancing risk identification, efficiency, compliance with auditing standards, and, most importantly, reinforcing professional skepticism, which ultimately contributes to increased audit quality.

Despite its contributions, this study has several limitations. First, the focus on auditors from the Big Four firms in Palestine may limit the generalizability of the findings to other regions or auditors from smaller firms. Second, the reliance on the TAM as a theoretical framework may not capture all aspects related to utilizing BDA in the risk assessment process. Third, the cross-sectional nature of the study may not fully capture the dynamic changes in technology adoption and its impacts over time.

Future research should consider expanding the geographical scope and including auditors from various firm sizes to enhance generalizability. Incorporating longitudinal approaches to track changes in the adoption and impacts of BDA over time would provide valuable insights. Additionally, exploring other theoretical frameworks or models to address the utilization of BDA in risk assessment procedures could offer new perspectives.

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