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Awareness and Big Data Technology Adoption Readiness in Public Sector Auditing in Tanzania: Mediation Effect of Knowledge Management Practices

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Abstract. Big data technology enables auditors to identify patterns and anomalies across extensive datasets, supporting improved audit quality. However, its adoption in Tanzania's public sector auditing remains limited. This study examines the mediating role of knowledge management practices in the relationship between awareness and readiness to adopt big data technology. Drawing on Diffusion of Innovation (DOI) theory and Knowledge Management Theory (KMT), it proposes that awareness provides the foundation for adoption readiness, while knowledge creation, sharing and application translate awareness into practical capabilities. Data were collected from 221 randomly selected respondents and analysed using descriptive statistics and binary logistic regression. The findings indicate that knowledge management practices mediate the relationship between awareness and adoption readiness, highlighting their role in developing skills for technological adoption. Descriptive results reveal high operational awareness but low technical awareness among auditors, indicating a technical skills gap. These findings suggest that awareness alone is insufficient without mechanisms for acquiring, sharing and applying relevant knowledge. Public sector auditing institutions in Tanzania should strengthen knowledge management through targeted training programmes and knowledge sharing platforms. The study contributes an integrated DOI–KMT perspective explaining how awareness and knowledge management jointly support readiness for big data adoption in public sector auditing.

Keywords: Awareness, Big data technology adoption, Knowledge Management Theory, Diffusion of Innovation, Public sector auditing

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1. INTRODUCTION

Big data technology plays a transformative role in auditing sectors by enabling organizations to analyze vast datasets, uncover patterns, and generate actionable insights that enhance decision-making, drive innovation, and improve operational efficiency. It refers to tools, systems, and frameworks that are used to store, process, and manage large volumes of data [1]. These datasets encompass both structured and unstructured data which traditional systems and methods are often unable to manage [2]. Big data technology is reshaping the auditing profession by enabling auditors to analyze entire datasets rather than relying on traditional sampling methods. In Tanzania, Auditors play a critical role in verifying the accuracy of financial reports, assessing the effectiveness of internal controls, and identifying any discrepancies or areas for improvement [3, 4]. Auditors adheres to the International Standards of Supreme Audit Institutions (ISSAI) and International Federation of Accountants (IFAC) which ensure that auditors apply standardized procedures and principles when evaluating financial statements and assessing compliance with regulations [5].

The auditing field is experiencing a rapid increase in data volumes due to the digitization of government records, the implementation of e-governance platforms, and the adoption of diverse information systems across public sector entities [6]. While IFAC and ISSAI provide structured guidelines for conducting audits, these frameworks remain grounded in traditional approaches such as sampling and manual verification, which are increasingly inadequate for addressing the growing demand for comprehensive data analysis [7]. As government entities generate vast and complex datasets, public sector auditing in Tanzania has invested in auditing management systems, currently the Teammate Audit System, which allows auditors to plan engagements, document evidence, track findings, and generate reports in a structured way; however, it lacks the advanced analytical capabilities required to extract, process, and interpret large, heterogeneous datasets from multiple sources, constraining auditors to rely on manual processes. [8, 9]. Existing big data technologies Such as CaseWare IDEA (Interactive Data Extraction and Analysis), ACL Analytics (Audit Command Language), IBM Watson (Natural Language Processing and AI Platform), and SAS Text Miner (Statistical Analysis System Text Miner) can offer the ability to process both structured data (e.g., payroll records, procurement transactions,

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financial ledgers) and unstructured data (e.g., contracts, policy documents, emails, reports), enabling comprehensive verification and compliance checks without reliance on sampling or manual review. Big data technologies offer a transformative solution by enabling full-population testing and advanced analytics that align more effectively with the complexity of available public sector data [10]. Nevertheless, despite its significant potential, its adoption is limited in public sector in Tanzania [11, 12]. Previous studies on the adoption of big data technology in auditing have largely concentrated on organizational and technological factors [13, 14], little attention have been paid on the mediating effect of KMP between awareness and adoption of big data technology in public sector auditing in Tanzania. This gap stresses the need for research that integrates awareness and KMP to explain adoption dynamics in the context of public sector auditing in Tanzania

Awareness is viewed in two dimensions which are operational awareness, which reflects auditors' recognition of the importance and benefits of big data [15], and technical awareness, which refers to familiarity with big data tools in practice [16]. KMP encompasses processes that create, capture, share, and apply knowledge. It is critical as it can transform awareness into actionable technical skills. KMP facilitates the creation, sharing, and application of knowledge, enabling organizations to leverage intellectual capital to remain competitive and responsive to dynamic environments [17, 18]. By translating awareness into actionable insights, organizations can optimize operations and strengthen audit effectiveness. Ignoring the critical role of awareness and KMP places public sector auditing at a disadvantage, as it risks failing to unlock the value of big data to improve audit quality. Thus, this study aims to (i) examine the levels of technical and operational awareness and (ii) test the mediating effect of KMP on the relationship between awareness and adoption readiness of big data technology in public sector auditing in Tanzania.

2. LITERATURE REVIEW

2.1. Theoretical Review

This study is grounded in the Diffusion of Innovations (DOI) theory, developed by Everett Rogers in 1962, which serves as the primary theoretical framework. DOI focuses on the

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process by which a new idea, practice, or technology spreads through a social system over time, emphasizing factors like awareness, communication channels, and the perceived characteristics of the innovation [19]. The focus on DOI is driven by its emphasis on technology awareness as a crucial precursor to the adoption process. This focus is particularly relevant for examining the relationship between levels of awareness of big data technology and its subsequent adoption. However, while DOI provides valuable insights into the awareness-adoption relationship, it does not fully capture internal organizational mechanisms for leveraging that knowledge. To address this limitation, the study incorporates the Knowledge Management Theory developed by Thomas H. Davenport in 1998. This theory is crucial because it helps to understand how auditors acquire, create, share, and utilize the knowledge about big data technology, which is essential for determining its practical application and facilitating the transition from awareness to actual implementation. The uniqueness of this theoretical framework lies in combining DOI and KMT into a DOI-KMP framework, which not only explains how awareness of big data technology emerges but also how knowledge management practices mediate the transition from awareness to adoption.

2.2. Research framework

2.2.1. Technical awareness

Technical awareness refers to the understanding and knowledge of specific technologies, tools, and systems relevant to a particular field or industry [20]. In the context of big data technology and auditing, it involves familiarity with various big data tools and software, such as data analytics platforms, databases and visualization tools. It encompasses understanding and familiarity of how these tools function, their capabilities in terms of data processing, storage, and analysis, as well as knowing how to apply these technologies effectively in practice [16]. Staying updated on emerging trends and advancements in technology enhances technical awareness. Studies shows that higher level of technical awareness facilitates the adoption of new technologies [21]. The following hypothesis have been developed

1) *H1a:* Technological awareness influence likelihood of big data technology adoption
2) *H1b:* Technological awareness influences the knowledge management practices

2.2.2. Operational awareness

Operational awareness refers to the familiarity of how specific technologies and processes can enhance the effectiveness and efficiency of an organization's operations [14]. In the context of big data technology, operational awareness plays a critical role in auditing by enabling auditors to recognize how insights generated from big data can be applied to improve auditing quality. Operational benefits of big data technology foster its adoption as auditors begin to realize its potential for transforming their auditing processes and practices. Studies show that when organization understand the tangible advantages of technology such as increased efficiency, reduced costs, and enhanced accuracy they are more likely to embrace its adoption [22]. The following hypothesis have been developed

1) *H2a:* Operational awareness influences the likelihood of big data technology adoption
2) *H2b:* Operational awareness influence knowledge management practices

2.2.3. Knowledge management practices

Knowledge management practices (KMP) refer to the systematic processes and strategies that organizations use to identify, create, store, share, and utilize knowledge to enhance their operational efficiency [17]. These practices are designed to facilitate the flow of information and expertise within an organization, ensuring that valuable insights are available for enhanced decision making. KMP plays a mediating role in the adoption of technologies by ensuring that employees possess the necessary knowledge and skills for practical application of technology [23]. In the context of public sector auditing, knowledge management practices (KMP) regarding big data technology can be employed through training programs, workshops, and seminars that focus on the functionalities and applications of big data tools in auditing. Studies show that knowledge management practices enhance awareness which is essential for the adoption of big data technology [24]. The following hypothesis have been developed

1) *H3:* Knowledge management practices influence likelihood of big data technology adoption
2) *H4a:* Knowledge management practices mediate technological awareness and big data technology adoption

3) *H4b:* Knowledge management practices mediate operational awareness and big data technology adoption

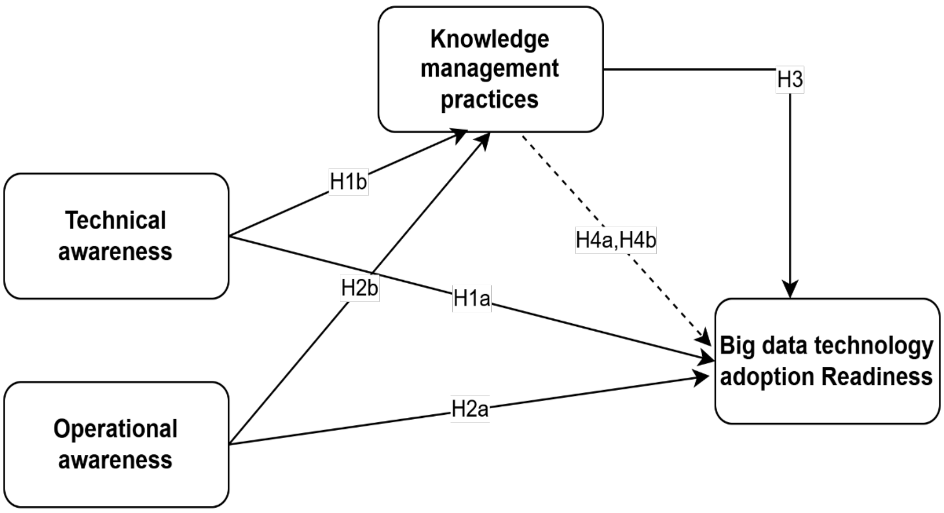

Figure 1. Research framework, Source(s): Figure by authors

2.3. Empirical Literature Review

The reviewed empirical studies provide valuable insights into the adoption of big data technologies across diverse contexts. For instance, the study conducted by [25] which focused on the impact of adopting big data and data analytics on enhancing audit quality in Egypt. Their research revealed that the adoption of big data analytics significantly improves audit quality. However, their theoretical framework primarily emphasizes empirical testing of adoption's direct outcomes. It focuses on the outcomes of adoption specifically the enhancements in audit quality without addressing how awareness and knowledge processes play a role in facilitating this adoption. In contrast, this study uniquely combines the Diffusion of Innovation (DOI) theory with Knowledge Management Theory (KMT) to explore how awareness translates into practical skills.

Similarly, the study conducted by [26] which focuses on the adoption of big data analytics (BDA) in public sector auditing in Indonesia**.** Their research investigates the determinants of adoption, examining organizational, technological, and environmental factors that influence adoption anchored in the Technology-Organization-Environment (TOE) framework. While it highlights the organizational and structural determinants influencing adoption, it does not delve into the precursors awareness and knowledge processes that shape auditors' readiness to adopt big data technology

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In Malaysia, the study conducted by [27] who investigates how the adoption of big data analytics (BDA) influences auditors' professional skepticism during risk assessment. The core idea of the research is that professional skepticism a critical behavioral trait in auditing reflects auditors' questioning mindset and vigilance concerning potential misstatements. The findings reveal a positive correlation between the adoption of BDA and heightened professional skepticism. While this study focuses on the behavioral impacts of BDA on professional skepticism, it does not highlight the cognitive and knowledge-based processes that precede adoption of big data technology in auditing practices.

The study conducted by [28] examines how awareness of big data analytics (BDA) influences its adoption and, subsequently, firm performance across various industries in China. The objective of the research is to understand the interplay between awareness and adoption, and how these factors contribute to enhancing competitive advantage. The findings reveal that awareness of the benefits of BDA serves as a critical precursor to its adoption. Moreover, the study indicates that adoption mediates the relationship between awareness and improved firm performance organizations with higher awareness are more likely to adopt BDA and, as a result, achieve better performance outcomes. While this study emphasizes general awareness of benefits and its impact on performance, Yet, it fails to explore the specific dimensions of technical and operational awareness as drivers for successful technology adoption, as framed by both the Diffusion of Innovation DOI and Knowledge Management Theory KMT.

3. METHODS

3.1. Research design

This study adopted a cross-sectional research design to capture data at a single point in time rather than tracking changes longitudinally. This design was particularly appropriate Since the constructs under investigation which are awareness, knowledge management practices and big data technology adoption represent perceptions and practices that can be meaningfully assessed in their current state providing an efficient and reliable snapshot of these relationships.

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3.2. Study population

The study population comprised 495 auditors drawn from various ministries, agencies, and parastatal organizations in Dodoma City, all of whom operate under the umbrella of the National Audit Office of Tanzania (NAOT). The research was conducted in Dodoma, the administrative capital of Tanzania, which hosts the headquarters of numerous ministries, agencies, and parastatal organizations. These entities serve as central repositories for data accumulated from other regions of the country, resulting in the generation of large and complex datasets that necessitate the application of big data technologies in auditing. Dodoma was therefore selected as a significant study location because it represents the core of governmental operations and data management in Tanzania.

3.3. Sampling and sample size

The study employed a stratified random sampling technique to ensure proportionate representation across ministries, agencies, and parastatal organizations. Within each stratum, simple random sampling was applied to select respondents, thereby minimizing selection bias and enhancing representativeness. The determination of sample size was guided by Yamane's (1967) formula, using a 95% confidence level and a significance level of p = 0.05. Yamane formula is expressed as shown in Equation (1).

$$n=\frac{N}{1+Ne^2} \tag{1}$$

where n is the required sample size, N is total population size, e is margin of error (0.05), desired confidence level is 95%.

Hence $n=\frac{495}{1+495(0.05)^2}=$ 221. Therefore, the sample size for the current study was determined to be 221.

3.3.1. Proportionate Stratified Sampling

The total sample size of 221 respondents was proportionally distributed across ministries, agencies, and parastatal organizations to ensure balanced representation, as shown in Table 1. Allocation within each stratum was further determined using the appropriate statistical formula as shown in Equation (2).

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$$ni = \frac{Ni}{N} \times n \quad (2)$$

Where

ni = Sample size for stratum i
Ni = population size of stratum i
N = Total population size
n = Total sample size

Table 1. Sampling frame

Stratum	Population size of stratum (Ni)	Sample size for stratum (ni)	Total population size (N)	Total sample size (n)
Ministries	230	103	495	221
Agencies	165	74		
Parastatal	100	44		

Hence, 103 respondents were selected from ministries, 74 from agencies, and 44 from parastatal organizations. This proportional approach ensured that the sample size from each stratum accurately reflected its size within the overall population.

3.4. Data collection instruments

Data were collected using a closed-ended questionnaire in which respondents were presented with a set of predetermined response options using a 5- Likert scale. Closed-ended questionnaires provided a standardized format for data collection, ensuring that all respondents are answering the same set of questions with the same response options which is important for ensuring the reliability and comparability of the data [29]. A multi-modal data collection approach was employed in data collection were both paper-based and online survey techniques were used. The rationale for employing a multi-modal approach in this study was to increase the response rate by providing multiple convenient options for data collection. The paper-based questionnaire administration ensured that all selected participants, regardless of their technological proficiency or access, could participate in the study. On the other hand, complementing the paper-based approach, the use of Google Form questionnaires was incorporated as it enabled participants who preferred digital modes of communication to easily access and complete the questionnaire at their own convenience without the need for physical delivery or return of the paper-based form

3.5. Validity and reliability

A pilot study was conducted in Dar es Salaam, selected because its auditing environment is comparable to that of Dodoma, where the main study was undertaken. The pilot involved a small sample of auditors and was primarily designed to assess the clarity of the questionnaire items. Feedback obtained from participants was systematically analysed and used to refine and adjust the wording of questions, ensuring that the instrument was clear, unambiguous, and ready for large-scale data collection. Furthermore, expert review was undertaken to establish content validity by examining the questionnaire and confirmed that the items adequately captured the constructs under investigation and were consistent with the study objectives. Finally, internal consistency reliability was assessed using Cronbach's alpha. All constructs had values above the recommended threshold of 0.70, indicating satisfactory reliability. These results confirm that the measurement items were both valid and reliable for analysis, as shown in Table 2.

Table 2. Construct reliability results

Variable	Code	Cronbach's alpha
Technical awareness (TA)	TA1	0.761
	TA2	
	TA3	
	TA4	
	TA5	
Operational awareness (OA)	BDOA1	0.719
	OA2	
	OA3	
	OA4	
	OA5	
	OA6	
Knowledge management practices (KMP)	KMP1	0.804
	KMP2	
	KMP3	
	KMP4	
	KMP5	

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3.6. Data analysis

The study employed both descriptive analysis and binary logistic regression analysis to provide a comprehensive understanding of the relationship between awareness, knowledge management practices (KMP), and the adoption of big data technology in public sector auditing. Descriptive analysis was used first to establish the levels of operational and technical awareness among auditors, offering a diagnostic view of the existing skill gaps and awareness patterns. Binary logistic regression analysis was then applied to statistically test the mediating effect of KMP on the relationship between awareness and adoption, allowing the study to move beyond description into causal inference. This dual design provides unique empirical contribution and insights than studies that rely solely on descriptive statistics or regression alone, as it captures both the contextual reality of auditors' awareness levels and the mechanisms through which knowledge management practices mediate adoption dynamics.

3.6.1. Construct measurement

For descriptive analysis, the computation of the mean and standard deviation was employed to identify the respondents' level of big data technology awareness. The scoring procedure for assessing level of big data technology awareness was based on the established scales from [30, 31]. In the scoring procedure, the level of technology awareness was interpreted with the following scale: a Mean of 1.00 – 1.9 indicated a very low level of awareness, 2.0 – 2.9 low level of awareness, 3.0 – 3.4 moderate level of awareness, 3.5 – 3.9 high level of awareness, and 4.0 – 5.0 reflected a very high level of awareness. In this study, knowledge management practices were operationalized across four major dimensions: creation, storage, sharing, and application [17, 32, 33] Although these sources are somewhat dated, they remain seminal works in the knowledge management literature, providing the foundational theoretical frameworks upon which subsequent studies have been built. To capture these dimensions empirically, the items were measured using a five-point Likert scale, ranging from strongly disagree (1) *to* strongly agree (5). Big data technology adoption was conceptualized in this study as readiness rather than actual usage, given that adoption remains at an early stage within public sector auditing in Tanzania. This operationalization is consistent with prior research that regards readiness as a reliable proxy for adoption behavior, allowing for meaningful assessment of adoption potential in contexts where actual implementation is at infant stage[34]. Also, according to the Technology Acceptance Model [35], measures of readiness or behavioral intention serve as reliable approximations of actual adoption outcomes. Readiness was measured in binary terms, categorized as high readiness (coded as 1) and low readiness (coded as 0), in line with the requirements of binary logistic regression analysis [36] The mediation analysis was conducted using regression techniques to examine both the direct and indirect effects of awareness on the adoption of big data technology, with knowledge management practices (KMP) specified as the mediating variable.

Mediator, Outcome equation as shown in Equation (3) dan (4)

$$M = \propto_0 + \propto_1 X_1 + \propto_2 X_2 + \in \quad (3)$$

$$ln \frac{P(Y-1)}{1-P(Y=1)} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 M + \in \quad (4)$$

Where

M = Mediator (Knowledge Management Practices, KMP)

Y = Binary outcome (Adoption of big data technology)

X = predictor variables (operational and technical awareness)

α and β = Regression coefficients

The study also assessed multicollinearity and outliers for both models. To evaluate multicollinearity, the Variance Inflation Factor (VIF) was calculated, yielding values less than 5, which indicates an absence of multicollinearity among the variables [37]. Additionally, Cook's distance was analysed, with all values being below 1, signifying no significant outliers in the dataset [38].

3.7. Ethical considerations

Ethical standards were strictly adhered to throughout the study. Formal permission for data collection was obtained from the Regional Administrative Secretary of Dodoma, following the introduction of an official data collection letter issued by Moshi Cooperative University. Prior to participation, respondents were informed of the study's purpose and were asked to provide their voluntary consent. They were also clearly advised of their right to decline participation without any consequences. All responses were treated anonymously, and data were used solely for academic purposes. These measures ensured compliance with ethical research practices.

4. RESULTS AND DISCUSSION

4.1. Demographic of respondents

The results in Table 3 presents the demographics of the respondents, providing insights into gender, age, education, and work experience. The results indicate that a significant portion of respondents have attained a high level of education. A significant portion of respondents holds a Bachelor's degree (45%), followed by Master's degree holders at 36% suggesting they possess a foundational knowledge of information systems, as higher education often emphasizes the use of ICTs in the workplace. Furthermore, the majority of respondents (41%) reported having 5 to 9 years of work experience. This level of experience likely contributes to a more informed perspective on the applicability and benefits of big data technology in auditing practices.

Table 3. Demographics of the respondents

Demographic variable	Category	Frequency	Percentage
Gender	Male	138	62.
	Female	83	38
Education	Diploma	40	18
	Bachelor degree	100	45
	Master degree	80	36
	PhD	1	1
Work experience	Less than 5years	68	31
	5-9 years	90	41
	10-15years	42	19
	Greater than 15 years	21	9

Source: Field data, (2023)

4.2. Level of awareness

4.2.1. Technical awareness

Table 4 provides indicators related to the level of technical awareness of big data technology, accompanied by their respective mean and standard deviation values. These indicators assessed the respondents' understanding of the technical aspects and tools that underpin big data technology.

Table 4. Level of technical awareness of big data technology

Code	Indicators	Mean ± SD	Description
TA1	Familiarity with big data concepts.	2.31 ± 1.20	Low level of awareness
TA2	Familiarity with big data tools.	1.82 ± 0.86	Very low level of awareness
TA3	Familiarity with data processing techniques	1.37 ± 0.92	Very low level of awareness
TA4	Awareness on data visualization techniques	1.78 ± 0.71	Very low level of awareness
TA5	Awareness on cloud computing support on big data technology	1.92 ± 0.82	Very low level of awareness
TA6	I am aware of best practices for big data such as validating data accuracy, addressing missing or inconsistent values, and implementing security/privacy protections.	1.79 ± 0.78	Very low level of awareness
	overall mean	1.84 ± 0.88	Very low level of awareness

The results in Table 4 demonstrate that respondents exhibit a very low level of technical awareness regarding big data technology. The overall mean score of 1.84 ± 0.88 reflects this limited understanding of the technical aspects essential for effectively utilizing big data technology in auditing. Among the specific indicators, BDTA5 revealed that respondents have very low level of awareness in prompt engineering skills

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(mean=1.92±0.82) which is necessary for them to design specific queries that will guide big data solutions to produce relevant and desired audit outputs. Without the capacity to craft precise and effective prompts, auditors may struggle to extract valuable insights from big data. This aligns with the conclusions drawn by [39], which suggest that lack of technological awareness can hinder its actual adoption. This similarity of findings implies that a limited understanding of the technical aspects of big data technology can significantly hampers its effective adoption in auditing practices. This emphasizes the importance of fostering technological awareness and education among auditors. Without a strong understanding of these tools, organizations may find it challenging to harness the full potential of big data, which can ultimately affect their efficiency and decision-making processes.

4.2.2. Operational awareness

Table 5 presents indicators that reflect the level of operational awareness of big data technology, along with their corresponding mean and standard deviation values. These indicators collectively reflect the respondents' understanding of how big data technology can be utilized in practical scenarios to improve efficiency and decision-making processes.

Table 5. Level of operational awareness of big data technology

Code	Description	Mean ± SD	Description
OA1	I understand that big data technology can enhance financial risk assessment	3.77 ± 1.01	High level of awareness
OA2	I am aware that using big data instead of more conventional auditing techniques would allow me to find irregularities and frauds.	3.76 ± 1.01	High level of awareness
OA3	I am aware that using big data technologies to audit the entire population instead of just a	4.27 ± 0.69	Very high level of awareness

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Code	Description	Mean ± SD	Description
	sample increases the efficacy of audits.		
OA4	I am familiar that big data technology ensure compliance with regulatory requirements	4.16 ± 0.93	Very high level of awareness
OA5	I understand that big data can enable organizations to be more responsive to audit technological changes, identify new opportunities, and adapt more quickly to evolving auditing professional needs.	4.35 ± 0.66	Very high level of awareness
OA6	I familiar that big data technology can inform and improve decision-making processes in auditing activities	4.39 ± 0.68	Very high level of awareness
	overall mean	4.12 ± 0.83	Very high level

The results in Table 5 demonstrate that respondents exhibit a very high level of operational awareness of big data technology in auditing. The overall mean score of 4.12 ± 0.83 indicates a strong understanding of how big data can enhance auditing practices. Notably, two specific indicators reflect this high awareness: BDOA3**,** which states that respondents are familiar with how big data technology enhances auditing effectiveness by allowing for the auditing of entire populations rather than relying on sample-based approaches, received a mean score of 4.27 ± 0.69**.** BDOA5 highlights the ability of big data to enable organizations to respond more effectively to technological changes and adapt to evolving auditing needs, achieved a mean score of 4.35 ± 0.66**.** These indicators illustrate the respondents' clear recognition of the significant advantages that big data technology brings to the auditing field. This align with the observations made by [40], which suggest that operational awareness is a key driver of technology adoption which emphasizes that a strong awareness of the operational benefits of big data technology

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is crucial for driving its adoption in auditing. The implication is that auditors are more inclined to adopt and use big data technology when they see the benefits it may offer to their operations. Therefore, fostering operational awareness is essential for enhancing audit practices and leverage the full capabilities of big data technology. In general, the findings on awareness revealed that level of technical awareness regarding big data technologies among is notably low, while level of operational Awareness is high. This disparity indicates that auditors possess a good understanding of how big data can be operationalized within their auditing practices, but they lack the technical knowledge required to effectively leverage these tools

4.3. Mediation effect of knowledge management practices

Two logistic regression models were formulated to analyze the relationships among the variables. The first model regressed the mediator which is Knowledge Management Practices (KMP) on both Technical Awareness (TA) and Operational Awareness (OA)**.** The Hosmer and Lemeshow test resulted in a p-value of 0.324, which is greater than 0.05. This non-significant result indicates that the goodness of fit of the model is adequate, suggesting that the model predicts the observed outcomes. Additionally, the Nagelkerke R^2 value was 0.631, which indicates that approximately 63.1% of the variability in Knowledge Management Practices can be explained by Technical Awareness and Operational Awareness. power of the model, signifying a meaningful relationship among these variables. The second model regressed the binary outcome, Adoption of Big Data Technology, on Technical Awareness, Operational Awareness, and the mediator which is Knowledge Management Practices. The Hosmer and Lemeshow test showed a p-value of 0.243, further indicating a good fit for this model as well. The Nagelkerke R^2 value for this model was 0.640, indicating that about 64.0% of the variability in the adoption of big data technology can be explained by the independent and mediating variables.

4.3.1. Direct effect

The direct effect aimed to measure the immediate influence of auditors' awareness both technical awareness (TA) and operational awareness (OA) on the adoption of big data technology, without considering the mediating role of knowledge management practices (KMP). This allowed to establish whether awareness alone is sufficient to drive adoption decisions. This step was crucial before introducing KMP as a mediator, as it ensured that

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the study could distinguish between the pure effect of awareness and the enhanced effect of awareness when supported by organizational knowledge processes, as shown in Table 6.

Table 6. Direct effect results

Hypothesis	Path	β	SE	Exp(β)	95% CI for OR	Wald $(\beta/SE)^2$	p-value
H1b	TA → KMP	0.65	0.18	1.91	(1.32, 2.77)	13	0.001
H2b	OA → KMP	0.8	0.2	2.23	(1.50, 3.32)	16	0.001
H1a	TA → BDA	0.2	0.25	1.22	(0.73, 2.05)	0.64	0.423
H2a	OA → BDA	0.18	0.22	1.2	(0.76, 1.89)	0.67	0.416
H3	KMP → BDA	0.75	0.17	2.12	(1.50, 2.99)	19.4	0.001

The direct effect analysis was examined using binary logistic regression. The results showed that technical awareness (TA) had a significant positive effect on knowledge management practices (KMP) ($\beta = 0.65$, $Exp(\beta) = 1.91$, $p = 0.001$), supporting H1b. Similarly, operational awareness (OA) significantly predicted KMP ($\beta = 0.80$, $Exp(\beta) = 2.23$, $p = 0.001$), thereby supporting H2b. In contrast, the direct paths from awareness to big data technology adoption (BDA) were not statistically significant. Technical awareness (H1a) ($\beta = 0.20$, $Exp(\beta) = 1.22$, $p = 0.423$) and operational awareness (H2a) ($\beta = 0.18$, $Exp(\beta) = 1.20$, $p = 0.416$) did not reach significance, leading to the rejection of H1a and H2a. Moreover, knowledge management practices (KMP) demonstrated a strong and significant effect on BDA ($\beta = 0.75$, $Exp(\beta) = 2.12$, $p = 0.001$), accepting H3.

4.3.2. Indirect effect

The indirect effect aimed to capture how auditors' awareness both technical awareness (TA) and operational awareness (OA) influences the adoption of big data technology through the mediating role of knowledge management practices (KMP). In this pathway, awareness does not act alone; instead, it is mediated by knowledge management practices, which in turn drive adoption outcomes, as shown in Table 7.

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Table 7. Indirect effect results

Hypothesis	Path	β	Boot SE (5000)	95% CI bootstrap (5000)	p-value
H4a	TA → KMP → BDA	0.32	0.08	(0.18, 0.48)	0.001
H4b	OA → KMP → BDA	0.28	0.07	(0.15, 0.42)	0.001

The results of the indirect effect analysis provide strong evidence that knowledge management practices (KMP) mediate the relationship between awareness and big data technology adoption. Specifically, the bootstrapped estimates revealed that the indirect path from technical awareness (TA) through KMP to adoption (H4a) was significant ($\beta = 0.32$, $p = 0.001$). This indicates that technical awareness enhances adoption indirectly by strengthening knowledge management practices. Similarly, the indirect path from operational awareness (OA) through KMP to adoption (H4b) was also significant ($\beta = 0.28$, $p = 0.001$), showing that operational awareness contributes to adoption indirectly via its positive effect on knowledge management practices.

The direct and indirect effect results together demonstrate the presence of full mediation in the model. This conclusion arises because the direct paths from both operational awareness (OA) and technical awareness (TA) to big data technology adoption (BDA) were statistically insignificant, while their indirect paths through knowledge management practices (KMP) were significant. In other words, awareness alone does not directly drive adoption; instead, its influence is fully channeled through KMP, which acts as the mediating mechanism. This finding aligns closely with prior studies done by [41] who concluded that internal organizational factors including culture, leadership, and employee attitudes play a decisive role in ICT adoption.

These findings also confirm the extended Diffusion of Innovation (DOI) theory with knowledge management theory which revealed that while DOI emphasizes awareness as an early stage in the innovation-decision process, alone is insufficient; it must be operationalized through knowledge management practices to lead to adoption. This theoretical extension offers a novel perspective by showing that awareness and

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knowledge management practices together form a pathway that bridges the gap between initial recognition of innovation and its actual implementation. This demonstrates that awareness builds the foundation, but knowledge management practices drive the adoption process, The results call for a clear strategic response within public sector auditing institutions, requiring them to strengthen and invest in knowledge management practices (KMP)**.** Such practices include systems for knowledge sharing, structured training programs, and collaborative platforms, which are essential to ensure that awareness of big data technology is effectively translated into adoption among auditors

5. CONCLUSION

The study aimed to examine the mediating effect of Knowledge Management Practices (KMP) on the relationship between Technical Awareness (TA) and Operational Awareness (OA)**.** Before delving into mediation, the study first assessed the levels of awareness among participants and revealed a significant disparity between the high level of operational awareness of big data technology and the corresponding low level of technical awareness necessary for effective adoption of big data technology in auditing. This divergence suggests while the "why" of big data technology is well-recognized, the "how" remains a challenge among auditors. The key findings of the study shows that auditors are aware of the value and opportunities that big data technology can bring to auditing but they lack the deeper technical knowledge and skills required to effectively implement and leverage big data technology in practice. Furthermore, the mediation analysis confirmed that KMP fully mediate the relationship between awareness and adoption of big data technology, showing that awareness is necessary but insufficient, adoption occurs only when awareness is operationalized through structured knowledge management systems. Theoretically, this contributes to the literature by demonstrating that awareness must be embedded within organizational knowledge frameworks to translate into adoption. Practically, it highlights that investment in KMP is essential for enabling auditors to move from recognition of big data technology value to its integration in audit processes.

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