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The Effect of Awareness on Big Data Adoption Readiness in Public Sector Auditing in Tanzania: Assessing TAM Model

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Big data plays a pivotal role in auditing by unlocking unprecedented opportunities to extract meaningful insights from vast volumes of data. However, the usage of big data in public sector auditing in Tanzania is still limited, highlighting the need to explore the factors that influence its adoption readiness. This study explores the effect of awareness on auditors' perception towards big data adoption readiness in public sector auditing. Specifically, it focuses on two key Technology acceptance model (TAM) factors, which are perceived ease of use and perceived usefulness. Data were collected from a sample of 221 auditors by using random sampling technique. Confirmatory factor analysis using Partial least square structural equation modelling performed the analysis. The findings revealed that awareness on big data adoption readiness plays a crucial role in shaping the

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perceived ease of use and perceived usefulness of big data technology. Higher levels of awareness are associated with increased perceived usefulness and perceived ease of use and consequently perceived usefulness was found as a major predictor of big data adoption readiness. The study concludes that empowering auditors with a deeper understanding of big data and its practical applications in public sector auditing could significantly increase their adoption readiness. Specifically, the findings suggest that providing targeted training programs, workshops, and seminars to enhance auditors' awareness and knowledge of big data technologies and their potential benefits would be an effective strategy to promote the readiness for big data adoption.

Keywords: Awareness; technology acceptance model; big data adoption readiness; public sector auditing; perceived usefulness; perceived ease of use.

1. INTRODUCTION

Globally, the awareness and big data adoption readiness in auditing have been growing gradually. Auditing firms and regulatory bodies around the world have recognized the potential of big data analytics to enhance audit quality, improve risk assessment, and identify fraudulent activities [1]. The advancements in technology, increased availability of large volumes of data, and the need for more efficient and effective auditing processes have contributed to the global focus on big data adoption in auditing [2]. Big data entail the aggregation of large amounts of structured and unstructured data and sophisticated analyses using artificial intelligence and natural language processing techniques [3]. For instance, each day 2.5 quintillion of data are generated every day and is expected to reach 463 exabytes as of 2025 [4]. Big data is multifaceted concept described by its 4vs: volume, veracity, velocity and variety. Volume refers to large data sets that traditional database cannot handle [5]. Variety reflects multiple data formats including structured and unstructured [6]. Velocity refers to rapid rate at which data are generated and become available [7]. Veracity refers to the quality and relevance of the data generated over time.

Big data awareness has the potential to revolutionize the auditing profession by impacting auditors' perception of perceived usefulness and perceived ease of use of big data [8]. The effect of big data awareness on perceived ease of use and perceived usefulness within the TAM model has been significant on its adoption [9]. Awareness increases better understanding of big data tools, techniques, and their usability as a result, individuals perceive big data technologies as more accessible and easier to use, which enhances big data adoption readiness [10]. Awareness of big data also involves familiarity and exposure to various analytics tools, software, and platforms. Exposure enhances familiarity with these tools, making them appear less complex and easier to use [11]. Awareness of big data and its potential to uncover valuable insights and patterns from large volumes of data increased individuals' perception that using big data analytics can lead to improved decision-making and operational efficiency [11]. Awareness of big data in addressing common business challenges such as customer behavior, predictive modeling, and fraud detection enhanced individuals to perceive big data analytics as a useful tool for overcoming these challenges in their own work atmosphere [12]. Success stories of organizations that have effectively leveraged big data to gain competitive advantages, optimize operations, and achieve better decision-making. For instance, in healthcare [13], manufacturing [14] and agriculture (Javaid et al.,2023) contributed to the perception of big data's usefulness, as individuals recognize the potential benefits in terms of improved performance and enhanced insights.

Public sector in Tanzania plays a vital role in the country's socio-economic development, providing essential services and infrastructure that support the well-being of its citizens [15]. The awareness and adoption of big data in auditing are also gaining attention in Tanzanian public sector. The auditing profession in Tanzania is gradually recognizing the potential benefits of big data analytics in enhancing audit quality and effectiveness. Big data analytics provide auditors with powerful tools to analyze large volumes of data and identify patterns, anomalies, and potential risks [1]. However, without awareness of big data and its potential applications, auditors may not recognize the opportunities to extract valuable insights from data sets beyond traditional audit procedures [16]. Lack of awareness can result in missed opportunities to enhance audit effectiveness, efficiency and quality.

The increasing digitalization of financial systems, growth in data generation, and the need for more robust and efficient audit procedures have created a situation conducive to exploring big data adoption in auditing [17]. However, While the awareness of big data analytics is growing globally [18,16], big data adoption in public sector auditing in Tanzania is very limited [19,20]. It is unclear whether comprehensive knowledge and familiarity in big data influence big data adoption readiness. Therefore, the key focus of this study is to examine the effect of awareness on perceived ease of use and perceived usefulness within the TAM model which in turn determine big data adoption readiness in public sector auditing in Tanzania.

2. LITERATURE REVIEW

It is evident that data generation in public sector has exponentially increased in past few years [21]. Big data refers to massive and multifarious data sets that traditional relational database cannot handle [22]. Big data is characterized and defined by 4vs which are volume due to massive data generated and collected, variety due to different data format from multiple sources, velocity which is the speed at which data are generated and collected and veracity which refer to data quality and insight that can be extracted. Big data itself is not a technology and has limited value until captured and analyzed [23]. Big data are very complex to be processed due to its multifaceted nature comprises of high velocity and extremely large data sets with different format from multiple sources [10]. To extract insight from big data, alternative way to capture and analyze these data sets must be a choice by organization [24]. With the development of analytical technologies, tools to capture and analyze big data have become more accessible [5]. Big data technology provides auditors with tools capable to analyze audit relevant data from entire population that previous were done traditionally by taking sample population. The previous traditional auditing is not satisfying the current digital complex environment [25]. Auditors come across with hundreds of diverse accounting systems and, in many cases, multiple system within the same organization [26]. This necessitates the importance of using big data technology that can extract insight from data generated and captured from different systems [27]. This section introduces the existing literature on the constructs of the TAM, including perceived ease of use and perceived usefulness, along with its extended external variable, awareness.

2.1 Awareness

Awareness refers to having knowledge and being mindful on the existence of something [28]. Awareness is a state of knowing that something exists based on experience or available information [29]. In the context of this study, awareness implies familiarity with big data and its benefits in public sector auditing. Literature reveals that individuals who already have experience with technology and data analysis tools are more likely to perceive big data as useful and find it easier to use [30]. It is unclear if public sector auditing has prior exposure to analytics or data-driven decision-making which can reduce the perceived complexity of big data and enhance its perceived usefulness. Literature on big data has put forward evidence to indicate that big data awareness has been growing tremendously [12,31]. It is evident that increasing awareness enhances users' perceptions of the usefulness and ease of use of technology, while also likely reducing perceived security risks through knowledge of the technology and its security features [32]. This factor is highly relevant to the readiness for adopting big data in public sector auditing in Tanzania, given that it is a relatively new technology, necessitating user awareness of its usage and benefits in auditing. Given unclear awareness on knowledge and understanding of big data in Tanzania public sector auditing we hypothesize that:

H1: Awareness has a positive effect on perceived usefulness

H2: Awareness has a positive effect on perceived ease of use

2.2 Perceived Usefulness and Perceived Ease of Use

The primary constructs of the TAM, developed by Venkatesh and Davis, (2000), are perceived usefulness and perceived ease of use, which are commonly used to elucidate technology acceptance and use. Based on Davis (1989), perceived usefulness (PU) is defined as the extent to which an individual believes that utilizing a specific system would enhance his/her job performance. Further, perceived ease of use

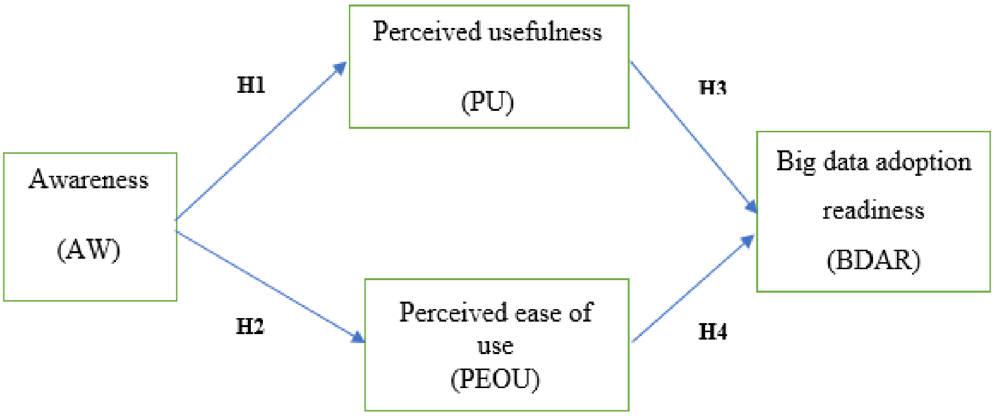

Fig. 1. The proposed conceptual model for this study

(PEOU) is defined as the extent to which an individual believes that utilizing a specific system would entail minimal effort (Erdogan, 2024). These two fundamental constructs of TAM have been empirically validated as significant precursors of user intention to adopt various technological applications [33,34]. In the context of this study perceived usefulness represents the extent to which auditors perceive that utilizing big data can enhance the effectiveness, efficiency, and quality of their auditing practices while perceived ease of use represents the extent to which auditors perceive that utilizing big data is convenient and requires minimal effort or technical expertise. Thus, TAM offers a comprehensive and validated framework to examine the impact of perceived usefulness and perceived ease of use on big data adoption readiness among auditors. Literature on perceived usefulness of big data in auditing and its effect on big data adoption readiness has been gradually growing [1,35,36] and revealed to affect big data adoption readiness. Literature reveals that Perceived benefits of big data, such as enhanced decision-making, improved insights, cost savings, and increased efficiency, can have an impact on perceptions [37]. When individuals recognize the significant advantages that big data can bring to their work, they are more persuaded to perceive it as valuable and find it easier to use [10]. Despite benefits offered by big data in public sector auditing in Tanzania, innovative usage of big data has been unsatisfactory [19]. The advocates for improved auditing quality argue that perceived usefulness of big data is the key component that encourage big data adoption readiness [38]. Due to big data innovative usage recessions in public sector auditing in Tanzania, the following hypotheses was developed.

H3: Perceived usefulness has a positive effect on big data adoption readiness

H4: Perceived ease of use has a positive effect on big data adoption readiness

2.3 Conceptual Model

This study is grounded on the TAM developed by Davis in 1989. This conceptual framework aims to build upon the TAM model and integrate additional factors to enhance its explanatory power. TAM has been substantiated and endorsed as a robust framework by various studies, including those related to Mobile Banking [39,40], e-commerce [41,42]. By considering the complexities of big data, this framework provides a holistic view of the factors influencing big data adoption readiness. The TAM posits that perceived usefulness (PU) and perceived ease of use (PEOU) are the key determinants of individual intention to adopt and use big data. This conceptual framework extends the TAM with awareness construct to provide a comprehensive understanding of big data adoption readiness.

The conceptual model for this study (Fig. 1) was developed through theoretical review.

3. METHODOLOGY

The study adopted quantitative approach based on cross-sectional research design. The quantitative approach was chosen as it established cause-and-effect relationships between awareness and big data adoption readiness and enhanced hypotheses testing [43]. The study area was the headquarter of the national audit office of Tanzania located in

Dodoma. Dodoma is well suited as the research context as it is the capital city of Tanzania where all Ministries, department and agencies resides. National audit office of Tanzania (NAOT) is exposed to vast amount of information from public sectors they audit such as Ministry, department and agencies (MDAs), local government authorities (LGAs) and parastatal organizations compared to any sector in Tanzania necessary for application of big data for auditing purpose. The population of the study included 495 auditors obtained from the human resource database from national audit office of Tanzania. Yamane formula was used to estimate the sample size, as follows: n=$\frac{N}{1+Ne^2}$ 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 hence the sample size for the current study was 221 respondents. Using simple random sampling technique, 221 self-administered questionnaires were distributed to the selected sample. The collected data was analyzed using structural equation modelling (SEM). SEM was preferred because it allows researchers to model latent constructs (such as perceptions) using multiple observed variables (measurement items), enabling a more comprehensive understanding of the underlying relationships [44,45]. The latent constructs in the study were measured using multiple measurement items adapted from literatures and slightly modified to suit the specific context of the research (Appendix 1). A 5-point Likert scale was selected for capturing respondents' perceptions, as it is considered the most appropriate scale for this purpose [46]. To ensure the reliability and validity of the measurement items, factor loading analysis was conducted. Items that did not load sufficiently onto their respective constructs were eliminated from the analysis. The remaining items demonstrated significant factor loadings of 0.7 and above [47].

4. RESULTS AND DISCUSSION

4.1 Demographic Profile of Respondents

Three categories of the demographic characteristics of 221 respondents of this study were analyzed, namely gender, work experience and ICT knowledge. Thirty-seven-point six percent of the respondents were male, while 62.4% were female. In terms of work experience, less than six years were 18.1%, five up to nine years were 22.2% and greater than ten years were 59.8%. For ICT knowledge, only 23.1% were basic users, 57% intermediary users and 19.9% advanced users. Details of the demographic distributions are explained more in Table 1.

4.2 Non Response and Common Method Biases Check

In order to address the issue of non-response bias in data collection process, wave analysis approach was conducted [48]. The sample was divided into two sub-samples consisting of the first 111 respondents and the last 110 respondents. Then the means of selected demographic variables between the sub-samples was compared, and no statistically significant differences were found, as indicated in Table 2. This suggests that there is no significant non-response bias present in the sample.

To further examine the presence of common method bias, Herman's single factor tests was applied together with the recommended cutoff points [49]. The single factor analysis revealed that the created factor accounted for approximately 15% of the variation, which is significantly below the threshold of 50%. This finding confirms that there is no significant issue of common method bias in the study.

Table 1. Demographics of the respondents

Categories	Values	Frequency	%
Gender	Female	83	37.6
	Male	138	62.4
Work experience	Less than 6 years	40	18.1
	5-9 years	49	22.2
	Greater than 10 years	132	59.8
ICT knowledge level	Basic user	51	23.1
	Intermediary user	126	57
	advanced users	44	19.9

Source: Field data, (2023)

4.3 Measurement Model Assessment

Measurement model assessment aims to assess whether the proposed structural equation model is consistent with the sample data before testing hypothesis [45,44]. The model should fit the recommended model fit indices (Hair et al., 2018; Hofman et al., 2017). These indices are absolute fit indices, goodness of fit indices, incremental fit indices and parsimonious fit indices. Absolute fit indices measure how well theoretical model fit the sample data which is evaluated by Root Mean Square Error of Approximation (RMSEA) and Goodness of Fit Index (GFI) whose cut off criteria should be <0.06.and >0.9 respectively (Shmueli et al., 2019). Incremental fit was used to assesses the fitness of a structural equation model and it is evaluated by Tucke-Lewis Index (TLI) and Comparative Fit Index (CFI) whose acceptable criteria should be > 0.95 respectively [44,45,50].

Table 2. Non response Bias Test: Mean comparison between two sub samples

Variable	Test value	df	P-value
Gender	0.356	1	0.233
Work experience	0.313	1	0.495
ICT knowledge level	0.225	1	0.864

The analysis of the impact of awareness on big data adoption readiness yielded favorable results. The absolute fit indices indicate a strong model fit, with the RMSEA coefficient at 0.058, signifying good fit. Moreover, the Incremental fit indices, specifically the normed fit index (NFI) and comparative-fit-index (CFI), both scoring at 0.911 and 0.96 respectively, demonstrate a satisfactory fit (Shmueli et al., 2019). Additionally, the Parsimony fit indices, represented by the goodness of fit index (GFI) at 0.941 and the parsimony normed fit index (NFI) at 0.911, reinforce the well-fitting nature of the model. It's noteworthy that the Confirmatory factor analysis (CFA) approach in this study simultaneously tested all variables, not individually, due to the integration of a small number of items for each latent variable in the hypothesized model. In summary, the overall model fit, as reported in Table 3, is deemed acceptable, supported by the satisfactory fulfillment of Incremental fit indices and parsimony fit indices [44].

4.3.1 Convergent validity check

Before testing the hypotheses, the Confirmatory Factor Analysis (CFA) model was tested for convergent validity. This involved assessing factor loadings, composite reliability, and average variance extracted (AVE). According to Hair et al., [50] high factor loadings of at least 0.50 suggest that the items converge on a common point. Similarly, composite reliability, which shares an acceptable cutoff of at least 0.70 with Cronbach's alpha, was analyzed. Furthermore, high AVE values exceeding 0.5 demonstrate strong convergent validity for the latent variables [44]. The results shown in Table 3 indicate composite reliability values greater than 0.7 and AVE values higher than 0.5, affirming the convergent validity of all variables [50]. The measurement utilized was based on a five-point scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

4.3.2 Discriminant validity check

The Fornell-Larcker criterion was employed in evaluating discriminant validity. It involves comparing the average variance extracted (AVE) with the latent variable correlations [51]. The

Table 3. Model goodness fit indices

Indices	Estimate	Threshold	Interpretation
CMIN	169.904	--	--
DF	98	--	--
CMIN/DF	1.734	Between 1 and 3	Excellent
CFI	0.96	>0.95	Excellent
SRMR	0.058	<0.08	Excellent
RMSEA	0.058	<0.06	Excellent
PClose	0.185	>0.05	Excellent
TLI	0.951	>0.95	Excellent
GFI	0.941	>0.9	Excellent
AGFI	0.88	<0.9	Excellent
NFI	0.911	>0.9	Excellent

average variance extracted (AVE) should surpass the correlation with any other construct to establish discriminant validity [52]. In the present study, the application of the Fornell-Larcker criterion confirms discriminant validity, as the AVE values exceed the squared correlations between the latent constructs.

4.3.3 Structural model and hypotheses testing

The structural equation modeling illustrated in Fig. 2, was used to evaluate all the hypotheses. The assessment of the fit of the structural model provided the groundwork for testing the hypotheses. Significance at an alpha level of 0.05 was determined using the p-values associated with each standardized path estimate.

The findings presented in Table 6 outline the results of the four hypotheses formulated for this study. The structural equation modeling (SEM) analysis reveals that awareness significantly influences perceived usefulness ($\beta = 0.167$, $p < 0.009$) and perceived ease of use ($\beta = 0.184$, $p < 0.011$), thereby confirming support for H1 and H2. Moreover, perceived usefulness significantly predicts big data adoption readiness ($\beta = 0.711$, $p <=0.000$), supporting H3. Similarly, perceived ease of use emerges as a significant predictor of big data adoption readiness, with values ($\beta = 0.295$, $p=0.000$). The coefficient of determination for the proposed model indicates that awareness accounts for 51% of the variance in big data adoption readiness. The substantial R^2 of big data adoption readiness in the current study is significant [53,50].

Table 4. Construct measurement

Item	Factor Loading	CA (>0.7)	CR (>0.7)	AVE (>0.5)
AW1	0.87	0.917	0.917	0.689
AW2	0.796			
AW3	0.801			
AW4	0.862			
AW5	0.818			
PU1	0.835	0.801	0.809	0.519
PU2	0.797			
PU3	0.588			
PU4	0.631			
PEOU1	0.661	0.714	0.714	0.454
PEOU2	0.706			
PEOU3	0.653			
BDAR1	0.753	0.862	0.867	0.621
BDAR2	0.845			
BDAR3	0.7			
BDAR4	0.844			

CA: Cronbach's alpha, CR: composite reliability, AVE: Average Value Extracted, AW: Awareness, PU: Perceived usefulness, PEOU: Perceived ease of use, BDAR: Big data adoption readiness

Table 5. Discriminant validity

Variables	PU	AW	BDAR	PEOU
PU	0.721			
AW	0.19	0.83		
BDAR	0.718	0.196	0.788	
PEOU	0.542	0.195	0.576	0.674

Table 6. Structural path analysis result

			Estimate	P value
PU	<---	AW	0.167	0.009
PEOU	<---	AW	0.184	0.011
BDAR	<---	PEOU	0.295	***
BDAR	<---	PU	0.711	***

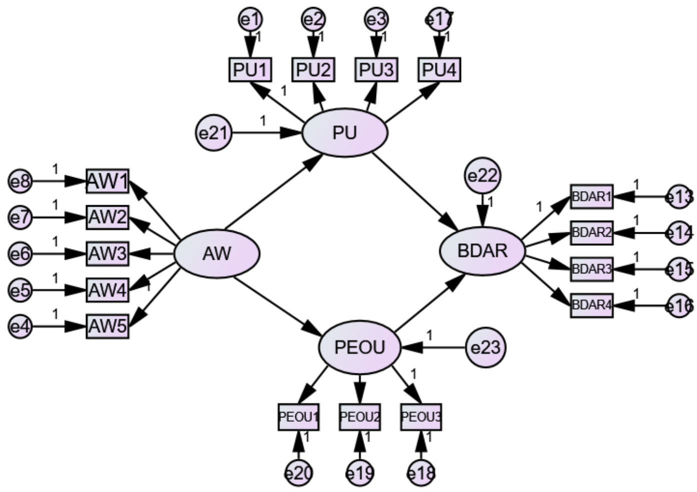

Fig. 2. Research structural model results

4.4 Discussion

The main objective of this study was to investigate the impact of awareness on the two key factors outlined in the TAM - perceived usefulness and perceived ease of use, and thereby ascertain big data adoption readiness. The study results indicate that awareness of big data technology had a statistically significant impact on perceived usefulness (β = 0.167) and perceived ease of use (β = 0.184). These findings align with those of (Lutfi et al., 2022; Verma et al.,2018) who observed that the Individuals who are already familiar with technology and data analysis tools may perceive big data as more useful and easier to use. Moreover, the study reveals that the original TAM factors proposed by Davis (1989), which are perceived ease of use (PEOU) and perceived usefulness (PU), both serve as predictors of big data adoption readiness, with values (β = 0.711, p = 0.000) and (β = 0.295, p = 0.000) respectively. This signifies that a greater perception of the ease of use of big data technology corresponds to a higher perception of its usefulness among auditors. This is consistent with prior research by Verma, et al., [54-56] in varied contexts and applications, revealing a significant positive influence of perceived ease of use on perceived usefulness. Auditors perceive that when big data is easy to use, their perception of its usefulness is likewise enhanced, leading to increased readiness for its adoption. Contrary based on the aforementioned, H3 and H4, the complexity of big data technologies and the required technical skills can affect individuals' perceptions. If individuals perceive big data as highly complex or if they lack the necessary technical skills, they may perceive it as less useful and more difficult to use. Generally, the findings clearly demonstrate that ease of use and usefulness are essential predictors of big data adoption readiness. Finally, the results indicate that perceived usefulness is the core determinants of big data adoption readiness with highest estimate β =0.711, p=0.000 while awareness is the main driver for perceived usefulness and perceived ease of use [57-60]. In overall, the study provides robust evidence supporting the role of awareness in enhancing perceived usefulness and ease of use, thereby promoting big data adoption readiness among auditors in public sector. The alignment with TAM and prior research reinforces the validity of the findings of this study [61-63]. However, potential limitations such as the complexity of big data technologies, and the cross-sectional design suggest areas for further research.

5. CONCLUSION AND IMPLICATIONS

5.1 Conclusion

The primary objective of this study was to examine the effect of awareness on main constructs of TAM (perceived usefulness and perceived ease of use) in big data adoption readiness in the context of public sector auditing in Tanzania. The results have shed some encouraging light on how awareness plays a crucial role in shaping individual perceptions. If individuals are familiar with big data, they are more likely to perceive big data as useful and easy to use. Moreover, the study revealed that perceived usefulness acts as a driving force for big data adoption readiness. As demonstrated by this study, when individuals are aware of the potential benefits and value that a big data offers, they are more likely to perceive it as useful to their needs. Awareness creates an understanding of how the big data can enhance productivity, efficiency, decision-making, and overall outcomes. The comprehensive understanding of the effect of awareness on perceived ease of use and perceived usefulness contributes to a deeper comprehension of the factors influencing big data adoption readiness. By harnessing the power of awareness, organizations can create an environment that promotes positive perceptions, facilitates big data adoption, and drives successful implementation of innovative solutions.

5.2 Theoretical Implications

TAM is underpinning theory in this study. Based on TAM, the conceptual model validates the role of awareness that drive the perceived ease of use and perceived usefulness, therefore affecting the big data adoption readiness. By extending the TAM model to include awareness as an external variable, this study enriches the understanding of how awareness influences perceived usefulness and perceived ease of use, which consequently impacts big data adoption readiness. This expansion of the TAM framework aligns with the evolving landscape of technological adoption and underscores the importance of considering external factors such as awareness in shaping users' attitudes and perception towards new technologies. Additionally, the findings affirm the relevance of TAM by demonstrating its applicability in the context of big data technology within the context of auditing. The study's outcomes not only validate the core constructs of TAM, namely perceived usefulness and perceived ease of use, but they also highlight the significant influence of awareness on these factors and their subsequent impact on big data adoption readiness. This further solidifies the TAM as a robust and adaptive theoretical framework capable of explaining technology acceptance and adoption in diverse settings. Moreover, the study provides empirical evidence of the interconnectedness between awareness, perceived usefulness, perceived ease of use, and big data adoption readiness. This deeper understanding of the interplay between these variables contributes to the ongoing development and refinement of the TAM, shedding light on the nuanced dynamics of technology acceptance and offering insights into the factors that drive users' willingness to embrace new technologies such as big data.

5.3 Practical implication

The results of this study provide public sector auditing with awareness factors that impact auditor’s perception on adoption of big data. The findings revealed that when individuals are aware of a big data and its functionalities it develops a better understanding of how it works and perceive it ease of use. Awareness reduces uncertainty, fear, and resistance in adopting the big data which positively influences its adoption readiness. More precisely, the findings highlight that awareness help individual to recognize the relevance and applicability of big data in auditing. To ensure a higher level of uptake of the big data, individuals need to have access to user-friendly analytics tools, availability of support and guidance, such as technical support and documentation which impact their perception on perceived ease of use. When individuals feel supported and have access to resources to address challenges or questions related to big data, they are more likely to perceive it as easier to use.

The Practical contribution of this study lies in highlighting the crucial role of awareness-building initiatives in promoting the adoption of big data technologies, particularly in the context of public sector auditing and government institutions. This insight can guide these entities in designing effective training programs, seminars, and collaborations that enhance awareness and knowledge of big data. By empowering auditors with a deeper understanding of big data and its practical applications, these initiatives enable more informed decision-making regarding big data adoption.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Authors hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of manuscripts.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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APPENDIX

Appendix 1. Instrument for construct

Construct	Items	Source
Awareness (AW)		Acciarini et al. [12]
AW1	I am aware of structured and unstructured data found within the organization	
AW2	I am aware of big data characteristics	
AW3	I am familiar with big data analytical tools, software and platforms	
AW4	I have heard stories and news about the benefits of big data analytic in auditing	
AW5	In general, I know about big data capability in auditing	
Perceived usefulness (PU)		Garmaki et al. [38]
PU1	I think using big data in auditing would enable me to accomplish auditing tasks effectively and efficiently	
PU2	I think big data would enable me to uncover anomalies and identify frauds compared to traditional auditing approaches	
PU3	In general, I would find big data useful	
PU4	I think that using big data analytics in auditing will enhance my effectiveness by auditing the entire population rather than sample based	
Perceived ease of use (PEOU)		Tahar et al. (2020)
PEOU1	I would find big data easy to use	
PEOU2	Learning to use big data analytics would be easy	
PEOU3	I would find big data analytics to be flexible to interact with	
Big data adoption readiness (BDAR)		Hezam et al., [1]
BDAR1	Assuming I have access to big data, I intend to use it	
BDAR2	I would use big data analytics in conducting auditing tasks	
BDAR3	If I have access to big data, I want to use it as much as possible	
BDAR4	In general, if I have access to big data analytics, I am ready to use it	

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