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Big Data Analytics Adoption and Professional Skepticism: The Role of Auditors' Experience, Self-Efficacy, and Trust

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ABSTRACT

This paper addresses a gap in the literature regarding how auditors' adoption of big data analytics influences professional skepticism, a behavioral dimension often overlooked in technology adoption models. It examines how specific auditor characteristics, namely prior experience, self-efficacy, and trust, shape their perceived usefulness and perceived ease of use of big data analytics tools. Additionally, it examines how these perceptions affect their behavioral intentions to adopt big data analytics tools, whether this leads to actual usage, and, subsequently, whether actual usage of big data analytics impacts professional skepticism. A questionnaire was prepared and distributed via census to 94 external auditors from the Big Four auditing firms in Palestine (86% response rate). The findings indicate that certain auditors' characteristics positively influence perceptions of the usefulness and ease of use of big data analytics, thereby affecting adoption intentions and actual adoption. However, not all auditors' characteristics show this positive influence. Furthermore, the actual use of big data analytics has been found to significantly impact professional skepticism, suggesting that such tools could enhance audit quality. The study's results emphasize the importance of keeping professional skepticism strong as technology evolves. These findings are essential for audit firms looking to use big data analytics to improve audit quality. This study extends the Technology Acceptance Model by linking auditors' technology

adoption behavior to professional skepticism, highlighting the behavioral implications of digital transformation in auditing.

Keywords: Big Data analytics, Professional skepticism, Technology acceptance model, Prior experience, Self-efficacy, Trust

INTRODUCTION

The rapid expansion of big data has revolutionized how businesses operate, analyze risk, and make strategic decisions. In this evolving landscape, auditors face growing pressure to adapt by leveraging advanced big data analytics (BDA) tools to remain practical and relevant. As organizations increasingly adopt data-driven decision-making processes, expectations rise for auditors to enhance audit quality, detect fraud more accurately, and provide real-time insights (International Federation of Accountants [IFAC], 2017). These technological advancements not only reshape audit practices but also challenge the core professional competencies required, particularly the need to maintain a high level of professional skepticism (PS) in an increasingly automated environment (Arens et al., 2017).

PS involves evaluating the audit evidence with a critical mindset. This approach is essential for auditors to identify material misstatements in financial statements effectively (International Auditing and Assurance Standards Board, 2008; Para. 13-I; Nelson, 2009). The use of new tools by auditors, such as big data analytics, may undermine skeptical behavior when auditors over-rely on tool-generated outputs and become less motivated to critically evaluate such evidence (Barr-Pulliam et al., 2020; No et al., 2019).

To more deeply assess big data analytics adoption among auditors, this study examines selected external variables related to auditors' attributes to understand better the factors influencing their behavior. These factors are prior experience, self-efficacy, and trust. These constructs are well established in the technology adoption literature as key individual-level determinants of perceived ease of use and usefulness. In the auditing context, these attributes are particularly relevant given the profession's reliance on professional judgment, confidence, and the ability to engage with complex tools. Experienced auditors demonstrate greater proficiency in integrating big data analytics tools into their audit work. Additionally, auditors with higher self-efficacy may exhibit more confidence in utilizing these technologies effectively. Furthermore, trust in the accuracy and reliability of big data analytics outputs may influence auditors' reliance on these tools during audit evidence (Barr-Pulliam et al., 2020; No et al., 2019).

Despite the potential benefits of big data analytics in auditing, several issues persist in current audit methodologies. Recent fraud cases involving the manipulation of financial data in big data environments highlight the limitations of current audit practices in detecting fraud (Davis Polk team, 2021; Magubane, 2022; University of Colorado Denver, 2019). These cases highlight the need to reassess and enhance audit approaches to address the challenges posed by technological advancements.

Big data analytics literature essentially provides insights using TAM about companies in various sectors, whereas its application in auditing firms has received comparatively less research attention. However, the lack of focus on the impact of big data analytics adoption in developing countries is a significant gap that should be addressed. Furthermore, there is a need for more in-depth research addressing different external variables that affect perceived usefulness (PU) and perceived ease of use (PEU), as few studies have been conducted in the auditing context. Moreover, there is a lack of advanced studies examining the adoption of big data analytics in relation to PS.

While many prior studies have applied TAM to understand technology adoption in auditing, the current research extends this framework by examining a critical and underexplored outcome: PS. As a core component of audit quality, PS remains essential in the digital audit landscape, where excessive reliance on analytics tools may compromise auditors' critical judgment. By analyzing how the actual use of big data analytics influences PS, this study provides novel insights that bridge the gap between technology adoption and behavioral audit outcomes, an area that has received limited attention in the literature.

The research aims to explore how auditors' characteristics affect the PU and PEU of big data analytics tools, investigate the relationship between PU and PEU with behavioral intention (BI) to adopt big data analytics, and assess the subsequent impact on PS. This study is particularly timely given the increased adoption of data-driven audit tools and the evolving role of auditors in developing economies. By focusing on the Palestinian context, where empirical research remains limited, this paper adds valuable regional insights into how auditor characteristics influence big data analytics adoption and how such adoption affects PS. These findings aim to inform audit practices and training strategies that preserve skeptical judgment while embracing digital transformation.

Based on the identified gaps and the conceptual model, this study seeks to address the following research questions:

RQ1: How do individual auditor characteristics (prior experience, self-efficacy, and trust) influence perceived usefulness and perceived ease of use of big data analytics tools?

RQ2: How do perceived usefulness and perceived ease of use affect auditors’ behavioral intention and actual use of big data analytics tools?

RQ3: How does the actual use of big data analytics tools impact auditors' professional skepticism?

THEORETICAL FRAMEWORK

Audit quality theory highlights the importance of acting with competence and objectivity without compromising professional judgment in the field of auditing (DeAngelo, 1981). Professional judgment is intricately connected with the concept of PS, as articulated by Nelson (2009). Both concepts—professional judgment and professional skepticism—play vital roles in ensuring accurate audit execution and achieving high audit quality (Puspitasari et al., 2019). Simultaneously, structure, often referred to as the technological tools in auditing, such as big data analytics, necessitates the application of the TAM to analyze the information technology adoption behavior of this technology in the audit process. Structure contributes to auditors' expertise and professional knowledge; therefore, both judgment and structure are integral elements in enhancing audit quality (Tiron-Tudor & Deliu, 2022).

To attain the desired level of PS, auditors need to maintain a sense of comfort in both structure and judgment (Carrington & Catasús, 2007). Auditors are required to carry out their responsibilities with precision and correctness to become comfortable. When auditors focus on performing tasks in alignment with correct procedures and practices, their reliance tends to be more on structure. Conversely, when auditors concentrate on executing tasks with precision, judgment assumes a dominant role. Nevertheless, it is indispensable for auditors to attain sufficient levels of comfort in both structure and judgment to deliver a high-quality audit (Carrington & Catasús, 2007; Pentland, 1993).

PU and PEU are TAM variables that influence users' BI to adopt technology (Davis & Venkatesh, 1996). Studies have addressed the importance of understanding how these factors affect technology adoption behavior (Al Amin et al., 2020; Cabrera-Sánchez & Villarejo-Ramos, 2020; Olufemi, 2018). Additionally, there is a clear interrelation between PU and PEU in predicting users' BI to adopt new technology (Grimaldo & Uy, 2020). The intention to use big data analytics tools leads to their actual utilization (Davis & Venkatesh, 1996; Shahbaz et al., 2019). The actual usage (AU) of these tools results in outputs that practicing auditors rely on. Past studies have provided examples of such outputs, including checklists, templates, and other computer-based procedures and working papers (Hurtt et al., 2013; Knechel, 2007; Pedrosa et al., 2020). Hurtt et al. (2013) suggested examining whether these predefined tasks and outputs might overly influence auditors, potentially diminishing their motivation to perform their duties carefully.

BI's use of a specific technology is influenced by PEU and PU (Davis & Venkatesh, 1996). PEU affects PU, as technology is more likely to increase job performance (being more useful) when it is easier to use (Davis, 1986; Sánchez-Mena et al., 2017). BI refers to the tendency to engage in certain behaviors in the future and serves as a key predictor of new technology adoption. Thus, the intention and perceived need to use a technology ultimately lead to its AU (Shahbaz et al., 2019).

This study integrates audit quality theory and the TAM through the lens of comfort theory. Audit quality theory emphasizes the importance of professional judgment and skepticism, while TAM focuses on the technological structure that shapes auditors' perceptions of usefulness and ease of use. Comfort theory bridges these perspectives by explaining how auditors balance reliance on technological tools, such as big data analytics, with the application of PS to achieve an appropriate level of audit comfort. This integration supports the study's conceptual model linking auditors' characteristics, technology adoption behavior, and PS.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

The concept of audit quality, rooted in DeAngelo's seminal work (1981), emphasizes the importance of auditor competence and objectivity in maintaining high auditing standards, as reiterated by Nelson (2009) and Puspitasari et al. (2019). PS, closely linked to audit quality, is underscored as vital for accurate audit execution and reliability, particularly amid technological advancements such as big data analytics, as highlighted by Tiron-Tudor and Deliu (2022). These technological shifts bring the TAM into focus, serving as a framework for understanding auditors' adoption of new technologies, such as big data analytics, in their audit processes.

Auditors find comfort vital because it involves turning numbers into trustworthy ones (Carrington & Catasús, 2007). To enable auditors to perform their work effectively, two crucial elements require special consideration: structure and judgment (Carrington & Catasús, 2007; Pentland, 1993). Carrington and Catasús (2007) emphasize the importance of balancing technological structure and judgment to achieve the requisite level of PS.

TAM is used to understand the technological aspect of the research model developed for this paper, represented by the "structure". PU and PEU are considered the most significant variables in the TAM that influence users' BI in adopting new technology (Davis & Venkatesh, 1996). Previous studies have emphasized the importance of understanding PU and PEU as key determinants of technology adoption behavior (Al Amin et al., 2020; Cabrera-Sánchez & Villarejo-Ramos, 2020; Olufemi, 2018; Tarabasz & Poddar, 2019). PU and PEU have a significant relationship with predicting users' BI to adopt new technology (Grimaldo & Uy, 2020). Although limited research has examined the impact of external variables on PU and PEU, scholars such as Davis et al. (1989) have identified examples, including support and documentation, that may influence these perceptions. Additionally, Davis and Venkatesh (1996) developed the TAM model based on the assumption that specific external variables influence PU and

PEU. Other studies have examined factors such as trust, social influence, and support systems, highlighting the complexity of adopting new technology (Grimaldo & Uy, 2020; Sharma & Mishra, 2014). Accordingly, some external variables have been identified, and the most relevant variables to the research topic have been selected (Prior experience, self-efficacy, and trust).

External Variables

The selection of prior experience, self-efficacy, and trust as both theoretical frameworks and practical relevance informed the selection of external variables. These variables are frequently identified in TAM extensions as key individual-level predictors of PU and PEU (Davis et al., 1989; Venkatesh et al., 2003). Given the auditor-focused scope of this study, individual traits such as confidence in one's own abilities (self-efficacy), previous exposure to similar technologies (experience), and belief in the reliability of new tools (trust) are more directly influential than organizational or environmental factors. Moreover, existing literature on big data analytics adoption in auditing has paid limited attention to these personal attributes, especially in developing-country contexts. Therefore, prioritizing these variables contributes both theoretically and empirically to closing this gap.

Prior experience

Prior experience significantly influences auditors' perceptions of technological tools such as big data analytics, thereby affecting their acceptance and use. Previous studies highlight this correlation, showing that auditors with past technology use (Alfadda & Mahdi, 2021; Harryanto et al., 2018; Saadé & Kira, 2007; Xia et al., 2018), especially audit-specific tools like CAAT, are more receptive to adopting advanced tools like big data analytics (Pedrosa et al., 2020). This familiarity enhances their belief in the usefulness and ease of new technologies. Conversely, auditors with limited experience with technology may exhibit skepticism, viewing new tools as complex (Salijeni et al., 2021). H. L. Li and Lai (2011) found that experienced auditors show a stronger correlation between BI and AU, indicating greater confidence in assessing new technologies.

Auditors with greater experience and accumulated expertise demonstrate a stronger ability to articulate conclusions than their less experienced counterparts (Bahtiar et al., 2017; Sayed Hussin et al., 2017). H. L. Li and Lai (2011) identified a pronounced difference in the acceptance and utilization of big data analytics tools between experienced and inexperienced auditors. This difference stems from a strong correlation between BI and AU among those with more experience. Therefore, experienced auditors are generally more confident in the ease of use of technology, suggesting that experience is a critical external factor influencing technology adoption. Saadé and Kira (2007) demonstrated that direct, repeated use enables users to evaluate the costs and benefits of specific technologies more accurately. Therefore, an auditor's technological experience positively shapes their perceptions and beliefs about similar emerging technologies, influencing perceived usefulness and ease of use. This leads to H1a and H1b hypotheses:

H1a: *Prior experience with technology positively impacts the PU of big data analytics technological tools.*

H1b*: Prior experience with technology positively impacts the PEU of big data analytics technological tools.*

Self-efficacy

Self-efficacy can significantly affect how individuals perceive the usefulness and ease of use of technology. As technology becomes more accessible, auditors are increasingly likely to adopt it out of necessity, believing it will support their audit work. When a new technology is initially complex for the auditor to use, the auditor's sense of self-efficacy grows as they learn to use it. However, once an auditor has learned how to use new technology, they tend to become immune to its initial difficulties (Lee et al., 2016; Sánchez-Prieto et al., 2016). This satisfaction often leads auditors to overlook initial difficulties when evaluating their ability to learn a new technology. Instead, they focus on their confidence in managing the learning process required for its use. As long as the auditor is satisfied that they can learn to use the technology, they remain convinced they will adopt and use it properly. Adoption rates for new technologies often increase when professionals feel they have control over how to use the technology (Zheng et al., 2018). Self-efficacy plays a significant role when auditors adopt new technologies, as they have learned skills that have significantly improved their work processes (Venkatesh et al., 2003). Although Zheng et al. (2018) did not specifically study auditors, their findings can be applied to the audit profession. When auditors adopt new technology, they must believe they can learn to use and control it properly so it benefits them. Without sufficient confidence, auditors are unlikely to adopt technologically advanced tools that have enhanced the audit profession. Auditors' lack of self-confidence and effort prevents them from adopting newer technologies in their audit process; however, self-efficacy has a significant effect on adoption rates when auditors feel confident in their ability to learn the technology. (Zheng et al., 2018).

Auditors who perceived the usefulness and ease of use of big data analytics technological tools also reported higher attitudes toward technology use. Furthermore, self-efficacy plays a key role in shaping auditors' perceptions of new technology. (Lee et al., 2016). These results complement previous studies (Gyamfi, 2017; Lule et al., 2012;

Ofori & Appiah-Nimo, 2019; Shahbaz et al., 2021; Teo, 2009; Zheng et al., 2018) that typically assessed relevant variables, including self-efficacy in using new technology in various fields. Although these studies did not specifically examine external auditors, their findings on self-efficacy and technology adoption are relevant to understanding auditors' behavior towards new technological tools. Furthermore, this study contributes to the existing literature by examining auditors at Big Four firms to assess their perceptions of technology acceptance and the influence of technology-related self-efficacy on the adoption of new technologies. Based on the above, H1c and H1d were formulated:

H1c: *Self-efficacy positively impacts the PU of big data analytics technological tools.*
H1d: *Self-efficacy positively impacts the PEU of big data analytics technological tools.*

Trust

Trust plays a crucial role in technology adoption, particularly in practice, influencing PU and PEU (Davis, 1989). Users who trust a technology are more inclined to see it as effective and reliable, thereby increasing their willingness to adopt it. Conversely, a lack of trust can deter adoption (Sternberg et al., 2021). Trust is built on factors such as the technology provider's reputation and transparency in how the technology operates (Cole et al., 2019). X. Li et al. (2008) emphasize the importance of initial trust in shaping perceptions of usefulness and the intention to use new technology. Trust has been integrated into the TAM model across various domains (Bayraktaroglu et al., 2019; Yudhistira & Sushandoyo, 2018), demonstrating its role in enhancing users' control and positive perceptions. In auditing and big data analytics, trust is fundamental to effective information system adoption and communication (Shahbaz et al., 2019), underscoring its significance in technology adoption within these contexts.

Tarabasz and Poddar (2019) noted that if wearable technology is easy to use, it is perceived positively by users, thus suggesting the inclusion of trust as an additional variable to improve predictive capability. Sharing insights through data analysis is a key function of big data applications. Therefore, integrating data analytics tools can build trust in them and enhance communication (Félix et al., 2018). Perceived trust in terms of big data analytics is fundamental to the success of information system adoption (Shahbaz et al., 2019). Sharma and Mishra (2014) noted that technology adoption may require more than BI and technical knowledge; thus, they identified trust as a factor that may affect technology adoption. Based on the above, H1e and H1f hypotheses were formed as follows:

H1e: *Trust positively impacts the PU of big data analytics technological tools.*
H1f: *Trust positively impacts the PEU of big data analytics technological tools.*

BDA and TAM

In recent years, growing scholarly attention has been directed toward the integration of big data analytics across various sectors. This body of research has explored not only the advantages and potential obstacles associated with big data analytics implementation but also evaluated the most suitable theoretical frameworks for analyzing its adoption and utilization. Despite ongoing challenges, the literature consistently highlights the critical role of big data analytics in improving operational and strategic outcomes across industries and national economies (Abdelwahed et al., 2025; Alkhatib & Valeri, 2024; Krieger et al., 2021).

The integration of big data analytics and the TAM in current research has increased, as big data analytics is regarded as a new technology adopted by individuals and organizations, replacing traditional methods of interpreting information in big data environments. The unknown user adoption behaviors regarding the introduction of this new technology have led scholars to adopt TAM as a relevant framework. The TAM was developed to explain users' attitudes toward adopting new technologies. TAM is based on two major beliefs: PU and PEU, which impact user attitudes toward new technologies (Davis et al., 1989; Koul & Eydgahi, 2017; Oliveira & Martins, 2011). These beliefs have been widely applied across various fields, such as education, information technology, and healthcare (Buabeng-Andoh, 2018; Hossain et al., 2020).

Big data analytics is defined by a large volume of data and a diversity of sources and types. Therefore, advanced technologies are required at the decision-making level within organizations, particularly among senior management, to effectively analyze this vast data and support informed decision-making (Adnan & Akbar, 2019; Brock & Khan, 2017). Previous studies across various sectors, including healthcare, retail, and manufacturing, have highlighted the strategic impact of big data analytics on organizational performance, contributing to improvements in areas such as customer satisfaction, operational efficiency, and smart manufacturing (Félix et al., 2018; Shahbaz et al., 2019; Tao et al., 2018).

Financial reporting and accounting are also fields in which big data analytics have been employed extensively. Big data analytics is a powerful tool for financial professionals to gain deeper insights into their business and activities. Additionally, these professionals rely on big data analytics to analyze financial data related to complex accounting issues and daily operations, which motivates them to increase their use of it (Austin et al., 2018; İdil & Akbulut, 2018). The widespread adoption of Big Data analytics across industries and regions places increased pressure on auditors to adopt advanced technologies to remain aligned with this development.

Big data analytics in external auditing is the process of analyzing and transforming big data to improve the efficiency and effectiveness of auditing and enhance decision-making (Dagilienė & Klovienė, 2019). Though auditors work with financial data, the volume and complexity of business require continuous analysis of non-financial data from both internal and external sources, demanding the use of big data analytics tools and changes in the audit processes (Dagilienė & Klovienė, 2019). Several factors, such as competition and regulatory requirements, can drive the adoption of data analytics technologies. These technologies refer to IT-related tools and systems adopted by companies, with big data analytics directly influencing compliance procedures, substantive testing, and reporting. Additionally, Dagilienė and Klovienė (2019) found that strategic orientation motivates audit firms to adopt big data analytics to explore emerging trends in both technology and organizational strategy. They also observed that the extent of big data analytics use often depends on the organization's size. Another factor identified by Dagilienė and Klovienė (2019) is organizational structure, which reflects the relationships among team members that support the implementation of big data analytics tools.

Eilifsen et al. (2020) identified limitations and concerns in regulatory bodies' evaluation of audit evidence collected through big data analytics. Furthermore, audit through big data analytics remains limited to supplementary evidence, despite a global strategy for its use and auditors' positive attitude towards it. Its broader adoption remains constrained until it is fully embraced by clients, supported by regulators, and proven to be both efficient and effective in generating audit evidence (Eilifsen et al., 2020).

In the context of big data analytics adoption, PU and PEU remain essential drivers of auditors' BI use of these tools. When auditors view big data analytics as beneficial and user-friendly, their likelihood of adopting them increases. This study applies TAM to highlight how these perceptions, shaped by individual characteristics, ultimately influence actual usage, with implications for audit quality and PS (Davis & Venkatesh, 1996; Sánchez-Mena et al., 2017). Based on this discussion and the related findings from the literature review, we propose the following hypothesis:

H2a: *PU has a positive effect on BI's adoption of big data analytics technological tools in the audit process.*

H2b: *PEU has a positive effect on BI's adoption of big data analytics technological tools in the audit process.*

H2c: *The PEU of big data analytics tools positively affects their PU.*

H2d: *The BI's adoption of big data analytics technological tools in the audit process positively affects their AU.*

PS in the Context of BDA and Auditing

Recent studies, including Puthukulam et al. (2021) and Handoko and Rosita (2022), have demonstrated that big data analytics significantly enhances fraud detection and improves audit efficiency. These works also emphasize that integrating big data analytics into the auditing process requires considerable investments in auditor training, technological infrastructure, and alignment with regulatory standards. Additionally, Rezaei and Ansary (2024) found that firms using big data analytics report higher client satisfaction due to more insightful audits; however, challenges persist in adapting these technologies to smaller datasets and resource-constrained environments.

The integration of big data analytics into auditing represents a paradigm shift from a traditional audit approach to a technology-based audit approach. This shift poses various challenges in maintaining the required level of PS. The importance of PS comes from its being the core element of audit quality (Hurtt et al., 2013; Nelson, 2009; Sayed Hussin et al., 2017; Septian & Astika, 2019).

Recent literature emphasizes that integrating technological tools such as big data analytics into audit workflows is a necessary response to the growing complexity of the business environment (Abu Al Rob et al., 2024; Salijeni et al., 2021). However, while automation can enhance efficiency, it may also inadvertently reduce auditors’ cognitive effort, thereby affecting their level of professional skepticism (Cristea, 2021). Abu Al Rob et al. (2025) highlight that skepticism can be shaped by multiple factors, including auditors’ attitudes toward data analytics, the nature of the data, and the organizational environment in which analytics are applied. Poor data quality or inappropriate mindsets can undermine auditors' assessment of anomalies, while social influences, such as management tone and IT governance, can also affect the application of skeptical judgment.

PS involves the critical assessment of audit evidence to identify potential misstatements, whether arising from fraud or error (International Auditing and Assurance Standards Board, 2008; Para.13-I; Nelson, 2009). PS should be maintained throughout the audit process, from the acceptance phase to the issuance of the auditor's report. Failure to maintain the appropriate level of PS may lead to audit failures and impact audit quality (Grenier, 2017; Septian & Astika, 2019).

Utilizing big data analytics in auditing enhances efficiency and analytical capabilities but also introduces challenges related to PS (Al-Hiyari et al., 2019; Cristea, 2021; Pedrosa et al., 2020). Auditors are now required to adapt to new technologies that can handle the vast volume of data, such as big data analytics, but this shift necessitates balancing the use of new tools with maintaining a high level of skepticism, especially in automated audit processes (Barr-Pulliam et al., 2020; Sayed Hussin et al., 2017).

Prior literature has extensively examined the development and implementation of big data analytics tools by global audit firms in response to technological advancements.

Pedrosa et al. (2020) discuss the use of innovative templates and computer-assisted audit techniques (CAATs) to enhance audit assurance, while Al-Hiyari et al. (2019) emphasize the need to upskill auditors to manage these innovations effectively. However, Barr-Pulliam et al. (2020) caution that, despite improved efficiencies, reliance on pre-coded outputs may weaken an auditor’s skeptical mindset. This divergence in findings highlights the need to evaluate further the impact of big data analytics tools on PS, particularly in emerging audit environments such as Palestine. A growing body of research has explored the interplay between big data analytics and PS, particularly in the context of fraud detection and audit quality. For instance, Janvrin et al. (2009) and Appelbaum et al. (2017) illustrate how big data analytics tools support fraud detection through anomaly analysis, while Barr-Pulliam et al. (2020) and Hurtt et al. (2013) warn that automation may reduce auditors’ critical engagement.

X. Li (2022) and Robinson et al. (2018) expand this discussion by addressing behavioral challenges, suggesting that while big data analytics offers powerful insights, it may alter the way skepticism is exercised. These contrasting perspectives underscore the importance of examining how actual big data analytics usage affects PS, precisely the focus of the present study.

In contrast, several studies examining the impact of big data analytics on PS have identified key challenges associated with its application. These include issues related to the quality of client-provided data used in analytics and the broader social context in which data analytics practices are implemented (Cristea, 2021; Handoko & Rosita, 2022; X. Li, 2022; Puthukulam et al., 2021; Sari & Musyarofah, 2020).

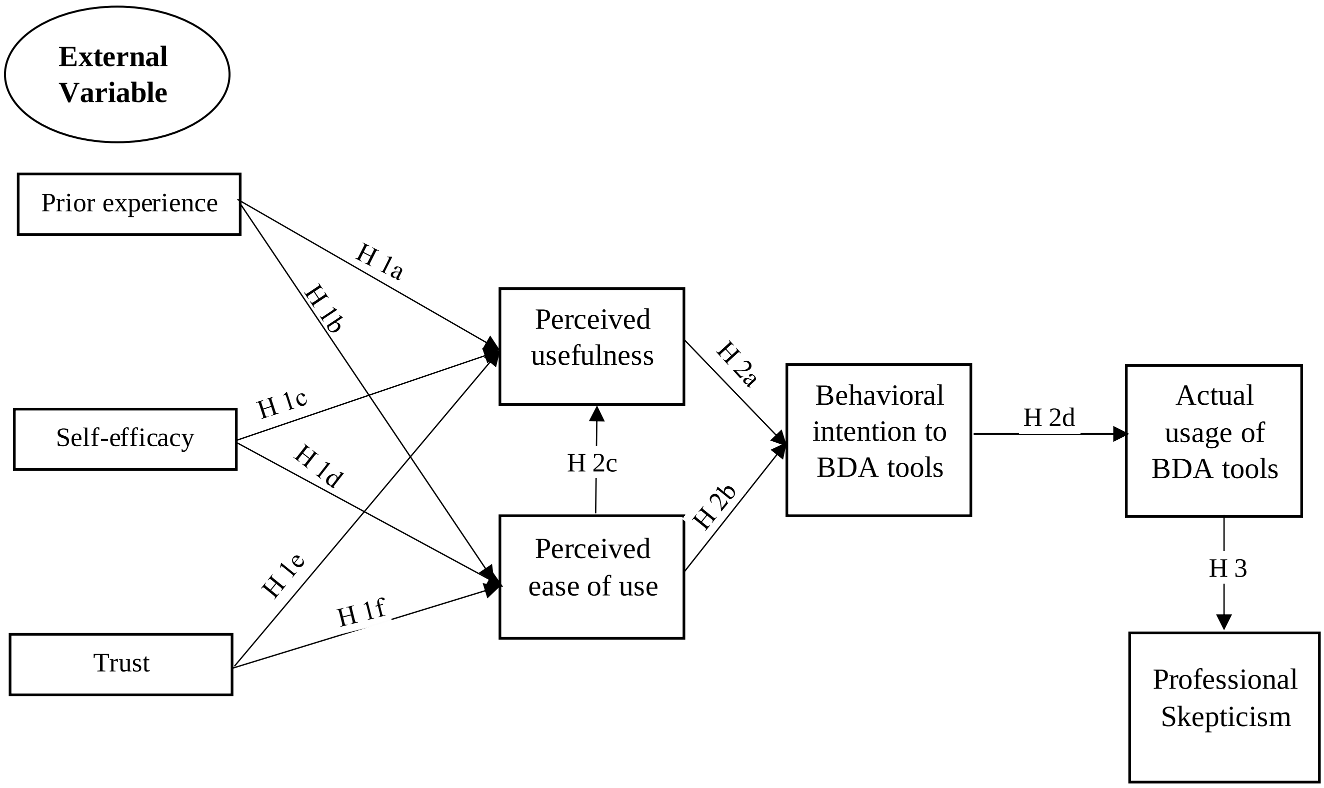
Multiple studies recognize the central role of data quality in determining how effectively auditors can exercise PS when using big data analytics tools. X. Li (2022) notes that flawed data may impair judgment, while Handoko and Rosita (2022) argue that high-quality analytics support proactive fraud detection. Similarly, Sari and Musyarofah (2020) find that while the use of big data analytics improves skepticism, its efficacy depends on the auditor's interpretation of anomalies. Collectively, these findings point to a nuanced relationship between the utility of big data analytics tools and the necessity of human oversight, an area this study explores by linking actual big data analytics usage with PS outcomes.

Incorporating Comfort theory is pertinent because it explains how auditors issue audit opinions based on their level of comfort. Achieving comfort with big data analytics output and PS is crucial for ensuring high-quality audits. The exploration of audit quality, PS, and comfort contributes to formulating Hypothesis 3 as follows:

H3: *The use of big data analytics technological tools by auditors positively affects their PS.*

The conceptual framework of this research is grounded in the literature on technology adoption and PS, employing the TAM, audit quality theory, and comfort theory as its theoretical base. Figure 1 graphically depicts the proposed causal relationships among the study's key factors and variables. Initially derived from Davis's TAM, the research model incorporates the assumption by Davis and Venkatesh (1996) that specific external variables influence PU and PEU. The literature review in this paper identifies various external variables that potentially impact PU and PEU. These variables are prior experience, self-efficacy, and trust. Figure 1 illustrates how auditors' experience, self-efficacy, and trust can shape their perceptions of the usefulness and ease of use of big data analytics technological tools.

Figure 1 *Conceptual Study Model.*



RESEARCH METHODOLOGY

This study employs a quantitative research methodology. The questionnaire was used to examine relationships among variables statistically (Khaldi, 2017; Reio, 2016), drawing on TAM, big data analytics, and PS literature. Participants consisted of auditors from the Big Four firms operating in Palestine. This approach enabled correlation analysis without influencing respondent behavior, although it does not imply causation

(Glasofer & Townsend, 2020). The selection of closely aligned independent and dependent variables is crucial for interrelationship analysis (Glasofer & Townsend, 2020).

Sampling Techniques

The research focuses on auditors from the Big Four firms in Palestine, given their strong emphasis on adopting big data analytics (H. L. Li & Lai, 2011; Saadé & Kira, 2007). Understanding their use of big data analytics is essential for capturing broader trends in global data transformation. The Big Four's commitment to big data analytics adoption provides a competitive edge, particularly for auditing large multinational companies with significant data volumes (Dagilienė & Klovienė, 2019).

Adopting a census approach, the study encompasses the entire relevant population (Gibbins et al., 2001; Levy & Lemeshow, 2013), justified for smaller populations (<100 units) to eliminate sampling errors and enhance data precision (Levy & Lemeshow, 2013; Vinzi et al., 2010). Logistically, this approach offers cost-effectiveness and efficiency benefits for smaller populations.

The sample includes auditors from Palestine's Big Four firms as identified by PACPA. From an initial total of 105 auditors, 11 were excluded for having less than 1 year of experience, yielding a final sample of 94 auditors and ensuring a focus on proficient participants (Bahtiar et al., 2017; Sayed Hussin et al., 2017). An 86% response rate was achieved through direct distribution of questionnaires to the remaining auditors. Of the 81 respondents, 73% were male and 27% female. The majority were aged 25–34 years (52%), followed by those under 25 (31%), 35–44 years (13%), and 45 years or older (4%). In terms of audit experience, 57% had less than 5 years, 23% had 5–9 years, 14% had 10–14 years, and 6% had 15 years or more. Most respondents held a bachelor's degree (81%) and were employed as associates (37%), seniors (31%), managers (27%), or partners (5%).

Measurement Development

The research questionnaire is structured into four main sections, comprising 58 statements designed to collect data relevant to the study objectives. It also includes items to capture demographic information. The first section, comprising 24 statements, examines external variables related to auditors' characteristics (prior experience, self-efficacy, and trust). The second section, comprising 14 statements, evaluates the impact of PEU and PU on auditors' intention to adopt big data analytics in auditing. The third section, consisting of 8 statements, measures the AU of big data analytics technological tools. The final section contains 12 statements that examine the effect of AU on PS. Except for the demographic section, all responses are gathered using a 7-point Likert scale, ranging from 1 ('strongly disagree') to 7 ('strongly agree'). This scale is selected for its efficiency in assessing subjective perceptions, attitudes, and opinions in survey research (Schrum et al., 2020).

To enhance clarity and support understanding of the measurement scales used in this study, Table 1 presents the operationalization of each theoretical construct included in the structural model. It lists all measurement items alongside their corresponding literature sources, providing a comprehensive overview of the instruments used for each variable.

Table 1 *Measurement Items and Their Literature Sources.*

Variable	Instrument item	No. of items	Source
Prior Experience	• My previous exposure to technology helps me complete tasks using big data analytics tools more efficiently. • My technological background improves the effectiveness of my work with big data analytics tools. • I can achieve desired outcomes from big data analytics tools due to my prior tech experience. • My earlier experience with technology makes it easier to use big data analytics tools during audits. • Overall, my technological experience enhances the usefulness of big data analytics tools. • I find learning to use big data analytics tools straightforward because of my prior tech exposure. • With my prior tech experience, I can easily control and operate big data analytics tools. • I find it simple to interact with big data analytics tools due to my technological background. • Big data analytics tools are more adaptable for me to use because of my previous tech experience. • I can quickly become proficient in using big data analytics tools thanks to my experience. • In general, prior experience with technology simplifies the use of big data analytics tools.	11	(Xia et al., 2018)
Self-efficacy	• I feel confident in completing my tasks using big data analytics tools. • I believe I am capable of applying big data analytics tools in my work. • I possess the skills needed to utilize big data analytics tools in auditing effectively. • I can successfully incorporate big data analytics tools into my audit engagements. • I can work with big data analytics tools without requiring assistance. • I can independently create procedures and tasks involving big data analytics tools.	6	(Zheng et al., 2018); (Sánchez-Prieto et al., 2016)
Trust	• I believe encouraging the use of big data analytics tools will yield positive outcomes. • I trust that sharing client data with big data analytics tools will produce favorable results.	7	(X. Li et al., 2008)

Variable	Instrument item	No. of items	Source
	• I expect beneficial outcomes from my use of big data analytics tools. • I feel confident relying on big data analytics tools in my work. • I am comfortable supporting the implementation of big data analytics tools in my firm. • I am open to providing client information to big data analytics systems. • I feel secure using big data analytics tools in audit engagements.		
Perceived usefulness (PU)	• Utilizing big data analytics tools helps me complete audit tasks more quickly • These tools enhance the quality of my job performance. • Big data analytics tools increase my work productivity. • They make me more effective in fulfilling my responsibilities. • These tools simplify my daily tasks. • I consider big data analytics tools beneficial for my auditing work.	6	(Davis, 1989)
Perceived ease of use (PEU)	• I believe operating big data analytics tools would be simple for me. • It would be easy for me to get these tools to perform desired tasks. • I expect the interface with big data analytics tools to be intuitive and clear. • I find these tools adaptable and user-friendly. • I would be able to learn how to use them effectively in a short period. • Overall, I think big data analytics tools are easy to work with.	6	(Davis, 1989)
Intention to use	• If big data analytics tools were available, I would use them. • Provided I had access, I would plan to apply them in my work.	2	(Davis & Venkatesh, 1996)
Actual use of BDA tools	• During the audit assignment, I applied big data analytics tools to assess fraud risks. • I used big data analytics tools for selecting audit samples. • I utilized these tools to identify journal entries for testing. • I applied big data analytics tools to evaluate and verify control effectiveness. • I used these tools for testing Information Produced by the Entity (IPE). • I employed big data analytics tools in substantive testing of balance sheet items. • I used them in the substantive testing of income statement components. • I relied on big data analytics tools to perform final analytical procedures.	8	(Janvrin et al., 2009)
Professional skepticism	• I questioned the information provided by the client during the assignment. • I often challenged the validity of what I observed or read.	12	Robinson et al. (2018)

Variable	Instrument item	No. of items	Source
	• I was hesitant to accept statements without supporting evidence. • I took time to deliberate before forming conclusions. • I preferred to wait for complete information before deciding. • I was reluctant to make quick decisions without thorough review. • I made sure to consider all relevant data before making judgments. • I postponed decisions until I could gather more facts. • I actively searched for all available information. • I believed reviewing supporting documents carefully improved decision-making. • I looked for extra evidence to ensure accurate conclusions. • I leveraged all resources available to gather comprehensive information.		

DATA ANALYSIS AND RESULTS

Questionnaire Analysis

To achieve the research objectives and test the proposed hypotheses, SmartPLS 4 software was employed. Currently, the partial least squares structural equation modeling (PLS-SEM) technique is widely used by researchers across various fields, including business, statistics, and marketing disciplines (Hair et al., 2010). Path analysis was conducted to examine the relationships between the dependent and independent variables.

Assessment of the Measurement Model

In this research, measurement models are used to estimate the relationships between each latent variable and its indicators. They focus on checking the reliability, internal consistency, and validity of the variables. Table 2 presents the results of the measurement models for reflective constructs, including specific characteristics of auditors, TAM factors (PU, PEU, and BI), the AU dimension, and the PS dimension.

To evaluate item loadings and assess convergent validity, the Average Variance Extracted (AVE) was calculated. At the same time, internal consistency was measured using Composite Reliability (CR) for the eight constructs in the model. A CR value above 0.708, within the acceptable range of 0.60 to 0.70, indicates adequate internal consistency (Hair et al., 2019). Similarly, item loadings should exceed 0.708 to confirm indicator reliability (Hair et al., 2010). Finally, an AVE value greater than 0.50 is required to establish convergent validity, indicating that the construct explains more than half of the variance in its indicators (Fornell & Larcker, 1981).

Table 2 shows that the item loadings ranged from 0.749 to 0.977. The CR for each construct was above 0.925, indicating that both CR and Cronbach's alpha demonstrate reliable consistency for the scales. Additionally, the AVE exceeded the 0.5 threshold for all constructs, confirming the model's convergent validity. Taken together, this evidence supports the measurement model's strong internal consistency and convergent validity. Furthermore, testing discriminant validity is essential to ensure that different measurement tools for various factors are distinct. Following Fornell and Larcker's (1981) criterion, this is confirmed when the square root of each construct's AVE is greater than its correlations with other constructs.

Table 2 *Reflective Constructs Measurement Properties.*

Reflective constructs	Construct items	Items loading	CR	AVE	Reference
Prior experience	EX1	0.823	0.964	0.710	Xia et al. (2018)
	EX2	0.818			
	EX3	0.817			
	EX4	0.822			
	EX5	0.835			
	EX6	0.785			
	EX7	0.877			
	EX8	0.907			
	EX9	0.797			
	EX10	0.901			
	EX11	0.875			
Self-Efficacy	SE1	0.834	0.925	0.674	Zheng et al. (2018) Sánchez-Prieto et al. (2016)
	SE2	0.883			
	SE3	0.778			
	SE4	0.810			
	SE5	0.808			
	SE6	0.810			
Trust	TR1	0.840	0.952	0.741	X. Li et al. (2008)
	TR2	0.880			
	TR3	0.859			
	TR4	0.880			
	TR5	0.895			
	TR6	0.761			
	TR7	0.901			
Perceived Usefulness	PU1	0.930	0.977	0.874	Davis (1989)
	PU2	0.964			
	PU3	0.949			
	PU4	0.947			
	PU5	0.899			
	PU6	0.920			
Perceived ease of use	PEU1	0.869	0.961	0.804	Davis (1989)
	PEU2	0.904			
	PEU3	0.943			
	PEU4	0.923			
	PEU5	0.899			
	PEU6	0.837			
Behavioral intention	BI1	0.976	0.976	0.954	Davis & Venkatesh (1996)
	BI2	0.977			

Reflective constructs	Construct items	Items loading	CR	AVE	Reference
Actual use	AU1	0.858	0.959	0.743	Janvrin et al. (2009)
	AU2	0.854			
	AU3	0.915			
	AU4	0.800			
	AU5	0.845			
	AU6	0.880			
	AU7	0.846			
	AU8	0.893			
Professional Skepticism	PS1	0.871	0.982	0.823	Robinson et al. (2018)
	PS2	0.952			
	PS3	0.749			
	PS4	0.912			
	PS5	0.929			
	PS6	0.895			
	PS7	0.921			
	PS8	0.883			
	PS9	0.933			
	PS10	0.931			
	PS11	0.938			
	PS12	0.956			

Table 3 presents the results of implementing the Fornell-Larcker criterion within the study model, confirming that this criterion is met.

Table 3 *The Measurement Model Discriminant Validity- Fornell-Larcker Criterion.*

Constructs	Actual Use	Behavioral Intention	Perceived Ease of Use	Perceived Usefulness	Prior Experience	Professional Skepticism	Self-Efficacy	Trust
Actual Use	**0.862**							
Behavioral Intention	0.474	**0.977**						
Perceived Ease of Use	0.613	0.632	**0.897**					
Perceived Usefulness	0.649	0.713	0.710	**0.935**				
Prior Experience	0.592	0.468	0.587	0.624	**0.843**			
Professional Skepticism	0.658	0.481	0.401	0.563	0.452	**0.907**		
Self-Efficacy	0.699	0.525	0.638	0.590	0.642	0.330	**0.821**	
Trust	0.649	0.659	0.670	0.712	0.656	0.621	0.644	**0.861**

To further assess discriminant validity, the heterotrait-monotrait ratio (HTMT) of correlations was calculated, following the approach recommended by Ab Hamid et al. (2017). An HTMT value below 0.90 is considered acceptable, indicating adequate discriminant validity, while values exceeding 0.90 suggest potential issues.

As shown in Table 4, all HTMT values in this study were below the 0.90 threshold, confirming that the constructs are empirically distinct and that the model demonstrates strong discriminant validity.

With the measurement model validated, the study proceeded to assess the structural model and test the proposed hypotheses.

Table 4 *Heterotrait-Monotrait Ratio (HTMT).*

Constructs	Actual Use	Behavioral Intention	Perceived Ease of Use	Perceived Usefulness	Prior Experience	Professional Skepticism	Self-Efficacy	Trust
Actual Use	-							
Behavioral Intention	0.493	-						
Perceived Ease of Use	0.646	0.661	-					
Perceived Usefulness	0.673	0.739	0.738	-				
Prior Experience	0.600	0.469	0.588	0.633	-			
Professional Skepticism	0.675	0.495	0.412	0.573	0.462	-		
Self-Efficacy	0.748	0.559	0.686	0.624	0.655	0.345	-	
Trust	0.681	0.692	0.694	0.739	0.666	0.646	0.684	-

Assessment of the Structural Model

The next step involved evaluating the structural model to assess its predictive relevance, the relationships between constructs, the strength and quality of the model, and to test the study’s hypotheses. This evaluation focused on four primary 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. Bootstrapping analysis was employed to facilitate this assessment. According to Hair et al. (2010), R^2 values of 0.75, 0.50, and 0.25 can be interpreted as high, moderate, and low, respectively, indicating that the R^2 values obtained in this study are high. The Q^2 values serve as indicators of the model's predictive relevance, with the obtained values confirming the model's efficacy in prediction.

Similarly, Q^2 values serve as indicators of a model's predictive relevance. In this study, all Q^2 values exceeded zero, confirming that the exogenous constructs have predictive relevance for the endogenous constructs, in line with the threshold suggested by Hair et al. (2010). Table 5 displays the cross-validated redundancy values for PEU, PU, BI, AU, and PS, which were recorded at 0.491, 0.454, 0.372, 0.277, and 0.152, respectively. Additionally, the effect size (f^2) was used to quantify the impact of each exogenous latent construct on its corresponding endogenous construct. This measure helps evaluate the extent to which each predictor contributes to explaining variance within the structural model.

Table 5 *R^2, Communality, and Redundancy.*

Construct	R^2 adj	Q^2	f^2 Perceived Ease of Use	f^2 Perceived Usefulness	f^2 Behavioral Intention	f^2 Actual Use	f^2 Professional Skepticism
Prior Experience	-	-	0.021	0.036	-	-	-
Self-Efficacy	-	-	0.096	0.001	-	-	-
Trust	-	-	0.153	0.125	-	-	-
Perceived Ease of Use	0.514	0.492	-	0.167	0.068	-	-
Perceived Usefulness	0.603	0.453	-	-	0.307	-	-
Behavioral Intention	0.527	0.371	-	-	-	0.289	-
Actual Use	0.214	0.277	-	-	-	-	0.762
Professional Skepticism	0.425	0.152	-	-	-	-	-

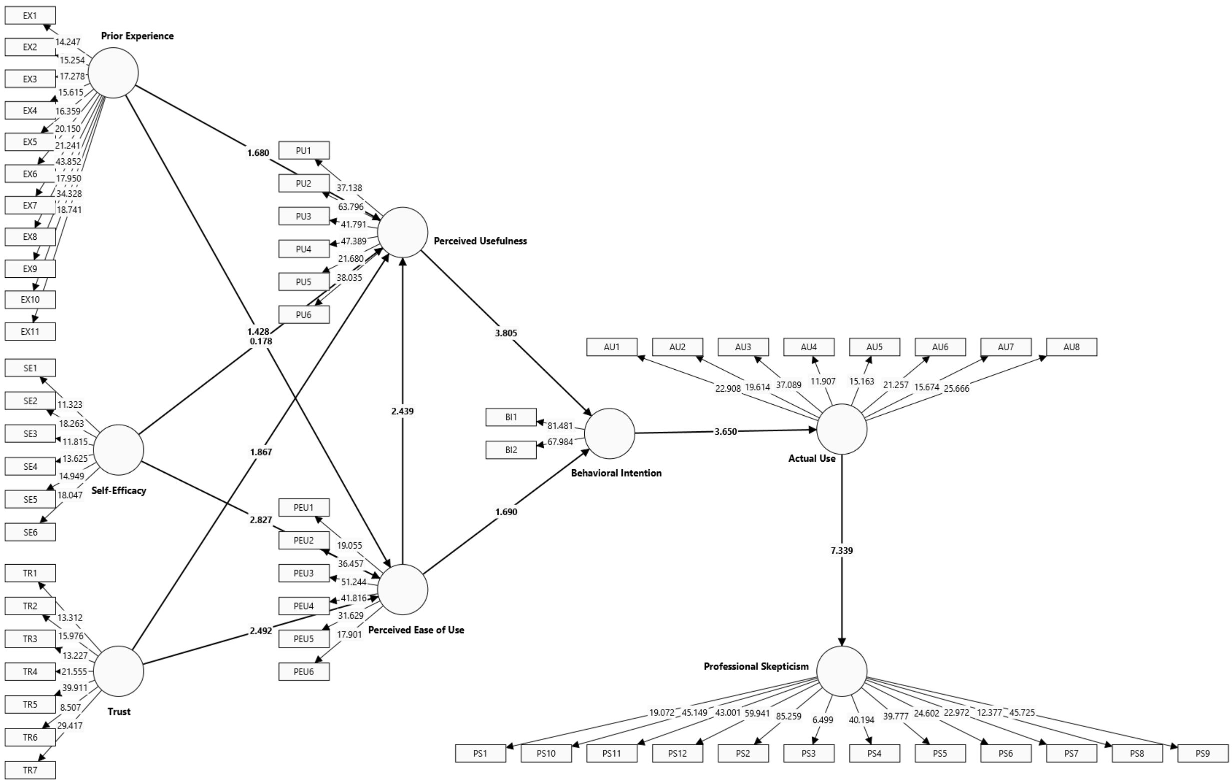
Following Cohen's (1988) guidelines, f^2 values of 0.02, 0.15, and 0.35 are classified as representing small, medium, and large effect sizes, respectively. As shown in Table 5, the f^2 values in this study ranged from a small effect, with a value of 0.001 for the impact of self-efficacy on PU, to a high effect, with a value of 0.762 for the influence of AU on PS. Finally, the Q^2 values for the endogenous constructs exceeded 0, thereby establishing the model's predictive relevance.

The analysis also employed path coefficients to evaluate the hypothesized relationships. Following Hair et al. (2019), the bootstrapping method was applied to generate statistical outputs including beta coefficients, standard errors, *t*-values, and *p*-values. The results are presented in Table 6.

Table 6 *Hypothesis Testing Results.*

Hypothesis	Beta coefficients	Standard deviation	T statistics	P values	Decision
H3: Actual Use -> Professional Skepticism	0.658	0.090	7.339	0.000	Supported
H2d: Behavioral Intention -> Actual Use	0.474	0.130	3.650	0.000	Supported
H2b: Perceived Ease of Use -> Behavioral Intention	0.251	0.149	1.690	0.046	Supported
H2c: Perceived Ease of Use -> Perceived Usefulness	0.367	0.150	2.439	0.007	Supported
H2a: Perceived Usefulness -> Behavioral Intention	0.534	0.140	3.805	0.000	Supported
H1b: Prior Experience -> Perceived Ease of Use	0.143	0.100	1.428	0.077	Rejected
H1a: Prior Experience -> Perceived Usefulness	0.168	0.100	1.680	0.047	Supported
H1d: Self-Efficacy -> Perceived Ease of Use	0.299	0.106	2.827	0.002	Supported
H1c: Self-Efficacy -> Perceived Usefulness	0.033	0.184	0.178	0.429	Rejected
H1f: Trust -> Perceived Ease of Use	0.384	0.154	2.492	0.006	Supported
H1e: Trust -> Perceived Usefulness	0.334	0.179	1.867	0.031	Supported

Figure 2. *Structural Model with Path Coefficients and t-Values.*



As shown in Table 6, the analysis of the hypotheses offers a detailed examination of the interrelationships among the key constructs, with each hypothesis numbered for clarity. The study found a significant positive effect of AU on PS (H3), as evidenced by a beta coefficient of 0.658, a T statistic of 7.339, and a p-value of 0.000. This strong result highlights the substantial influence of AU on enhancing PS. Similarly, the relationship between BI and AU (H2d) was strongly supported, with a beta coefficient of 0.474, a T statistic of 3.650, and a p-value of 0.000, indicating BI's predictive power over AU.

The analysis further revealed that PEU significantly influences both BI (H2b) and PU (H2c), with beta coefficients of 0.251 and 0.367, T statistics of 1.690 and 2.439, and p-values of 0.046 and 0.007, respectively. These results highlight the pivotal role of PEU in shaping both BI and PU. Additionally, the effect of PU on BI (H2a) was confirmed, supported by a beta coefficient of 0.534, a t statistic of 3.805, and a p-value of 0.000, demonstrating PU's significant impact on BI.

However, the relationship between Prior Experience and PEU (H1b) did not reach statistical significance, with a beta coefficient of 0.143, a T statistic of 1.428, and a p-value of 0.077, leading to its rejection. In contrast, Prior Experience had a significant effect on PU (H1a), with a beta coefficient of 0.168, a T statistic of 1.680, and a p-value of 0.047.

The impact of self-efficacy on PEU (H1d) and PU (H1c) produced mixed results. While H1d was supported with a beta coefficient of 0.299, a *t*-statistic of 2.827, and a p-value of 0.002, H1c was not supported, showing a beta coefficient of 0.033, a *t*-statistic of 0.178, and a p-value of 0.429, indicating no significant effect.

Trust was found to significantly influence both PEU (H1f) and PU (H1e), with beta coefficients of 0.384 and 0.334, *t*-statistics of 2.492 and 1.867, and p-values of 0.006 and 0.031, respectively. These findings underscore the essential role of Trust in enhancing both PEU and PU. Collectively, these results illustrate the complex interactions among constructs such as PS, BI, PEU, and Trust, offering valuable insights for future research and practical applications.

GENERAL DISCUSSION AND CONCLUSION

Discussion of Key Findings

The primary aim of this research was to address a gap in the literature concerning practicing auditors' adoption of big data analytics in the audit process and its influence on PS. The TAM model was extended by incorporating selected external variables, namely prior experience, self-efficacy, and trust, representing key auditor attributes that may influence attitudes toward big data analytics adoption. The detailed interpretation of hypothesis testing results is presented in the following discussion.

The findings revealed that prior experience has a significant positive effect on PU. This highlights the importance of auditors' technological background in enhancing their proficiency with big data analytics tools. Consequently, auditors' transition from traditional audit approaches to those incorporating big data analytics appears to be influenced by their accumulated skills and technological competence. These findings are consistent with those of Sayed Hussin et al. (2017) and Bahtiar et al. (2017), who emphasize the role of experience in shaping auditors' attitudes toward technology. Similarly, H. L. Li and Lai (2011) distinguish between experienced and inexperienced auditors in their acceptance and utilization of big data analytics tools. Collectively, these results support the conclusion that prior experience fosters a more favorable environment for big data analytics adoption.

In contrast, the findings revealed an unexpected outcome regarding the relationship between prior experience and PEU. Specifically, the hypothesis proposing a positive impact of prior experience on the PEU of big data analytics tools was not supported. This suggests that experience alone may not directly or consistently translate into a higher perception of ease of use. This surprising result invites a reassessment of the assumed link between experience and PEU, pointing to the possible influence of additional moderating factors. The findings diverge from previous studies, such as Salijeni et al. (2021), who reported that auditors with technological experience perceive new tools as easy to use. Similarly, H. L. Li and Lai (2011) highlighted that experienced auditors tend to be more confident in using technology, especially compared to their less experienced counterparts. These contrasting results suggest that, although previous literature supports a positive association between technological experience and PEU, in auditing practice, other concerns, particularly those related to audit quality, may take precedence. It appears that auditors may not prioritize tool simplicity alone; rather, their focus on accuracy, risk management, and professional standards may temper the perceived ease of adopting new technologies.

The study's findings on self-efficacy revealed a differentiated impact on PU and PEU. The hypothesis regarding the influence of self-efficacy on PEU was supported, aligning with Shahbaz et al. (2021), who found that self-efficacy significantly enhances users' perceptions of their ability to effectively use big data analytics. This finding reinforces the notion that auditors' confidence in their technological capabilities significantly influences their adoption of big data analytics tools. However, the hypothesis proposing a direct effect of self-efficacy on PU was not supported, indicating a more complex relationship between auditors' self-efficacy regarding their capabilities and their valuation of the technology's benefits. These findings highlight the need for deeper exploration of the factors that mediate the relationship between self-efficacy and PU.

The results of hypothesis testing related to the trust factor were accepted. These findings are consistent with prior research, which has generally shown that trust enhances users' beliefs in new technologies, leading them to view such tools as effective, reliable, and ultimately worth adopting (Cole et al., 2019; Sternberg et al., 2021). In the auditing profession, trust in big data analytics tools was found to significantly influence both PEU and PU. This suggests that when auditors trust the technology, they are more likely to view it as both easy to use and beneficial to their work. Such trust facilitates a smoother transition from traditional audit methods to digital auditing approaches, thereby improving efficiency without compromising audit quality.

Moreover, the hypothesis testing related to TAM factors corroborates the observations of Davis and Venkatesh (1996) regarding the influence of PU and PEU on technology acceptance and utilization. The positive effect of PU on auditors' BI to adopt big data analytics tools, as well as the AU of these tools, is indicative of a pragmatic approach to technology adoption, where the perceived benefits significantly drive auditors' intentions. This practical orientation is further underscored by the relationship between PEU and PU, suggesting that big data analytics tools are perceived as more useful when they are user-friendly and enhance job performance. These findings align with the reciprocal relationship described by Davis (1986) and Sánchez-Mena et al. (2017), in which ease of use and usefulness reinforce one another, thereby strengthening the intention to adopt big data analytics in the audit process.

The current research was designed to identify the most influential factor in the adoption of big data analytics. Analysis of the related hypotheses revealed that PU was a more significant predictor variable. This finding aligns with Lee et al. (2016), who noted the significant motivational role of PU, and with H. L. Li and Lai (2011), who suggested that experienced users prioritize usefulness over ease of use. While the significance of ease of use was notable, it had a smaller impact than PU as an independent variable. This does not diminish the value of the TAM; rather, it reflects the reality that the benefits derived from big data analytics tools outweigh the importance of their ease of use.

Moreover, the supported hypothesis regarding the positive impact of AU of big data analytics tools on PS aligns with the observations of Handoko and Rosita (2022), which emphasize the enhancement of auditors' analytical capabilities and skepticism. This finding reflects a transformative shift in auditing practices, in which technology not only augments traditional methodologies but also enriches the PS central to effective auditing. The influence of the use of big data analytics on PS also resonates with Comfort Theory, suggesting that comfort with technological outputs and PS is critical to achieving high-quality audits.

Additionally, the findings contribute to the broader discourse on auditing standards (such as the International Auditing and Assurance Standards Board, 2009) regarding the integration of technology into audit processes. The results indicate that the adoption of big data analytics tools does not diminish the need for PS; instead, it reshapes and potentially intensifies it, as auditors adapt their skeptical mindset to increasingly data-driven environments.

Conclusion

This study examined the effects of prior experience, self-efficacy, and trust on the adoption of big data analytics in auditing and how this adoption subsequently influences PS. A key contribution of this research lies in positioning PS as a critical behavioral outcome of big data analytics usage. While much of the existing literature emphasizes improvements in audit efficiency or fraud detection, our findings reveal that big data analytics tools also enhance auditors’ skeptical mindset, an essential component of audit quality. By linking technology adoption with professional behavior, this study introduces a behavioral lens to the traditional TAM framework, offering new insights into how digital tools reinforce rather than replace human judgment. These implications are particularly relevant for audit regulators, firms, and educators who are navigating the evolving role of auditors in data-driven environments.

IMPLICATION AND FUTURE STUDIES

Theoretical Contribution

This study contributes to the literature by extending the TAM in the context of external auditing. By integrating three auditor-specific external variables- prior experience, self-efficacy, and trust- into the TAM, the research highlights how these individual attributes influence perceptions of PU and PEU, ultimately affecting adoption behavior. Furthermore, by linking actual usage of big data analytics tools to PS, the study adds a behavioral dimension to TAM, offering a novel perspective on how technology adoption intersects with audit quality.

Practical Implications

The findings of this study suggest that audit firms should develop targeted strategies to support the adoption of big data analytics tools. These include providing structured training programs that enhance auditors' self-efficacy, fostering trust in analytics tools, and offering hands-on experience to build familiarity. Firms should also tailor support based on auditors' levels of prior experience to maximize adoption effectiveness. Importantly, the results indicate that the use of big data analytics tools can enhance, rather than diminish, professional skepticism. This underscores the need to position such tools not merely as efficiency enhancers, but as instruments that reinforce critical thinking and audit quality.

Limitations and Future Research Work

While this study contributes valuable insights into the adoption of big data analytics in auditing, it acknowledges several limitations. These include the selection of specific external variables, the focus on auditors from Big Four firms in Palestine, the demographic characteristics of the participants, the study's contextual limitation to Palestine, the methodology for exploring PS, and the representation of structure and judgment through big data analytics tools and PS.

Future studies are encouraged to explore additional external variables that may impact the PU and PEU of big data analytics tools. Expanding the research scope to include auditors from smaller, local firms and individual practices, as well as extending the geographical scope beyond Palestine, could enhance the generalizability and applicability of the findings. Employing different theoretical frameworks, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), could offer new perspectives on auditors' BI toward big data analytics adoption. Furthermore, investigating alternative proxies for structure and judgment in the context of big data analytics adoption could yield deeper insights into the dynamic interplay between technology and PS in auditing.

Conflict of Interest

None

Expressions of Gratitude

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