International Journal of Accounting and Economics Studies, 12 (4) (2025) 64-73

International Journal of Accounting and Economics Studies

Website: www.sciencepubco.com/index.php/IJAES
https://doi.org/10.14419/19qcsm78
Research paper

Exploring External Auditors' Intention to Adopt Big Data Analytics: The Moderating Role of Perceived Risk

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Received: July 12, 2025, Accepted: July 30, 2025, Published: August 3, 2025

Abstract

External auditing is a profession dependent on data-driven technologies to satisfy the increasing expectations of regulators and stakeholders, and it is knowledge-intensive. The use of Big Data Analytics (BDA) can significantly improve the quality, efficiency, and risk assessment of audits. This study examines the factors that influence the behavioural intentions of external auditors in Jordan using big data analytics (BDA). This study implemented a quantitative and exploratory methodology by collecting and analysing data from 177 external auditors. The research results indicate that perceived usefulness and ease of use emerged as significant predictors. Perceived risk significantly moderated the relationship between perceived usefulness and behavioural intention, but had no significant effect on the relationship between perceived ease of use and intention. This study makes a substantial contribution to theory by extending the TAM by incorporating perceived risk as a moderating variable in the context of BDA adoption. It provides novel insights from an emerging economy, highlighting the role of risk perception in shaping auditors' behaviour. This study provides essential knowledge for audit firms and BDA providers by identifying the factors that influence auditors' intentions to adopt data analytics tools.

Keywords: *Big Data Analytics; Perceived Risk; Behaviour Intention; Technology Acceptance Model.*

1. Introduction

The auditing profession is increasingly challenged by the need to process vast volumes of structured and unstructured data, including text, images, audio, and videos. As a result, auditors face mounting pressure to extract relevant financial and nonfinancial insights from diverse sources. The adoption of innovative technologies, particularly Big Data Analytics (BDA), has become essential for enhancing audit quality, efficiency, and effectiveness (Cao et al., 2015; Tavares et al., 2022). BDA enables auditors to move beyond sample-based testing towards a full-population analysis, thereby improving audit assurance (Huang et al., 2022). However, despite its advantages, the adoption of BDA in auditing remains limited (Abdelwahed et al., 2023; Aboud & Robinson, 2022), mainly because of the conservative nature of the profession, regulatory constraints, and limited IT competencies among traditional auditors (Al-Farah, 2015).

According to Zhu et al. (2021), BDA refers to the methods, technologies, and application software used to analyse massive and complex datasets to enhance organisational performance. KPMG (2012) defines BDA as "a process by which insights are extracted from operational, financial, and other forms of electronic data internal or external to the organisation." BDA has gained widespread popularity across various industries, from business and government to science and academia (Ajana, 2015; George et al., 2016; Sivarajah et al., 2017; Vassakis et al., 2018)—including accounting and auditing sectors (Liu & Vasarhelyi, 2014; Moffitt & Vasarhelyi, 2013).

In auditing, BDA supports auditors in linking transactional data, identifying risks, and conducting procedures, such as reasonableness testing, client evaluation, and confirmation. It enhances audit coverage, improves timing and resource allocation, and contributes to operational cost reduction (PCAOB, 2017; Ernst & Young, 2021). Byrnes et al. (2014) note that data analytics facilitates the testing of an entire population of transactions, up to 100%, as opposed to traditional sampling. This capability, combined with a more comprehensive understanding of clients' financial systems, enables auditors to assess estimates, going-concern judgments, and other key financial indicators better. Moreover, the use of specialised tools allows for the integration of non-financial data, yielding additional insights into business risk and operational efficiency (Earley, 2015). Despite these benefits, there is a lack of empirical research, especially in developing countries, on the behavioural factors influencing external auditors' intention to adopt BDA.

Jordan is considered a regional leader in digital innovation among Arab countries, ranking 59th globally in terms of digital readiness (Al-Shanableh et al., 2024). While previous studies in Jordan have examined BDA in sectors such as telecommunications, SMEs, and general accounting (Aburub et al., 2024; El-Dalahmeh, 2020), the adoption in the external auditing profession remains underexplored. This gap limits the understanding of the behavioural drivers behind BDA adoption among Jordanian external auditors. Although several studies have applied the Technology Acceptance Model (TAM) in the auditing context, the role of perceived risk (PR) as a moderating factor has not

been sufficiently investigated, particularly in emerging economies. Prior research has not adequately explored how PR influences the relationships among perceived usefulness (PU), perceived ease of use (PEOU), and auditors' behavioural intention (BI) to adopt BDA.
To address this gap, the current study integrates PR as a moderator within the TAM framework and investigates its influence on Jordanian external auditors' adoption of BDA. This study provides actionable insights for audit firms and policymakers seeking to enhance digital transformation efforts within the audit profession. The study employs a quantitative approach using data collected from 177 external auditors in Jordan via an online survey conducted between July and September 2024. The results reveal that the model explains 28.7% of the variance in auditors' behavioural intentions to adopt BDA. Both PU and PEOU significantly affected BI, whereas PR significantly moderated only the relationship between PU and BI. These findings suggest that PR functions not only as a barrier, but also as a contextual influence that shapes post-adoption behaviour. The findings of this investigation are anticipated to make substantial contributions to the auditing sector, particularly in the context of external auditors, by providing insight into the following:
First, this research contributes to technology adoption literature by extending the Technology Acceptance Model (TAM) through the inclusion of perceived risk as a moderating variable. It provides empirical evidence on how perceived usefulness and perceived ease of use influence external auditors' intention to adopt BDA. Second, the study highlights the significance of risk perception in the decision-making processes of external auditors, demonstrating that perceived risk can weaken the positive relationship between perceived usefulness and behavioural intention.
Third, the research emphasises the practical implications for audit firms and BDA solution providers, offering insights into how different cognitive and perceptual factors shape auditors' openness to adopting advanced analytical tools. Lastly, the findings are particularly relevant for sectors such as auditing, where the adoption of data-driven technologies is critical for improving audit quality, efficiency, and risk assessment—especially in developing economies like Jordan. The study addresses the following research questions:
RQ1: What is the relationship between perceived usefulness, perceived ease of use, and external auditors' intention to adopt Big Data Analytics?
RQ2: To what extent does perceived risk moderate the relationship between perceived usefulness/perceived ease of use and behavioural intention?
To address these questions, the study is structured into five main sections: Introduction, Literature Review, Research Methodology, Findings and Discussion, and Conclusion.

2. Literature review

2.1. Big data analytics

Big Data Analytics (BDA) refers to analytical techniques used to examine large and complex datasets to detect errors, fraud, and opportunities that serve as a basis for strategic business decisions (Deniswara et al., 2020). According to Ernst and Young (2014), big data describes a rapidly growing volume of data, whereas data analytics refers to the process of analysing such data to derive meaningful insights. PwC (2014) defines big data as structured, semi-structured, and unstructured information generated within firms, sold by commercial data brokers, or provided freely by governments. These datasets range from demographic and psychographic information to customer reviews, social media content, blogs, and data generated in real-time from mobile devices, sensors, and other technology-enabled tools.
Big Data is typically categorised into four data types: structured (e.g., relational databases), semi-structured (e.g., XML-tagged content), unstructured (e.g., text, video), and multi-structured data (Moffitt & Vasarhelyi, 2013). For instance, emails and videos combine structured data, such as sender, recipient, and timestamp, with unstructured content, such as a message body or video file. Most web-based content today is semi-structured. Key sources of big data include end-user devices (e.g., PCs, smartphones, RFID sensors, and GPS), as well as online platforms such as social networks, blogs, forums, and streaming applications.
BDA encompasses four main categories of analytics, progressing from fundamental historical insights to advanced predictive and prescriptive modelling:

1) Descriptive Analytics: According to the Institute of Singapore Chartered Accountants (ISCA), this form of analytics focuses on understanding past events by answering the question "what happened?" It employs conventional business intelligence tools such as pie charts, line graphs, and dashboards (ISCA, 2021). Descriptive analytics allows firms to analyse customer behaviour and business performance retrospectively (Osinubi, 2017).
2) Diagnostic Analytics: Diagnostic analytics builds upon descriptive analysis by investigating "why it happened?" It uses techniques, such as data discovery, drill-down analysis, and correlation analysis, to uncover the root causes of historical outcomes (Vassakis et al., 2018; ISCA, 2021). This enables organisations to learn from past mistakes and improve their decision-making.
3) Predictive Analytics: This approach uses techniques such as machine learning, regression analysis, forecasting, and predictive modelling to anticipate future events or behaviours. Predictive analytics answers the question, 'What is likely to happen?' It supports proactive planning in areas such as customer engagement, marketing, and risk mitigation (Vassakis et al., 2018; ISCA, 2021).
4) Prescriptive Analytics: Going a step further, prescriptive analytics guides on "what should be done?" by simulating the impacts of various strategic actions. It leverages advanced tools, such as neural networks, heuristics, graph analysis, and recommendation engines, to propose optimal decisions and resource allocations (Vassakis et al., 2018; ISCA, 2021). This type of analytics plays a critical role in enhancing organisational agility, speed, and efficiency in the decision-making processes.

2.2. Auditing and big data analytics

Big data methods, particularly those used in the audit process, are beneficial (Liburd et al., 2015). Yoon et al. (2015) examined the costs and benefits of using big data as proof in audits; they considered important topics such as privacy protection and information sharing issues, and discovered that relevant external big data could help auditors when they have limited access to a client's internal information and traditional audit evidence is missing. Eilifsen et al. (2020) find that external auditors are increasingly pressured to adopt BDA due to rapid technological advances and client expectations. Kim et al. (2020) report positive capital market reactions to firms adopting BDA, suggesting improved operational insight and risk prediction.
Salijeni et al. (2021) identified that BDA transforms audit practices in three ways: automating evidence collection, generating visual insights, and enhancing the interaction between auditors and specialists. Krieger et al. (2021) and Dagilienė and Klovienė (2019) highlight that BDA adoption is affected by both firm-level capabilities and institutional factors, such as regulatory expectations and client sophistication. Liew et al. (2022) showed that BDA effectiveness depends not only on audit firms' transformation efforts but also on client firms'

IT infrastructure. Salijeni et al. (2019) note that audit clients using ERP systems significantly impact auditors' approaches to BDA. Tang and Karim (2019) proposed incorporating BDA into fraud brainstorming sessions to enrich risk detection.

Perols et al. (2017) demonstrate the potential of BDA in fraud detection. Fay and Negangard (2017) and Aboud and Robinson (2022) further identified training, costs, and expertise as critical adoption barriers. Santis and D'Onza (2020) stressed that despite growing legitimacy within audit firms, external barriers, such as a lack of standards and supervisory scepticism, hinder full adoption. Eilifsen et al. (2020) also observed inconsistent use of advanced analytics across audit engagements, with higher adoption rates among clients using integrated ERP systems.

Several studies have explored the implications of employing data analytics in the process of gathering audit evidence. For instance, Wadesango et al. (2021) conducted a document analysis to synthesise previous research findings on the impact of big data and data analytics on audit-evidence collection. Their review concluded that the adoption of data analytics generally has a positive effect on the audit evidence gathering process.

However, this view has not been universally supported. Drawing on cognitive load theory, Holt and Loraas (2021) suggest that evidence generated through big data sources, such as visualisations or emails, can increase perceptions of ambiguity, thereby affecting auditors' judgment and decision-making. Similarly, Huang et al. (2022) contended that the evolution of information technologies and business models, alongside global population growth, has eroded the reliability of traditional audit evidence obtained through sampling techniques.

Recent advances in audit data analytics and machine learning have offered the prospect of comprehensive population testing as an alternative to traditional sampling. This approach enables the analysis of the entire data population, which can significantly enhance the quality of audit evidence. However, their implementation has several challenges. From a financial perspective, the initial investment required for full-population testing is substantial, and auditors must overcome a steep learning curve to utilise such tools effectively. From the client's perspective, the provision of large datasets necessitates rigorous data cleansing and preparation, which places an additional burden on clients. Furthermore, from a regulatory standpoint, auditing standards must evolve to provide more explicit guidance on acceptable procedures for auditing data analytics.

In the context of the Middle East, Al-Rashidi et al. (2022) investigated the influence of BDA on external audit practices. The study surveyed auditors from various countries, including Kuwait, Saudi Arabia, the United Arab Emirates, Jordan, Bahrain, Egypt, Lebanon, and Iraq. Using an online questionnaire, the authors find that BDA affects all phases of the audit process. Specifically, it enhances auditors' understanding of clients' internal and external environments, thereby informing their decision to accept audit engagements. Furthermore, BDA supports the execution of analytical procedures, assessment of client risks, and evaluation of internal control systems by providing auditors with critical insights. The authors emphasise the necessity for auditors to develop competencies in BDA, as it adds substantial value to both audit quality and client services.

Similarly, Al-Ateeq et al. (2022) examined the influence of two core constructs from the Technology Acceptance Model (TAM)—perceived usefulness and perceived ease of use—on the adoption of BDA by external auditors in Jordan. Based on data collected via questionnaires from audit firms operating in Jordan, the findings demonstrate that both perceived usefulness and ease of use positively affect perceptions of audit quality, even in the absence of widespread practical implementation. Interestingly, the study found that the use of BDA strengthens the relationship between perceived usefulness and audit quality but does not significantly affect the relationship between perceived ease of use and audit quality.

These studies highlight the relevance of the TAM in understanding technology adoption within the auditing profession in the Middle East. However, a notable gap persists in the theoretical grounding of research on auditor adoption of BDA. Although the TAM provides a valuable lens, further studies are needed to explore the broader implications of BDA adoption. As noted by Austin et al. (2021), several critical aspects remain underexplored, such as the potential impact of BDA on labour market demands for traditional auditing skills or on public perceptions of the accounting profession as data-driven technologies become more prevalent in financial reporting. These findings underscore the relevance of TAM in explaining auditors' behavioural responses to BDA adoption and suggest that technological ease and utility remain key enablers. However, the current literature on BDA adoption in auditing—particularly in the Middle East—continues to lack robust theoretical integration. Despite the growing relevance of BDA in audit innovation, many dimensions of its adoption journey remain underexplored. This study addresses that gap by investigating the interplay between core TAM constructs and perceived risk within a theoretically grounded model specific to external auditors in Jordan.

2.3. Perceived risk (PR)

Perceived risk (PR) refers to an individual's subjective judgment regarding the uncertainty and potential negative consequences of adopting a new technology (Im et al., 2007). While Big Data Analytics (BDA) presents clear advantages in improving audit effectiveness and quality, particularly given the volume and variety of data available (Wang & Cuthbertson, 2015), concerns surrounding technological risks persist. These include the risk of material misstatements, data privacy issues, information security challenges, and the complexity of data management systems (Thottoli & Ahmed, 2022; Hashim et al., 2021; Cao et al., 2015).

Recent literature presents mixed findings regarding the role of perceived risk (PR) in technology adoption. For instance, Mutahar et al. (2018) found that PR had a significant adverse effect on perceived ease of use (PEOU), suggesting that the greater the perceived risk, the more users struggle to perceive a system as easy to use. In a later study, Mutahar et al. (2022) further examined PR as a moderating factor. They concluded that while PR significantly moderated the relationship between perceived usefulness (PU) and intention, it did not moderate the PEOU-intention link in the context of mobile banking. Similarly, Wang et al. (2023) reported that PR had a significant and negative effect on students' behavioural intentions to adopt digital platforms, aligning with earlier research such as Qi et al. (2009), where risk perceptions affected users' cognitive evaluation and behavioural intentions. These findings reflect the contextual sensitivity of PR's influence, which may vary depending on the domain, user group, or the type of technology being assessed. Therefore, the current study contributes to this ongoing debate by exploring the role of PR in the relatively underexplored setting of external auditing in Jordan, particularly regarding the adoption of BDA.

2.4. Conceptual model and hypotheses development

2.4.1. TAM constructs and behavioural intention

Researchers in the field of information and communication technologies (ICTs) advise comprehending well-known theories of technology acceptance to create a conceptual model related to accepting any developing technology in various sectors (Rasha& Alaa, 2023).

This study adopts the conceptual model developed by Davis (1989) to explain how individuals accept and use technology. The model identifies two primary determinants of technology adoption: Perceived Usefulness (PU) and the degree to which an individual believes that using a particular system would enhance their job performance. Perceived Ease of Use (PEOU): The degree to which an individual believes that using the system is free of effort.
TAM posits that an individual's attitude towards using a system influences their behavioural intention (BI), which in turn determines actual system usage. Moreover, PEOU influences PU as individuals often perceive easier-to-use systems as more useful. Later updates to the model, such as TAM2 (Venkatesh & Davis, 2000), added more factors, such as social influences and thought processes, to improve the model's ability to explain system usage. According to Legris et al. (2003), the TAM and its extension, TAM2, collectively explain approximately 40% of the variance in system usage behaviour.
Unlike other behavioural models, such as the theory of reasoned action (TRA) and the theory of planned behaviour (TPB), TAM explicitly focuses on PU and PEOU as core predictors of technology adoption (Bagozzi, 2007). Owing to its simplicity and predictive validity, the TAM has become one of the most widely utilised frameworks in technology adoption research across diverse domains (Lou & Li, 2017).
In the context of auditing, TAM offers a valuable theoretical foundation for understanding external auditors' intentions to adopt BDA by examining their perceptions, attitudes, and planned behaviour towards this emerging technology (Jen et al., 2009).
Based on the TAM framework, the following hypotheses are proposed:
H1: Perceived usefulness has a positive effect on behavioural intention to use BDA.
H2: Perceived ease of use has a positive effect on the behavioural intention to use BDA.
H3: Perceived ease of use has a positive effect on perceived usefulness of BDA.

2.4.2. Perceived risk (PR) as a moderator

Perceived risk (PR) refers to an individual's subjective judgment regarding the uncertainty and potential negative consequences of adopting a new technology (Im et al., 2007). While BDA presents clear advantages in improving audit effectiveness and quality, particularly given the volume and variety of data available (Wang & Cuthbertson, 2015), concerns surrounding technological risks persist. These include the risk of material misstatements, data privacy issues, information security challenges, and the complexity of data management systems (Thottoli & Ahmed, 2022; Hashim et al., 2021; Cao et al., 2015).
Risks can significantly influence an auditor's willingness to adopt BDA tools. Yoon et al. (2015) highlight that concerns over privacy protection and information sharing pose barriers to leveraging big data in audit practices. Similarly, Afsay et al. (2023) and Mutahar et al. (2018, 2022) found that perceived risk moderates the relationships between perceived usefulness (PU), perceived ease of use (PEOU), and behavioural intention (BI) in various technology adoption contexts. Higher levels of perceived risk are often associated with lower intention to adopt, as users fear potential losses of information, time, resources, and operational control (Chen, 2013; Salam, 2019).
Incorporating PR into the Technology Acceptance Model (TAM) provides a more comprehensive understanding of external auditors' adoption behaviour. As a moderating factor, PR may weaken the influence of PU and PEOU on BI, particularly in contexts where data privacy, security, and audit assurance are paramount. Based on this, the following hypothesis is proposed:
H4: Perceived Risk hurts the (BI) to use BDA.
H5: Perceived Risk negatively moderates the relationship between Perceived Usefulness (PU) and Behavioural Intention (BI) to using BDA.
H6: Perceived Risk negatively moderates the relationship between Perceived Ease of Use (PEOU) and Behavioural Intention (BI) to use BDA.

3. Methodology

3.1. Study design and data collection

This study examines the factors influencing external auditors' behavioural intentions to adopt Big Data Analytics (BDA) in the auditing profession, with a focus on the role of perceived risk in the Jordanian context. The research framework includes one main endogenous construct: the behavioural intention to adopt BDA to enhance audit effectiveness. The conceptual model consists of four key constructs: perceived usefulness (PU), perceived ease of use (PEOU), perceived risk (PR), and behavioural intention (BI). The model proposes a set of relationships among these constructs, including the direct effects of PU, PEOU, and PR on BI and the direct effect of PEOU on PU. Additionally, the model posits that perceived risk moderates the relationship between PU and BI as well as between PEOU and BI. By integrating perceived risk into the traditional Technology Acceptance Model, this study seeks to provide a deeper understanding of the factors shaping auditors' adoption of BDA in a developing-country setting.
This study targeted a population of 312 external auditors who were approached following a series of communication and engagement efforts conducted via email. Consequently, 226 valid responses were obtained, representing an acceptable response rate of approximately 72.4%. Data were collected using an electronic self-administered questionnaire distributed through Google Forms, and the data collection period extended over three months, from July 2024 to December 2024. Of the total collected responses, 47 participants who had already adopted BDA and two incomplete responses were excluded during data cleaning, resulting in a final sample size of 177 valid responses.
Table 1 presents the demographic profiles of the respondents, with most of the responses consisting of partner auditors (55.9%), defined as field auditors who perform technology-enabled auditing activities. A significant proportion of the respondents were employed by small audit companies (63.8%) and had 15 or more years of experience (51%), demonstrating their requisite expertise to address the questionnaire topics.

Table 1: Respondents' Demographics

Categories	Details	Frequency	Percent %
Age	20-29	12	6.8
	30-39	42	23.7
	40-49	52	29.4
	More than 50 years	71	40.1
	Total	177	100
Size of firm	Smal	113	63.8
	Medium	52	29.4

	Big	12	6.8
	Total	177	100
	Bachelor of Accounting	142	80.2
	Bachelor's in another field	5	2.8
	Master's in accounting	20	11.3
Highest Education Qualifications	Master's in another field	5	2.8
	Ph.D in Accounting	5	2.8
	Other (Please specify)	0	0
	Total	177	100
	Staff	22	12.4
	Senior	28	15.8
Job Position	Manager	28	15.8
	Partner	99	55.9
		177	100
	1-5years	28	14.3
	6-10	32	16.3
Work experience in Auditing	11-15	36	18.4
	More than 15	100	51.0
		177	100
	Jordan Certified Public Accountant (JCPA)	173	100
	Certified Public Accountant (CPA)	30	15.3
Professional qualification	Certified Management Accountant (CMA)	15	7.14
	Certified Financial Examiner (CFE)	3	1.5
	Certified Information System Auditor (CISA)	1	3
	Other	8	4

Source(s): Table created by authors.

3.2. The study variables and questionnaire

The measurement scale items employed in this study differed from those used in previous studies, which were valid and reliable. The constructs and observed variables are listed in Table 2. Items associated with using BDA were adapted from Venkatesh (2000), Lin (2007), and Wu et al. (2007). PR was incorporated from (Jamieson & Lui, 2003; Al-Faqih, 2017), and items related to PU and PEOU were sourced from Davis (1989). A structured questionnaire was developed to collect primary data from respondents. The survey questionnaire consisted of three sections: demographic, BI, and questions regarding PU and PEOU. The survey items asked respondents to rate their level of agreement or disagreement on a five-point Likert scale, which ranged from strongly disagree to strongly agree.

3.3. Data analysis

The study used two steps of structural equation modelling (SEM) to determine whether the proposed conceptual model was correct. First, confirmatory factor analysis was used to check the content and convergent and discriminant validity of the measurement model to ensure consistency and validity. In the second step, we conducted an SEM analysis to check the validity of the study's structural model's six routes (hypotheses) using SmartPLS v.4, depending on the level of significance. R value was used to determine the strength of the measurement and structural models in this investigation. Figure 1 presents the theoretical framework of the study, incorporating the core constructs of the Technology Acceptance Model (TAM): Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as predictors of Behavioural Intention (BI) to adopt Big Data Analytics (BDA). Perceived Risk (PR) is introduced as a moderating variable influencing the relationship between PU and BI. This framework serves as the conceptual foundation for the study's hypotheses and empirical analysis.

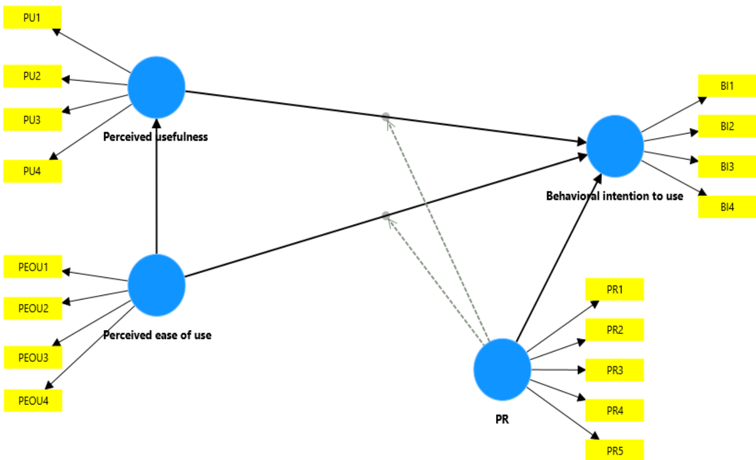

Fig. 1: Theoretical Framework.

4. Results

4.1. Confirmatory factor analysis

Convergent and internal consistency reliability were the two primary evaluation criteria. The analysis of indicator outer loadings, Cronbach's alpha (CA), composite reliability (CR), and average variance extracted (AVE) of the components of the study model were all included in the evaluation. Behavioural intention (BI), perceived usefulness (PU), perceived ease of use (PEOU), and perceived risk (PR) are among the constituents.

The first assessment of the outer loadings of all reflective constructs revealed that all loadings, except for items BI3 and BI4, exceeded a threshold value of 0.708 (Hair et al., 2014). The results provided sufficient levels of indication reliability. Hair et al. (2014) recommend that items with outer loadings below 0.708 may be retained if their loadings range from 0.4 to 0.7, contingent upon the AVE value meeting or exceeding the criterion of 0.5. As a result, two items-BI3 and BI4-with respective outer loadings of 0.695 and 0.694, were retained. The loadings of the various components range from 0.4 to 0.7, and the AVE values substantially surpass 0.5.

Table 2: Results of the Measurement Model

Variable	Item	Loading	Cronbach's Alpha	CR	AVE	Convergent Validity (AVE > 0.5)
PU	PU1	0.875	0.907	0.935	0.783	Yes
	PU2	0.888				
	PU3	0.922				
	PU4	0.854				
PEOU	PEOU1	0.782	0.796	0.866	0.618	Yes
	PEOU2	0.715				
	PEOU3	0.810				
	PEOU4	0.830				
PR	PR1	0.832	0.888	0.916	0.687	Yes
	PR2	0.861				
	PR3	0.888				
	PR4	0.733				
	PR5	0.821				
BI	BI1	0.840	0.780	0.858	0.605	Yes
	BI2	0.864				
	BI3	0.696				
	BI4	0.695				

Source(s): Table created by authors.

Discriminant validity was evaluated using the heterotrait-monotrait (HTMT) ratio of correlations. The outcomes of this evaluation are outlined in the subsequent section, including the HTMT criteria for discriminant validity. The HTMT values for all latent variables shown in Table 3 are below the HTMT.85 threshold of 0.85 (Kline, 2011). Thus, the results of all the evaluation criteria indicated that discriminant validity was established (Hair et al., 2014).

Table 3: Discriminant Validity Based on HTMT Criteria

	BI	PR	PEOU
BI			
PR	0.255		
PEOU	0.508	0.172	
PU	0.488	0.105	0.541

Source(s): Table created by authors.

4.2. PLS-SEM

A bootstrapping approach with 5000 resamples was used to assess the route coefficients. The No Sign Changes option and the Bias-Corrected and Accelerated (BCa) bootstrap technique. Standard Partial Least Squares Structural Equation Modelling (PLS-SEM) parameters were employed, and missing data were suitably addressed.

The (R^2) values for the dimensions were as follows: perceived usefulness (22%) and behavioural intention (28.9%). In addition to the R2 values, Q2 values were acquired to evaluate the prediction accuracy of the model. The Q2 values for the constructs were 0.162 for perceived usefulness and 0.153 for behavioural intention, indicating the model's satisfactory predictive relevance. The third phase evaluated the importance of the primary impacts. The R2 values, computed using SmartPLS 4 software, are illustrated in Fig. 2. Additionally, the path coefficients of the structural model were determined using bootstrap analysis, involving a resampling of 5000 to evaluate statistical significance. Table 4 shows the route coefficients and their corresponding significance levels. The t-values and p-values indicated that the four suggested hypotheses (H1, H2, H3, and H5) were significant, as anticipated. In contrast, H4 and H6 were insignificant.

Table 4: Hypothesis Testing

H	Relationship	Path coefficient	T-Value	P-Values	Decision
H1	PU->BI	0.306	3.766	0.000	Support
H2	PEOU->BI	0.248	3.048	0.002	Support
H3	PEOU-> PU	0.469	2.598	0.000	Support
H4	PR -> BI	-0.127	1.486	0.062	Not Support
H5	PR * PU -> BI	-0.159	1.662	0.046	Support
H6	PR * PEOU-> BI	0.019	0.425	0.414	Not Support

Source(s): Table created by authors.

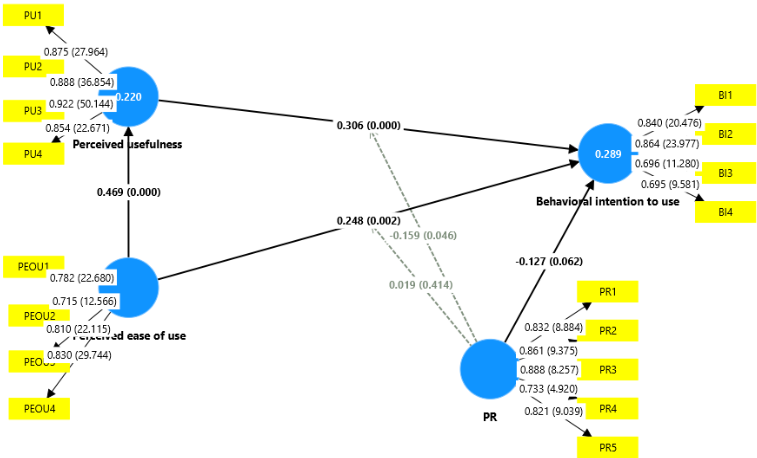

Fig. 2: Research Model and Path Coefficients.

Figure 2 displays the structural research model along with the path coefficients derived from the Partial Least Squares Structural Equation Modelling (PLS-SEM) analysis. The model confirms that Perceived Ease of Use (PEOU) significantly influences Perceived Usefulness (PU), which in turn positively affects Behavioural Intention (BI) to adopt Big Data Analytics (BDA). Additionally, PEOU has a direct, significant effect on BI. The moderating role of Perceived Risk (PR) on the PU–BI relationship is also illustrated, showing a statistically significant interaction effect. The model includes outer loadings, path coefficients, and t-values, all of which support the reliability and significance of the proposed relationships.

5. Discussion and implications

This study investigated the basic elements affecting Jordanian external auditors' behavioural intentions towards the use of BDA. Data from 177 survey respondents were used to test a model based on Davis's (1989) approach. There was considerable support for the two hypotheses at 99% and 95% confidence levels.

According to the first hypothesis, which examines the relationship between perceived usefulness (PU) and perceived ease of use (PEOU), PU is positively impacted by PEOU since individuals are more likely to consider systems that are simple to use to be advantageous (Davis, 1989). The results of this investigation are consistent with earlier empirical data, such as those of Ardelia et al. (2025) and Al-Ateeq et al. (2022), which show a noteworthy beneficial impact of PEOU on PU. External auditors are more inclined to use Big Data Analytics (BDA) technologies when they believe that using them requires less work. Their perception of BDA's value is strengthened by its greater usability, which eventually boosts its output and performance. These findings align with the underlying assumptions (Davis, 1989).

Hypotheses 2 and 3 investigate the direct effects of perceived usefulness (PU) and perceived ease of use (PEOU) on external auditors' behavioural intention (BI) to accept Big Data Analytics (BDA). The results of this study show that auditors' behavioural intentions to use BDA tools are considerably and positively influenced by both PU and PEOU. These findings are in line with Davis's (1989) original TAM paradigm, which highlights the importance of perceived usefulness and ease of use in influencing consumers' intentions to adopt technology. Additionally, the results are consistent with previous research by Hamadeh et al. (2025), who showed that auditors' propensity to use sophisticated technology in professional auditing is significantly influenced by their view of its advantages and usefulness. Therefore, external auditors are more likely to include BDA in their audit procedures when they are considered easy to use, which improves audit accuracy, efficiency, and decision-making.

Unexpected conclusions emerge regarding the influence of perceived risk (PR) on external auditors' intention to adopt Big Data Analytics (BDA). Thus, Hypothesis 4 was rejected, indicating that PR did not exert a significant direct effect on behavioural intention (BI). This finding is inconsistent with that of Wang et al. (2023), who found that perceived risk has a significant and negative effect on behavioural intention. This suggests that external auditors' intentions to adopt BDA are not directly inhibited by perceived risk alone.

Contrary to expectations and previous studies, Hypothesis H4 was not supported in this study, indicating that perceived risk (PR) did not have a statistically significant direct effect on behavioural intention (BI) to adopt Big Data Analytics (BDA). This finding contrasts with the work of Wang et al. (2023), who reported a significant and negative impact of perceived risk on students' overall intention to adopt new technologies. Wang et al. (2023) demonstrated that perceived risk significantly reduces individuals' willingness to engage in certain behaviours, particularly when they perceive high levels of uncertainty and potential loss.

However, the inconsistency in findings may be attributed to contextual and demographic differences. In the auditing profession, especially within the Jordanian context, auditors may already be accustomed to working with digital tools and may not view BDA adoption as highly risky. Professional norms, regulatory expectations, and increasing exposure to technological transformation may have diminished the perceived threat of such innovation. Moreover, auditors might perceive the benefits of BDA to outweigh any potential risks, especially when firm-level strategies or client demands support adoption. Therefore, while perceived risk remains theoretically important, its direct influence on BI may be context-dependent and possibly less relevant in environments where technological adoption is increasingly normalised.

In contrast, Hypothesis 5 was supported, revealing a significant negative moderating effect of PR on the relationship between perceived usefulness (PU) and BI ($\beta = -0.158$, $t = 1.662$, $p = 0.043$). This is consistent with Mutahar et al. (2022), who indicate that PR makes potential users believe that something is less valuable. These findings contradict the results of Zaky and Widuri (2025), who found that PR did not influence PU. The present study suggests that, as perceived risk increases, the positive influence of PU on BI weakens. In other words, when risk perceptions are high, external auditors may be less influenced by the perceived benefits of BDA when forming their intention to adopt BDA.

Hypothesis H6 was not supported, indicating that perceived risk (PR) did not significantly moderate the relationship between perceived ease of use (PEOU) and behavioural intention (BI) to adopt Big Data Analytics (BDA). This finding aligns with the results of Mutahar et al. (2022), who found that perceived risk did not alter the relationship between PEOU and intention. However, it contradicts the findings of Zaky and Widuri (2025), who reported that perceived risk negatively influenced PEOU, thereby indirectly affecting intention.

The lack of a moderating effect in the present study suggests that auditors' perceptions of ease of use are relatively stable and not strongly influenced by risk considerations. In other words, if BDA tools are perceived as easy to use, this perception remains consistent regardless of whether the auditor views the technology as risky. This could reflect a level of digital maturity among external auditors, where usability assessments are based more on interface design and functionality than on broader concerns about uncertainty or loss. It also reinforces the idea that, in this context, ease of use is an intrinsic system attribute rather than one shaped by risk-related attitudes.

Overall, the findings highlight the asymmetric moderating role of perceived risk, which impacts the PU–BI relationship, but not the PEOU–BI path. This underscores the notion that concerns related to data privacy, security, and technological uncertainty may dampen the perceived benefits of BDA without affecting the perceptions of ease of use. Therefore, mitigating perceived risks is essential to enhance external auditors' confidence and foster the broader adoption of BDA in the auditing profession.

In the context of Jordanian external auditors, this study is one of the first investigations into intention-based factors that impact the adoption of Big Data Analytics (BDA). By incorporating perceived risk (PR) into the Technology Acceptance Model (TAM), this study adds to the body of knowledge on the adoption of BDA in the accounting and auditing fields. It provides fresh perspectives on how risk perceptions influence auditors' behavioural intentions in developing nations. The final model shows interesting results that both support and contradict earlier findings. According to the Technology Acceptance Model (TAM), the findings corroborate previous research by Ardelia et al. (2025) and Al-Ateeq et al. (2022) that found strong positive correlations between Behavioural Intention (BI), Perceived Usefulness (PU), and Perceived Ease of Use (PEOU).

Finally, the study discovered that perceived risk (PR) had no significant direct effect on behavioural intention (BI), implying that auditors' concerns about risk alone may not inhibit their intention to use big data analytics. However, PR was found to have a significant negative moderating effect on the relationship between perceived usefulness (PU) and BI, indicating that, when perceived risk is high, the positive impact of perceived usefulness on adoption intention is weakened. The results of this study have several practical implications for audit professionals and politicians in Jordan and other developing countries.

The study provides practical implications for audit firms by highlighting the need to reduce perceived risks associated with Big Data Analytics (BDA) adoption. This includes implementing comprehensive training programmes to enhance auditors' technical competencies, as well as investing in secure data infrastructures to mitigate concerns around confidentiality and integrity. Additionally, BDA solution providers are encouraged to improve the usability and accessibility of their tools, aligning them more closely with auditors' workflows and cognitive expectations. The focus on perceived risk as a barrier to BDA adoption is especially pertinent within Jordan's auditing context, where concerns about data security, regulatory uncertainty, and technological readiness remain prevalent. While these insights are valuable, the study's policy implications could be further strengthened by recommending clear regulatory frameworks to support the standardised integration of BDA in audit processes. For instance, local authorities and professional bodies might introduce guidelines or certification schemes to ensure ethical and secure use of analytics tools.

Moreover, government-led incentives—such as grants, tax benefits, or subsidised training—for audit firms adopting advanced analytics could accelerate the digital transformation of the auditing profession. Extending the scope of implications to other emerging economies would also enhance the study's relevance. Countries with similar institutional, economic, or technological environments may face comparable challenges, making the study's recommendations applicable beyond the Jordanian context.

6. Conclusion

Big Data Analytics (BDA) is a significant change in the auditing profession. This allows auditors to go beyond standard sampling and provides full data-driven assurance. BDA is a new technology that allows the analysis of data in real time, identifies anomalies, and better assesses risk across a wide range of datasets. BDA is typically regarded as a means to enhance the quality, efficiency, and depth of insight in audits. However, it also presents new challenges in data interpretation, system integration, and auditor decision-making.

This study examines how two key aspects of the Technology Acceptance Model (TAM), perceived usefulness and perceived ease of use, affect external auditors' intention to adopt BDA. It also examines how perceived risk can alter these effects. The results show that, while BDA adoption can significantly improve audit performance, its integration depends heavily on auditors' perceptions of risk and trust in its veracity. This is because digital transformation is important in audit decision-making. These insights provide audit firms, legislators, and educators with valuable ideas on how to make sure that auditors' skills keep up with new technologies and help the profession prepare for the future.

The findings underscore the critical role of perceived risk (PR) as a moderating factor in the adoption of big data analytics (BDA) among external auditors. Specifically, PR was found to significantly moderate the relationship between perceived usefulness (PU) and behavioural intention (BI), suggesting that even when auditors recognise the potential benefits of BDA, heightened risk perceptions may diminish their willingness to adopt such technologies. This aligns with prior research (e.g., Mutahar et al., 2022; Wang et al., 2023), which highlights risk perception as a key barrier to digital adoption in sensitive professional settings. However, PR did not significantly moderate the relationship between perceived ease of use (PEOU) and BI, which may indicate that concerns about data security, reliability, or legal consequences are more likely to undermine the perceived utility of BDA rather than its ease of use. These results suggest that risk mitigation strategies—such as enhanced cybersecurity protocols, regulatory clarity, and continuous auditor training—are essential to facilitate wider BDA adoption. Future research may benefit from exploring other contextual factors (e.g., firm size, audit type, or auditor experience) that could influence how risk perceptions shape adoption decisions.

This study had some limitations. First, this study lies in its geographic and professional scope, as the data were collected exclusively from external auditors in Jordan. While this context provides valuable insights into BDA adoption in an emerging economy, the findings may not be fully generalisable to other settings, such as internal auditors, government audit institutions, or auditing professionals in more technologically advanced or culturally distinct environments. Differences in regulatory frameworks, organisational cultures, technological infrastructure, and audit practices across countries could influence the relevance and strength of the observed relationships. Future research should consider cross-national comparative studies or apply the model in different auditing contexts to assess the consistency and robustness of the findings.

Second, this study primarily focused on three core constructs—perceived usefulness (PU), perceived ease of use (PEOU), and perceived risk (PR)—based on the Technology Acceptance Model (TAM) and relevant extensions. While this approach ensures theoretical clarity and model parsimony, it does not account for other potential factors that may influence BDA adoption, such as organisational support, data privacy concerns, regulatory pressure, or technological anxiety. These variables could offer further explanatory power, especially in complex or rapidly evolving audit environments. Future research is encouraged to extend the current model by incorporating such variables to gain a more comprehensive understanding of the drivers and barriers to BDA adoption in various auditing and geographical contexts.

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