International Research Journal of
BUSINESS STUDIES

ISSN: 2089-6271 | e-ISSN: 2338-4565 | https://doi.org/10.21632/irjbs

Vol. 18 | No. 3

Driving Innovation in Data Analytics Adoption for Auditing in Tanzania's Banking Sector

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ARTICLE INFO

Keywords:
Data Analytics,
Auditing,
Organisational factors,
Innovative Behaviour,
Tanzania's Banks.

Kata Kunci:
Analisis Data,
Audit,
Faktor Organisasi,
Perilaku Inovatif,
Bank-Bank Tanzania.

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ABSTRACT

This study explores the factors affecting Data Analytics (DA) adoption in Tanzanian commercial banks' audit functions by expanding the Technology Acceptance Model (TAM) with Organisational Factors (OF) and Innovative Behaviour (IB). Using a quantitative approach, data were gathered from 193 internal auditors and analysed with SmartPLS through Partial Least Squares Structural Equation Modelling (PLS-SEM). The study found that perceived Usefulness, innovative behaviour, leadership support, Organisational culture, and technological infrastructure significantly influence DA adoption. Surprisingly, financial resources and regulatory compliance negatively affect adoption. Contrary to traditional TAM expectations, perceived ease of use and employee training do not have a significant impact. Practical implications indicate that banks should promote innovation, invest in infrastructure, and align regulatory frameworks with digital transformation objectives. Policymakers should create supportive environments, while practitioners must incorporate analytics into auditing workflows. Future research should examine longitudinal trends and cross-country comparisons, and provide qualitative insights into financial and regulatory challenges.

SARI PATI

Studi ini menelaah faktor-faktor yang memengaruhi adopsi Data Analytics (DA) dalam fungsi audit bank-bank komersial di Tanzania dengan memperluas Technology Acceptance Model (TAM) melalui penambahan Faktor Organisasi (Organisational Factors/OF) dan Perilaku Inovatif (Innovative Behaviour/IB). Menggunakan pendekatan kuantitatif, data dikumpulkan dari 193 auditor internal dan dianalisis dengan SmartPLS melalui Partial Least Squares Structural Equation Modelling (PLS-SEM). Hasil penelitian menunjukkan bahwa persepsi kegunaan, perilaku inovatif, dukungan kepemimpinan, budaya organisasi, dan infrastruktur teknologi berpengaruh signifikan terhadap adopsi DA. Secara mengejutkan, sumber daya keuangan dan kepatuhan regulasi berdampak negatif terhadap adopsi. Bertentangan dengan ekspektasi TAM tradisional, persepsi kemudahan penggunaan dan pelatihan karyawan tidak memberikan pengaruh yang signifikan. Implikasi praktis menunjukkan bahwa bank perlu mendorong inovasi, berinvestasi dalam infrastruktur, serta menyelaraskan kerangka regulasi dengan tujuan transformasi digital. Pembuat kebijakan perlu menciptakan lingkungan yang lebih mendukung, sementara para praktisi harus mengintegrasikan analitik ke dalam alur kerja audit. Penelitian selanjutnya disarankan untuk mengkaji tren longitudinal dan perbandingan antarnegara, serta memberikan wawasan kualitatif mengenai tantangan finansial dan regulasi.

INTRODUCTION

In recent years, the adoption of data analytics has transformed auditing practices by enabling auditors to process large volumes of data, detect anomalies, and generate timely, data-driven insights (Appelbaum et al., 2017). Globally, auditing functions are increasingly integrating DA tools to enhance audit quality, efficiency, fraud detection, and compliance with regulatory standards (Alles, 2015). However, the pace and extent of data analytics adoption remain uneven—particularly in developing economies such as Tanzania, where disparities in technological infrastructure, digital skills, and institutional readiness persist across financial institutions. Although data analytics had the potential to improve audit quality, fraud detection, and regulatory compliance, many internal audit functions in Tanzanian banks continued to depend on traditional, manual techniques that were time-consuming and less effective in a data-driven environment (Alles, 2015). Within Tanzanian commercial banks, internal audit departments played a crucial role in safeguarding assets, ensuring compliance, and enhancing governance frameworks. As the banking sector became more digitised, there was an increasing need for audit functions to modernise by adopting data analytics tools. Despite the recognised benefits, the adoption of these tools remained limited (Abdelwahed et al., 2024; Saud et al., 2025), prompting inquiries into the underlying factors that either facilitated or obstructed their adoption.

Organisational challenges such as inadequate IT infrastructure, limited managerial support, and insufficient training, along with individual factors such as low innovation orientation, contributed to the slow adoption of data analytics tools in audit functions (Awuah et al., 2022; Islam & Stafford, 2022). Since data analytics is being embraced worldwide by auditors (Abdelwahed et al., 2025; Ilori et al., 2024; Kamdjoug et al., 2024), the need arises to explore its use in the Tanzanian context. Nevertheless, to the best of the researcher's knowledge, there is a scarcity of empirical studies on the adoption of data analytics for auditing functions in Tanzania.

To investigate its adoption, the study employed the Technology Acceptance Model (TAM). TAM has been empirically validated and widely applied to explain technology adoption in various contexts, notably in auditing (Al-Ateeq et al., 2022; Bin-Nashwan et al., 2025; Ceki & Moloi, 2025; Jeon, 2014). Therefore, its selection is fitting in the context of the current study. However, its two primary constructs, perceived Usefulness and perceived ease of use, primarily emphasise individual perceptions and do not fully account for contextual and behavioural factors relevant to developing economies such as Tanzania.

This study addressed that gap by extending TAM with two additional constructs—Organisational Factors (OF) and Innovative Behaviour (IB)—to examine the multifaceted factors influencing DA adoption in Tanzanian commercial bank audits. These factors are crucial for successful technology implementation (Ifinedo, 2011). The lack of empirical research exploring these elements in this specific context hindered effective policy development, capacity building, and strategic technology investment in the audit profession. Therefore, gaining deeper insights into these influences was necessary to support the effective implementation of data analytics in internal auditing across the Tanzanian banking sector.

Literature Review, Theoretical Framework, and Hypotheses

Data Analytics and Auditing in Tanzania

Most banking operations in Tanzania are conducted through digital platforms linked to third-party services like Tanzania Instant Payment Systems (TIPS), Mobile Money Operators (MNOs), and the Government Electronic Payments Gateway (GePG). As a result, large volumes of data are generated during these processes. Consequently, conducting audits using traditional methods becomes increasingly challenging. Therefore, integrating ICT into auditing practices has become crucial to improve efficiency, accuracy, and the scope of audits (Abdelwahed et al., 2025; Ahmed Saad Abdelwahed et al., 2025; Dagilienė & Klovienė, 2019). Support for the use of ICT in auditing is endorsed by professional bodies in Tanzania; for example, the Institute of Internal Auditors (IIA, 2024) promotes data analytics and continuous auditing, while the NBAA has incorporated big data analytics into its recent curriculum updates (NBAA, 2023). These developments highlight a shift in Tanzania's auditing landscape towards embracing ICT, especially emerging technologies such as Artificial Intelligence and big data analytics.

Theoretical Framework and Hypotheses

The conceptual framework for this study is based on the Technology Acceptance Model (TAM). However, the original TAM, when used alone, was considered too general to explain the adoption of data analytics clearly. TAM has been applied across various areas of information technology and information systems. It was also confirmed that TAM is a robust research model that produces statistically reliable results. Therefore, TAM was integrated with context-specific external variables. TAM provides a psychological foundation for encouraging users to adopt technology by shaping their perceptions of its Usefulness and ease of use (Krah et al., 2024), while organizational factors (i.e., organizational culture, leadership support, financial resources, technology infrastructure, employee training and skills, and regulatory requirements) provide a favourable environment for the adoption and implementation of the technology (Oyetade et al., 2024).

Additionally, innovative behaviour may drive employees to experiment with new ideas, influence peers, and extend technology beyond its intended scope. While each factor (i.e., TAM, OR, and IB) contributes independently to the adoption of data analytics for auditing, their combined effect is often synergistic. The integrated effects of each factor form a theoretical framework shown in Figure 1, which was adopted in the current study to explore data analytics adoption in the internal audit functions of Tanzanian commercial banks. The relationship between the variables of the study is discussed in the following section.

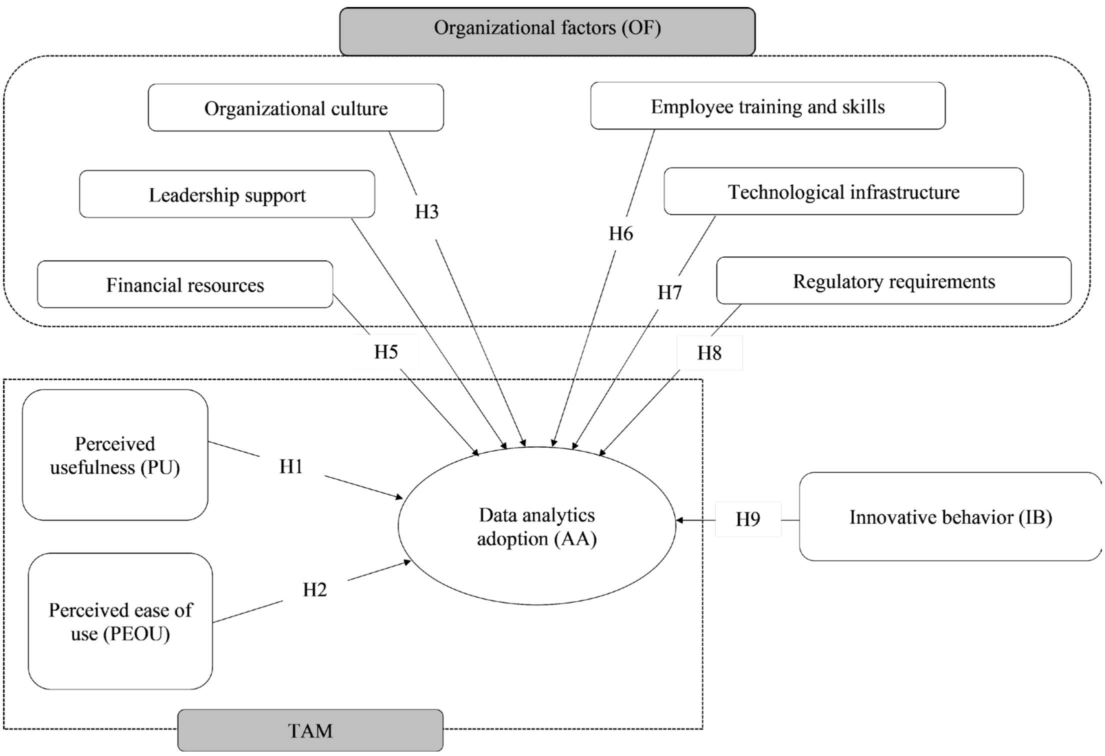


Figure 1. Theoretical Framework

Perceived Usefulness was introduced by Davis (1989) as a key factor in the Technology Acceptance Model (TAM), describing it as the extent to which an individual believes that using a system would improve job performance. In this study's context, it suggests that data analytics could enhance auditing performance. The variable has been recognised for its significant impact on users' intention to adopt technology across various settings (Venkatesh & Davis, 2000). Consequently, previous studies have confirmed that it has a direct and notable influence on the adoption of emerging technologies such as big data and artificial intelligence in auditing (Al-Ateeq et al., 2022; Hamadeh et al., 2025). Therefore, the study posits that:

H1: The perceived Usefulness of data analytics positively and significantly influences its adoption in Tanzanian commercial banks' audit functions.

Perceived ease of use refers to the extent to which an individual believes that using a particular system would require no effort (Davis,1989). As the system becomes easier to use, the likelihood of its adoption increases. Previous studies have demonstrated that perceived ease of use significantly affects the adoption of technology and innovation in accounting and auditing practices (Bin-Nashwan et al., 2025). Similarly, the current study predicts that:

H2: Perceived ease of use of data analytics positively and significantly influences its adoption in Tanzanian commercial banks' auditing functions.

Organisational factors include various internal and external factors that influence technology adoption, such as an innovation-driven culture, leadership backing, financial resources, employee training, technological infrastructure, and regulatory requirements (Al-Okaily et al., 2024; Clohessy & Acton, 2019; Sun et al., 2018). The study by Al-Okaily et al (2024) showed that organisational factors such as top management support, financial resources, and employee IT expertise play a significant role in technology adoption. Mushi (2024) also identified organisational components such as infrastructure, training, and leadership as affecting the adoption of e-government services. These factors shape organisations' readiness to implement technological innovations. Hence, the study hypothesises that:

H3: A supportive organisational culture positively influences the adoption of data analytics in audit functions.

H4: Strong leadership support positively affects banks' readiness to adopt data analytics in their audit functions

H5: The availability of adequate financial resources significantly affects the adoption of data analytics in audit functions.

H6: Employee training and expertise positively influence the adoption of data analytics in auditing functions.

H7: The presence of robust technological infrastructure positively impacts the adoption of data analytics in auditing functions.

H8: Compliance with regulatory requirements positively influences the adoption of data analytics in auditing functions.

Innovative behaviour demonstrates a willingness to embrace creativity and new ideas to improve performance (Bos-Nehles et al., 2017). Empirical evidence from Tarhini et al (2015) showed that 40 per cent of innovative organisations are quicker to adopt technologies that enhance their operational performance. In the current study, it is anticipated that organisational innovative mindsets and behaviour could help overcome resistance to adopting data analytics for auditing, reflecting global trends that associate innovation with openness to technology. Thus, the hypothesis:

H9: Innovative behaviour positively influences the adoption of data analytics in auditing functions.

METHODS

Research Design

The adopted positivist research philosophy emphasises the use of scientific methods to study observable phenomena, with a focus on empirical evidence, objectivity, and systematic analysis. It assumes that reality is independent of human perception and can be measured and understood through observation, experimentation, and logical reasoning (Creswell et al., 2018).

A positivist approach was utilised to examine data analytics adoption in Tanzanian bank audit functions, using structured questionnaires to assess perceived ease of use, perceived Usefulness, organisational context, and innovative behaviour. The data collected were analysed statistically to identify significant trends and relationships, aligning with the positivist belief in empirical validation (Saunders et al., 2019). Since the study focuses on establishing causal relationships between the variables, positivism is suitable for this research.

Instrument and Sampling

In line with positivism, the study employed a quantitative research approach and used closed-ended questionnaires for data collection. The questionnaires were developed by adopting measurement items from previous studies, as shown in Table 1.

Table 1. Measurement Items

Variable		Source
Perceived Usefulness (PU)	1. Using data analytics enhances my auditing performance. 2. Data analytics provides relevant insights that help in decision-making. 3. Data analytics is useful for achieving my job-related goals. 4. Data analytics enables faster completion of auditing tasks 5. Data analytics assists in the reduction of error rates	(Davis, 1989; Venkatesh et al., 2003)
Organisational Culture (OC)	1. The organisation's culture encourages innovation and creativity 2. Auditors are open to adopting data analytics 3. There is a shared commitment to achieving organisational goals 4. Teamwork and collaboration are strongly supported within the organisation	
Leadership support (LS)	1. Senior management is committed to adopting data analytics in auditing. 2. Leadership participates in training sessions or workshops related to auditing innovations. 3. Top management actively supports technology-driven initiatives. 4. Managers encourage employees to use analytics in their work 5. Resources are allocated by leadership for technology adoption	
Financial resources (FR)	1. The organisation has sufficient budget to invest in data analytics tools. 2. Investments are made in upgrading the IT infrastructure regularly. 3. Funds are readily available for training employees on data analytics. 4. The organisation prioritises funding for research and innovation.	(Ali et al., 2022)
Employee training and skills (ES)	1. Auditors receive adequate training to use data analytics tools effectively. 2. The organisation provides continuous learning opportunities for data analytics adoption. 3. Auditors possess the required skills to handle analytics software and systems. 4. There are workshops or programs to enhance employees' data analytics expertise. 5. Auditors are confident in applying data analytics in their roles.	

Variable		Source
Technological Infrastructure (TI)	1. Current technological infrastructure supports the integration of data analytics tools. 2. Systems and software are updated regularly to meet organisational needs. 3. The IT department provides timely support for data analytics-related issues. 4. The organisation has modern and reliable IT systems.	
Regulatory Requirements (RR)	1. Auditors are aware of regulatory requirements for data analytics. 2. Compliance with regulations is integrated into data analytics adoption processes. 3. Regulatory policies are considered in the design and implementation of data analytics systems.	
Perceived Ease of Use (PEOU)	1. Learning to use data analytics tools is easy. 2. Data analytics tools are user-friendly. 3. Using data analytics requires little effort. 4. Troubleshooting issues with the system is quick and straightforward. 5. Data analytics tools integrate seamlessly with other tools I use	(Davis, 1989; Venkatesh et al., 2003)
Innovative behaviour (IB)	1. Auditors frequently suggest creative ideas for improving work processes 2. Auditors proactively look for opportunities to incorporate new technologies into their work. 3. The organisation encourages experimentation with new tools and methods 4. There is a culture of adopting innovative technologies to stay competitive	(Kang & Lee, 2017)
Actual Adoption (AA)	1. I frequently use data analytics in my auditing tasks. 2. I use Data analytics as a core component of my auditing activities. 3. I rely on data analytics for critical auditing decisions. 4. The time I spend using data analytics has increased over time.	(Ifinedo, 2011)

The questionnaires were distributed to internal auditors responsible for audit functions within Tanzanian commercial banks in Dar es Salaam, as they are the end users expected to apply data analytics in their audit engagements. The target population remained unidentified due to the absence of a centralised registry of internal auditors for Tanzanian commercial banks. Regulatory bodies like the National Board of Accountants and Auditors (NBAA) and the Bank of Tanzania (BOT) provided general oversight. Still, they lacked specific data on internal auditors for each commercial bank. As a result, the study employed non-probability sampling, snowball sampling, focusing on auditors actively engaged in audit functions within these institutions. For sample size estimation, Cochran's formula for an unknown population (Cochran, 1977) was used, ensuring the research maintained statistical rigour despite the lack of concrete population data. The formula yielded a sample size of 384 respondents, as follows:

$$n = \frac{Z^2.p.(1 - p)}{e^2}$$

Where: ***n*** = required sample size, **Z** = Z-value (standard normal deviate corresponding to the desired confidence level; e.g., 1.96 for 95 percent), **p** = estimated proportion of the population (use 0.5 if unknown for maximum variability), and **e** = margin of error (e.g., 0.05 for ±5 percent precision) were assumed. Out of the 384 expected sample size, only 193 (50.3 per cent) valid questionnaires were collected and used in the subsequent data analysis. The respondents' profiles are reported in Table 2.

Table 2. The Profile of Respondents

Variable	Category	Frequency(f)	Percentage
Gender	Female	75	38.9
	Male	118	61.1
Age	22- 32	109	56.5
	33-43	59	30.6
	44-55	21	10.9
	Above 55	4	2.0

Data Analysis and Ethical Considerations

The researcher employed Partial Least Squares Structural Equation Modelling (PLS-SEM) using SmartPLS 4.1 to validate the measurement model and test the hypothesised relationships. PLS-SEM is a component-based approach that is particularly advantageous for analysing complex models with limited sample sizes and less restrictive assumptions about data distribution (Hair et al., 2022). Unlike covariance-based SEM techniques, PLS-SEM avoids issues such as inadmissible solutions and factor indeterminacy, making it well-suited for exploratory research and predictive modelling (Hair et al., 2022). Additionally, PLS-SEM is robust in handling both reflective and formative constructs, enhancing its applicability in social science and business research (Henseler et al., 2015). Given these strengths, PLS-SEM was deemed the most appropriate analytical tool for this study.

The study acknowledges the limitations of smaller sample sizes in generalizing the findings; however, the outcomes of the study are still relevant because PLS-SEM can handle models with small sample sizes (i.e., 193 out of 384, equivalent to a 50.3 per cent response rate). The study adhered to recognised ethical standards to ensure research integrity and protect participants' rights. Participants were informed of the study's purpose, the voluntary nature of participation, and their right to withdraw at any time. Informed consent was obtained prior to data collection. Confidentiality and anonymity were maintained, with no personal identifiers collected and data reported in aggregate form. Participation was voluntary, with no coercion or incentives provided.

RESULTS AND DISCUSSION

Measurement Model Validation

The quality of constructs in this study was assessed through a rigorous evaluation of the measurement model, following established PLS-SEM guidelines (Hair et al., 2022). The assessment examined construct reliability and validity, verified using indicators such as reliability, Cronbach's alpha (α), and composite reliability (CR), with thresholds exceeding 0.70 confirming internal consistency (Hair et al., 2019). Additionally, construct validity was established through convergent validity (average variance extracted, AVE > 0.50) (Hair et al., 2019), and discriminant validity was assessed via the Heterotrait-Monotrait ratio (HTMT) criterion (Henseler et al., 2015). The study found that all constructs exceeded 0.70 for Cronbach's alpha (α) composite reliability, demonstrating exceptional reliability. Further, convergent validity was established because the AVEs were >0.50. Overall, all constructs surpassed critical thresholds, as reported in Table 3.

Regarding discriminant validity, the HTMT results showed strong discriminant validity for most construct pairs in the measurement model, with all values falling below the conservative threshold of 0.85 (Henseler et al., 2015). Our analysis revealed HTMT values ranging from 0.516 to 0.858 (Table 4). The overall results supported the model's discriminant validity, as all construct pairs recorded HTMT values below the 0.90 threshold, indicating acceptable discriminant validity. In summary, the results provided compelling evidence for discriminant validity.

Table 3. Construct reliability and convergent validity

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AA	0.931	0.935	0.951	0.829
ES	0.884	0.916	0.912	0.675
FR	0.883	0.935	0.915	0.730
IB	0.894	0.904	0.926	0.758
LS	0.895	0.914	0.923	0.706
OC	0.917	0.957	0.940	0.795
PEOU	0.822	0.847	0.874	0.582
PU	0.935	0.947	0.951	0.794
RR	0.899	0.907	0.937	0.831
TI	0.932	0.939	0.952	0.831

Table 4. Heterotrait-Monotrait Ratios

	AA	ES	FR	IB	LS	OC	PEOU	PU	RR	TI
AA										
ES	0.585									
FR	0.362	0.731								
IB	0.843	0.619	0.266							
LS	0.534	0.477	0.782	0.298						
OC	0.288	0.242	0.486	0.117	0.732					
PEOU	0.144	0.236	0.084	0.249	0.097	0.054				
PU	0.140	0.475	0.401	0.232	0.271	0.261	0.100			
RR	0.224	0.173	0.131	0.250	0.148	0.048	0.162	0.363		
TI	0.793	0.785	0.607	0.791	0.531	0.216	0.183	0.259	0.245	

Hypotheses Testing

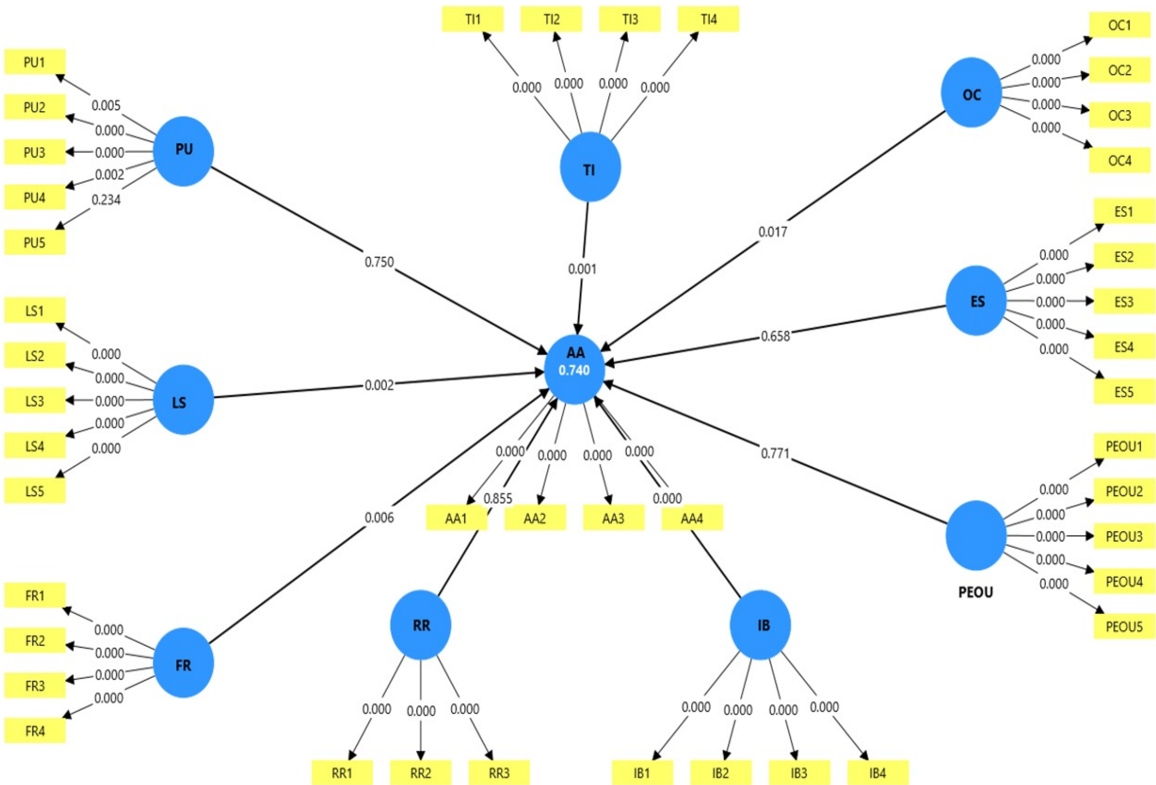
After successfully evaluating the measurement model, the study moved on to assess the structural model. The results of the structural model are presented systematically, in line with the study's hypotheses, as shown in Table 5 and Figure 2. Specifically, out of nine (9) hypotheses, seven (7) were supported.

Discussion

The study found that perceived Usefulness positively affects the adoption of data analytics for auditing functions. The findings indicate that audit professionals perceive data analytical tools as capable of enhancing their job performance. These results are consistent with prior studies, such as those of Hasnan et al (2023). Conversely, the

Table 4. Heterotrait-Monotrait Ratios

Paths	Original	T statistics	P values	Results
ES -> AA	0.073	0.996	0.319	Not supported
FR -> AA	-0.196	2.851	0.004	Supported
IB -> AA	0.551	6.735	0.000	Supported
LS -> AA	0.262	3.217	0.001	Supported
OC -> AA	0.124	2.915	0.004	Supported
PEOU -> AA	-0.037	0.846	0.398	Not supported
PU -> AA	0.154	3.213	0.001	Supported
RR -> AA	-0.096	2.103	0.035	Supported
TI -> AA	0.310	3.425	0.001	Supported



findings showed that perceived ease of use does not influence the adoption of data analytics. This contradicts conventional TAM expectations (Davis, 1989) but aligns with recent findings in professional contexts, where ease of use becomes less critical than utility (Venkatesh & Bala, 2008). This suggests Tanzanian auditors prioritise functional benefits over simplicity.

Furthermore, the study confirmed that five organisational context constructs influence the adoption of data analytics in audit functions. Specifically, the study found that supportive organisational culture (OC) fosters its adoption. These findings align with those of Behl et al (2022), who posit that organisational culture and assumptions shape technology adoption patterns. The positive coefficient indicates that innovation-supportive cultures enhance the implementation of analytics. Additionally, the study confirmed that leadership support (LS) positively impacts the adoption of data analytics tools in auditing. The findings suggest that strong leadership commitment improves the implementation of data-driven auditing in Tanzanian commercial banks. This aligns with the study by Baba et al (2023), which identified leadership as a key enabler of fintech adoption in African banking sectors.

Furthermore, the availability of adequate financial resources negatively influences the adoption of data analytics in audit functions. The finding, surprisingly, suggests that greater financial resource (FR) availability is associated with lower adoption rates in this context. Contrary to the Resource-Based View (RBV) theory (Barney et al., 2001), which states that financial capacity facilitates technology investment, possible reasons for this negative effect include that commercial banks with larger budgets may prioritise other IT investments over data analytics tools. For example, they might focus on cybersecurity implementation or core banking system upgrades. Additionally, organizational inertia—the tendency to stick to established patterns of thinking and activities (Hur et al., 2019)—could contribute to the adoption of innovative data analytics techniques for auditing purposes. Consequently, the availability of abundant resources may paradoxically discourage experimentation and delay the transition to data-driven auditing practices.

Next, the findings on the influence of employee training and skills (ES) on the adoption of data analytics tools for the auditing function showed that it has no effect. The finding implies that enhancing employee skills may not directly increase the adoption rates of data analytics tools for auditing. Existing training programmes may not have aligned with the technical requirements of data analytics. Therefore, redesigning training programmes to focus on applied analytics in auditing rather than generic upskilling could be beneficial.

Further analysis revealed that technological infrastructure (TI) strongly influences the adoption of data analytics. The finding is consistent with the Technology-Organisation-Environment (TOE) Framework (Tornatzky et al., 1990), which indicates that technological readiness (including infrastructure) is a critical factor for adoption. In addition to technological infrastructure, compliance with regulatory requirements (RR) is crucial. However, it negatively impacts adoption. The finding aligns with that of Christiansen et al (2022), which indicated that regulatory pressures hinder adoption rates. The results suggest that regulatory requirements may be perceived as barriers rather than enablers. At the moment, Tanzania lacks clear policies and regulations for accessing and using big data (NBS, 2025). The absence of these policies and regulations may have reduced banks' willingness to adopt data analytics for auditing.

Finally, the study confirmed that innovative behaviour positively influences the adoption of data analytics for auditing in Tanzanian commercial banks. Banks with a culture of innovation are significantly more likely to implement data analytics in their audit functions. Additionally, innovative banks are more willing to experiment with new tools, such as using data analytics for auditing. The finding aligns with Chipeta and Muthinja (2018), who discovered that innovative banks led digital transformation.

MANAGERIAL IMPLICATIONS

The findings indicate that data analytics tools are valuable for auditing functions. Therefore, it is imperative that practitioners, particularly in banks, actively integrate analytics into their auditing practices. The findings call for bank leadership to invest in modern technological infrastructure, such as cloud-based platforms and financial data integration tools, to enable data analytics at scale. Since innovative behaviour is crucial for adoption, cultivating a culture of innovation is vital. This involves encouraging experimentation through pilot programmes, recognising data-driven improvements, and overcoming resistance to change. Moreover, because increasing financial resources alone does not guarantee success, banks should optimise financial planning with cost-benefit analyses and explore innovative funding strategies. Since current generic employee training and upskilling programs fail to effectively promote the adoption of data analytics in auditing, banks must significantly revamp their training strategies to focus on specific data analytics tools and directly connect them to the auditing environment. Emphasis should be on experiential learning through real audit data, case studies, and ongoing mentorship to better link training with practice.

The NBAA's and BOT's endorsement of using data analytics for auditing should extend to establishing regulatory requirements that promote its adoption in banks' auditing practices. By doing so, banks could swiftly use data analytics without compromising policies and regulatory requirements governing organizational data access. Furthermore, regulators (such as BOT and NBAA) should collaborate closely with banks to align compliance frameworks with the goals of digital transformation, ensuring that regulatory expectations do not hinder innovation.

Simultaneously, banks should develop strategies to incorporate analytics into compliance procedures. Emphasising the importance of organisational culture and leadership support, it is necessary to foster a positive organisational culture that encourages the adoption of emerging technologies, such as data analytics tools for auditing. Likewise, bank management should lead the adoption process by allocating budgets for technology and training, and by engaging in high-level discussions with other key stakeholders in the profession and government to promote the use of data analytics tools within auditing functions.

CONCLUSION

Summary of Findings and Research Contributions

The study aimed to evaluate the factors influencing data analytics adoption in the auditing functions of Tanzanian commercial banks. It also sought to develop a conceptual model for assessing data analytics adoption. The findings indicated that key areas for adopting data analytics in the auditing functions of Tanzanian commercial banks include perceived Usefulness, innovative behaviour, leadership support, organisational culture, and technological infrastructure. Additionally, efforts should be directed towards mitigating the negative effects of financial resources and regulatory requirements on the successful adoption of data analytics for auditing purposes. Moreover, the study makes three significant contributions to the field of research. Firstly, based on the literature review and the researchers' expertise, this may be the first study to examine the adoption of data analytics tools in auditing functions within Tanzanian commercial banks. Secondly, it extends the Technology Acceptance Model (TAM) by incorporating organisational context and innovation behaviour factors, providing new insights on how TAM variables interact with these factors to influence data analytics adoption in auditing. Thirdly, the coefficient of determination suggests that the model has considerable explanatory power, further supporting the validity of the proposed theoretical framework.

Limitations of the Study and Areas for Future Studies

Although the study made valuable contributions, several limitations were observed. Firstly, the findings were specific to the Tanzanian banking sector and might not be applicable beyond it due to differences in institutional, regulatory, and technological environments. Secondly, the study used cross-sectional survey data, which limited the ability to detect trends or establish causality. Thirdly, the reliance on self-reported data raised the possibility of response bias, as participants may have exaggerated their institutions' readiness for adoption.

This study opens several pathways for future research. Long-term studies could monitor how data analytics adoption in Tanzanian banks evolves over time, helping differentiate between temporary challenges and ongoing barriers, such as regulatory constraints or financial limitations. Moreover, future research should examine contextual factors such as bank size, ownership, and technological maturity to understand how they influence adoption patterns. Comparative studies across East African countries could further clarify whether the findings are unique to Tanzania or indicative of broader regional trends.

The unexpected negative effects of financial resources and regulatory requirements also deserve further investigation. Qualitative studies could examine why larger budgets sometimes hinder the adoption of innovative solutions, such as data analytics. ■

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