Innovation Traits and Big Data Technology Adoption Readiness in Public Sector Auditing in Tanzania

Albert Moshi[1], Alfred Sife[2] & George Matto[2]
[1]*Tanzania Institute of Accountancy, Tanzania*
[2]*Moshi Co-operative University, Tanzania*

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Abstract
Big Data Technology (BDT) offers considerable potential for public sector auditing by enabling auditors to analyse large and heterogeneous datasets, detect anomalies and risks, verify compliance, and support audit decision-making. In Tanzania, public sector auditing has progressively incorporated information and communication technologies and information systems; however, the audit environment remains largely centred on structured data. BDT extends these capabilities by facilitating the analysis of structured, semi-structured, and unstructured data at greater scale. Despite this potential, auditors' preparedness to engage with BDT remains unclear, particularly in relation to perceived innovation traits. Drawing on Diffusion of Innovation (DOI) Theory, this study examined the associations between Complexity, Incompatibility, Relative Advantage, and BDT Adoption Readiness among National Audit Office of Tanzania (NAOT) auditors in Dodoma. A cross-sectional quantitative design was employed, with questionnaire data collected from 221 auditors selected using stratified and simple random sampling. Data were analysed using descriptive statistics and binary logistic regression. Results showed that Complexity ($\beta = -0.66$, OR = 0.52, $p = .0005$) and Incompatibility ($\beta = -0.63$, OR = 0.54, $p = .0017$) were significantly associated with lower odds of high BDT Adoption Readiness. Conversely, Relative Advantage ($\beta = 0.78$, OR = 2.18, $p = .0001$) was significantly associated with higher odds of high readiness. These findings demonstrate that BDT Adoption Readiness is associated with auditors' perceptions of technological benefits, complexity, and compatibility with existing audit practices. The study underscores the importance of addressing perceived technological barriers while strengthening auditors' recognition of BDT's practical value within public sector auditing.

Introduction

Big Data Technology (BDT) has become increasingly relevant to auditing as digitalisation generates growing volumes of heterogeneous data that require advanced approaches to storage, processing, and analysis. Big Data refers to large, complex, and heterogeneous datasets characterised particularly by high volume, velocity, and variety, whose management and analysis may exceed the capabilities of conventional data-processing approaches (Badshah et al., 2024; Tosi et al., 2024). BDT, in turn, encompasses the technological tools, platforms, architectures, and analytical capabilities used to capture, store, process, integrate, and analyse such data (Badshah et al., 2024). In auditing, these capabilities enable the analysis of large and diverse datasets, including structured, semi-structured, and unstructured data, thereby expanding the range of information that can be incorporated into audit processes. Such capabilities provide opportunities to identify patterns, anomalies, and risks and to generate insights that can strengthen audit evidence and support audit decision-making (Vasarhelyi et al., 2015). BDT is distinct from Big Data Analytics (BDA), which focuses on the systematic processing and analysis of large and complex datasets to identify patterns, relationships, and other insights (Han et al., 2024), and Audit Data Analytics (ADA), which applies data-analytical techniques specifically within auditing to identify patterns, anomalies, risks, and other information relevant to audit procedures and decision-making (Ruhnke, 2023). In this study, BDT therefore represents the technological environment and capabilities that enable the application of BDA and ADA in auditing.

In Tanzania, public sector operations have increasingly incorporated ICT and information systems as part of broader government digitalisation. This development has expanded the availability of digitally generated financial, administrative, and operational data relevant to auditing (e-Government Authority [e-GA], 2022). However, the presence of digital systems and technological infrastructure does not, by itself, establish whether individual auditors are prepared to engage with the broader data-processing and analytical requirements associated with BDT. This distinction is important because BDT extends conventional data environments by accommodating not only structured data typically associated with accounting and enterprise systems but also semi-structured and unstructured information from diverse sources (Vasarhelyi et al., 2015). Consequently, understanding BDT Adoption Readiness at the individual auditor level is important as public sector auditing operates within an increasingly digital environment.

Auditors' readiness to engage with BDT may partly be associated with how they perceive the characteristics of the technology. Diffusion of Innovation (DOI) Theory identifies Relative Advantage, Compatibility, Complexity, Trialability, and Observability as perceived characteristics relevant to innovation adoption (Rogers, 2003). Within Rogers' innovation-decision process, BDT Adoption Readiness is positioned within the pre-adoption phase, particularly the persuasion and decision stages, because it reflects auditors' preparedness, willingness, and intention to engage with BDT rather than actual technology use. In line with the study objective, the present study focuses on three Innovation Traits which are Relative Advantage, Complexity, and Incompatibility and examines their associations with BDT Adoption Readiness among public sector auditors in Tanzania. The selection of these three traits reflects the study's specific interest in auditors' perceptions of the benefits of BDT, the difficulty associated with understanding and using it, and its fit with existing audit practices and technological environments. Accordingly, the study represents a focused application of DOI, rather than an exhaustive examination of all perceived innovation attributes.

In this study, Compatibility is examined inversely as Incompatibility. Relative Advantage reflects the extent to which BDT is perceived as offering benefits over existing approaches; Complexity concerns the perceived difficulty associated with understanding and using the technology; and Compatibility concerns the extent to which an innovation is perceived as consistent with existing values, past experiences, and needs (Rogers, 2003). Accordingly, Incompatibility was operationalised in this study as perceived misalignment between BDT and auditors' existing practices, needs, experiences, and technological environments. Previous studies indicate that the relevance of these Innovation Traits varies across technologies and settings, suggesting that relationships observed in one technological or user environment cannot necessarily be assumed to apply uniformly in another. This contextual variation is particularly relevant to BDT because its requirements for handling large and heterogeneous datasets may differ from those associated with conventional information technologies.

Evidence from Tanzania has similarly examined Innovation Traits in relation to the adoption and use of technologies. Relative Advantage, Compatibility, and Complexity have been investigated in ICT-use contexts, including World Heritage Sites, whereas Relative Advantage and Compatibility have also been examined in relation to Software-as-a-Service adoption among

Tanzanian small and medium-sized enterprises (Majengo & Mbise, 2022; Mugobi et al., 2019). However, these studies were conducted in technological and professional settings different from BDT and public sector auditing and largely focused on technology adoption or use rather than individual users' preparedness for adoption. Moreover, international research on Big Data Analytics has predominantly examined adoption in organisational and business settings rather than individual auditors' readiness to engage with BDT (Lutfi et al., 2022). Thus, the present study specifically examines how three Innovation Traits—Complexity, Incompatibility, and Relative Advantage—are associated with BDT Adoption Readiness among public sector auditors in Tanzania. This focus provides evidence on auditors' perceptions of the characteristics of BDT in relation to their preparedness for adoption within the public sector audit environment.

Literature review

This section reviews the theoretical and empirical literature relevant to Innovation Traits and BDT Adoption Readiness. It first presents the theoretical foundation of the study, followed by empirical literature on Complexity, Incompatibility, and Relative Advantage.

Theoretical Review

This study was primarily grounded in the Diffusion of Innovation (DOI) Theory developed by Rogers (2003), which explains how individuals and other decision-making units progress towards adopting or rejecting an innovation. Rogers (2003) conceptualises this progression through five stages: knowledge, persuasion, decision, implementation, and confirmation. The present study locates BDT Adoption Readiness within the pre-adoption phase, particularly the persuasion and decision stages, during which potential adopters evaluate an innovation, develop favourable or unfavourable attitudes towards it, and form an intention regarding adoption. BDT Adoption Readiness therefore represents auditors' preparedness, willingness, and intention to engage with BDT rather than actual technology use. This positioning is consistent with Karahanna et al. (1999), who distinguish pre-adoption beliefs and attitudes from those operating after adoption.

Central to DOI are five perceived attributes of an innovation which are Relative Advantage, Compatibility, Complexity, Trialability, and Observability (Rogers, 2003). Relative Advantage reflects the perceived superiority of an innovation over existing approaches; Compatibility concerns its consistency with adopters' values, experiences, and needs; Complexity reflects perceived difficulty in understanding and use; Trialability concerns opportunities for experimentation before adoption; and Observability refers to the visibility of innovation outcomes. These attributes have subsequently been adapted to information systems contexts to explain users' perceptions of technological innovations (Moore & Benbasat, 1991).

This study focused specifically on Relative Advantage, Complexity, and Incompatibility because its objective concerned three evaluative dimensions considered particularly relevant to auditors' readiness: the perceived benefits of BDT, difficulty of engaging with it, and fit with existing audit practices and technological arrangements. Trialability and Observability were therefore outside the empirical scope of the specified objective. Their exclusion does not imply theoretical irrelevance; indeed, previous research indicates that such attributes may also contribute to pre-adoption beliefs (Karahanna et al., 1999). Rather, the study represents a focused application of DOI in which three theoretically specified Innovation Traits were examined. Compatibility was operationalised inversely as Incompatibility, such that higher scores indicate greater perceived misalignment between BDT and auditors' existing practices, work arrangements, and technological environment. This operationalisation retains the theoretical meaning of compatibility as perceived fit while expressing it in terms of potential barriers relevant to the audit setting.

The conceptualisation of the outcome construct was further informed by the Theory of Planned Behaviour (TPB) (Ajzen, 1991). TPB distinguishes behavioural intention from actual behaviour and regards intention as reflecting an individual's motivational readiness to perform a behaviour.

Accordingly, TPB complements DOI by clarifying why BDT Adoption Readiness is conceptualised as a pre-adoption outcome comprising preparedness, willingness, and intention, rather than actual BDT use. The theories therefore perform complementary roles: DOI provides the principal explanation for the Innovation Traits examined, whereas TPB clarifies the behavioural meaning of the readiness outcome.

The study is also theoretically distinguishable from the Technology Acceptance Model (TAM), which explains technology acceptance principally through Perceived Usefulness and Perceived Ease of Use (Davis, 1989). These constructs conceptually parallel aspects of DOI's Relative Advantage and Complexity, respectively. However, the present study additionally examines Incompatibility, capturing perceived fit between BDT and existing audit practices and technological arrangements. DOI was therefore more closely aligned with the specified Innovation Traits and was retained as the principal theoretical framework, while TAM represents a related acceptance perspective whose inclusion would introduce considerable conceptual overlap. Overall, the study does not seek to extend DOI to pre-adoption readiness, which has already been addressed in earlier technology adoption research (Karahanna et al., 1999); rather, it applies established pre-adoption reasoning to examine how selected Innovation Traits are associated with BDT Adoption Readiness among public sector auditors.

Complexity and Big Data Technology Adoption Readiness

Complexity refers to the perceived difficulty of understanding and using an innovation (Abulail et al., 2025; Rogers, 2003). Technologies perceived as complex may discourage adoption because potential users anticipate greater learning requirements, effort, and difficulty in integrating the technology into existing practices (Mertens et al., 2026). Empirical evidence across different technological contexts has generally associated greater perceived Complexity with less favourable adoption responses, although its influence varies across technologies and user settings (Mexhuani, 2025; Kaine & Wright, 2022; Lutfi et al., 2022). Evidence from Tanzania, however, is not entirely consistent with this pattern. Kwilasa and Koloseni (2025), in their study of data analytics adoption among internal auditors in Tanzanian commercial banks, found that perceived ease of use was not significantly associated with data analytics adoption. Although perceived ease of use is conceptually distinct from Complexity, this finding provides relevant local evidence that perceived technological difficulty or ease may not operate uniformly across audit settings. In the context of BDT, Complexity may be particularly relevant because engaging with advanced data analytics can require new analytical competencies, unfamiliar technological tools, and changes in established work practices (Werner & Dayeh, 2025). However, existing evidence has largely focused on technology adoption and related outcomes rather than whether individual auditors perceive themselves as prepared to adopt BDT. The mixed evidence, together with differences in technological and institutional settings, leaves uncertainty regarding the association between perceived Complexity and BDT Adoption Readiness among public sector auditors in Tanzania. Accordingly, the following hypothesis was developed:

H1: Perceived Complexity is negatively associated with BDT Adoption Readiness.

Incompatibility and BDT Adoption Readiness

Incompatibility represents the extent to which an innovation is perceived as inconsistent with users' existing values, experiences, needs, and practices. Within Diffusion of Innovation Theory, Incompatibility represents the inverse of Compatibility, which refers to the extent to which an innovation is perceived as consistent with existing values, past experiences, and needs (Rogers, 2003). In the context of BDT, Incompatibility may arise when auditors perceive misalignment between the technology and existing audit procedures, information systems, technological infrastructure, or established work practices.

Empirical evidence indicates that Compatibility is relevant to technology adoption decisions, although its importance may vary across technological and organisational contexts. In BDA research, Compatibility has been examined as a technological characteristic associated with adoption among SMEs (Maroufkhani et al., 2023; Babalghaith & Aljarallah, 2024). Babalghaith and Aljarallah (2024), for example, found technological compatibility to be significantly associated with BDA adoption among Saudi SMEs. In Tanzania, Majengo and Mbise (2022) similarly identified Compatibility as a significant factor in Software-as-a-Service adoption among SMEs. However, these studies predominantly examined organisational technology adoption rather than individual auditors' readiness to adopt BDT. Consequently, it remains unclear whether perceived Incompatibility is associated with BDT Adoption Readiness among public sector auditors in Tanzania. Accordingly, this study hypothesised that:

H2: Perceived Incompatibility is negatively associated with BDT Adoption Readiness among public sector auditors.

Relative Advantage and Big Data Technology Adoption Readiness
Relative Advantage refers to the extent to which an innovation is perceived as superior to the approach it supersedes (Rogers, 2003). Empirical studies have associated perceived Relative Advantage with technology adoption outcomes. In the context of Big Data Analytics, Relative Advantage has been examined as a technological characteristic relevant to organisational adoption decisions (Lutfi et al., 2022; Verma & Chaurasia, 2019). However, these studies have predominantly examined organisational adoption in business settings rather than individual auditors' readiness to adopt BDT. Consequently, it remains unclear whether auditors' perceptions of the Relative Advantage of BDT are associated with their BDT Adoption Readiness. Accordingly, this study hypothesised that:

H3: Perceived Relative Advantage is positively associated with BDT Adoption Readiness.

Conceptual framework
The conceptual framework presented in Figure 1 illustrates the hypothesised relationships between Innovation Traits and Big Data Technology Adoption Readiness. Guided by Diffusion of Innovation Theory, the framework proposes that auditors' perceptions of Complexity, Incompatibility, and Relative Advantage are associated with their readiness to adopt Big Data Technology. Complexity is hypothesised to be negatively associated with BDT Adoption Readiness (H1), suggesting that greater perceived difficulty corresponds with lower readiness. Incompatibility is similarly hypothesised to be negatively associated with BDT Adoption Readiness (H2), reflecting the potential importance of perceived misalignment between BDT and existing audit practices and technological systems. Conversely, Relative Advantage is hypothesised to be positively associated with BDT Adoption Readiness (H3), suggesting that auditors who perceive greater benefits from BDT are more likely to exhibit higher adoption readiness.

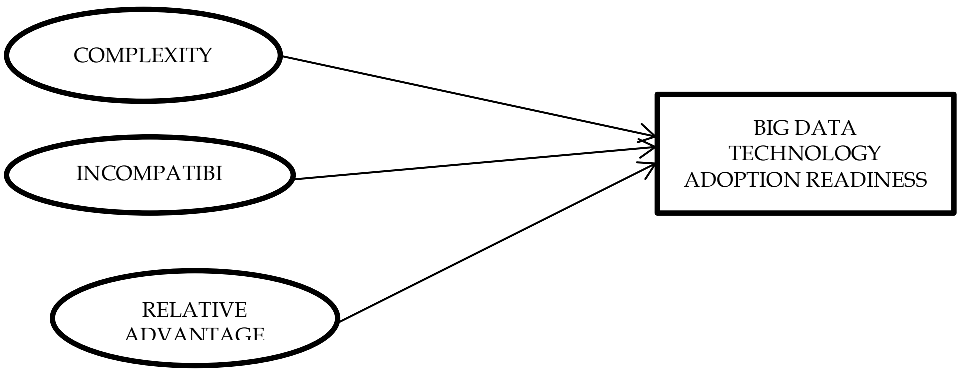

Figure 1: Conceptual framework of the study

Methodology

This section describes the methodological procedures employed in the study, including the research design, study population, sampling procedures, data collection, measurement of variables, and data analysis techniques.

Research Design

The study employed a quantitative cross-sectional research design to examine the associations between Innovation Traits and BDT Adoption Readiness among public sector auditors in Tanzania.

The quantitative approach was appropriate because the study tested hypothesised relationships between Complexity, Incompatibility, Relative Advantage and Big Data Technology Adoption Readiness using numerical data obtained from auditors. A cross-sectional design was adopted because data were collected from respondents at a single point in time, without manipulating the study variables or following respondents over time. The design was therefore appropriate for assessing the relationships between auditors' perceptions of the selected Innovation Traits and their readiness to adopt Big Data Technology during the study period.

Study Area

The study was conducted in Dodoma, Tanzania. Dodoma was selected because, as the country's capital and administrative centre, it hosts the headquarters of numerous central government ministries, agencies, and parastatal organizations that fall within the public sector audit environment. These institutions generate and manage substantial administrative, financial, and operational data arising from government activities and service delivery. Their concentration in Dodoma provides an appropriate setting for examining auditors who operate within an increasingly digital public sector environment and may consequently encounter growing demands for analysing large and diverse datasets. Since the study focused on auditors responsible for auditing ministries, agencies, and parastatal organizations, Dodoma provided a relevant setting for examining their readiness to adopt Big Data Technology in public sector auditing.

Sample Size and Sampling Procedures

The sampling frame as indicated in table 1 was obtained from the Human Resources Department of the National Audit Office of Tanzania (NAOT) and comprised 495 auditors based at the headquarters in Dodoma, together with their work locations and contact details. The required sample size was determined using Yamane's (1967) formula at a 95% confidence level and a 5% level of precision (e = 0.05), yielding a target sample of 221 respondents. Stratified random sampling was subsequently applied to ensure proportionate representation of auditors assigned to ministries, government agencies, and parastatal organisations. Proportional allocation was calculated according to the relative size of each stratum in the sampling frame. Because the proportional allocations produced fractional values, the largest-remainder method was applied to obtain whole-number allocations while maintaining the required total sample size of 221. This resulted in target allocations of 103 auditors from ministries, 74 from government agencies, and 44 from parastatal organisations. Within each stratum, auditors were randomly selected from the sampling frame.

Table 1: Sampling frame

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

Data Collection

Prior to data collection, formal authorisation procedures were undertaken. Following receipt of the official data collection letter from Moshi Co-operative University (MoCU), the Regional Administrative Secretary of Dodoma granted permission for the study. In addition, ethical clearance was obtained from the Moshi Co-operative University Research Ethics Committee, which reviewed and approved the research protocol. This clearance ensured adherence to established ethical standards, safeguarding participants' rights, privacy, and confidentiality throughout the research process. Institutional and ethical approvals together enabled the National Audit Office of Tanzania (NAOT) to provide access for data collection.. Data were collected using a closed-ended questionnaire that provided respondents with predetermined response options on a five-point Likert-type scale. The use of standardised questions and response options enabled respondents to answer the same set of items in a consistent manner, thereby supporting comparability of the responses across participants. A multi-modal administration approach was employed, combining paper-based questionnaires and an online version administered through Google Forms. The paper-based option facilitated participation among respondents who preferred or had easier access to physical questionnaires, while the online option provided a convenient alternative for respondents who preferred digital completion. The same questionnaire content, wording, and response structure were maintained across both modes of administration.

A total of 265 questionnaires were distributed, exceeding the target sample of 221 in order to mitigate potential non-response. Ultimately, 221 questionnaires were completed and returned, yielding a response rate of 83.4%. By mode of administration, 145 completed questionnaires were received through Google Forms and 76 through paper-based questionnaires, giving a total of 221 responses. Because the study relied on self-reported data collected through a single questionnaire, common method bias (CMB) was assessed using a marker variable unrelated to auditing ("I enjoy listening to music during my free time"). Correlational analysis indicated that this item was not significantly associated with the study constructs, suggesting that common method variance had limited impact on the results (Lindell & Whitney, 2001).

Validity and Reliability

Prior to the main data collection, the questionnaire was pre-tested with 30 randomly selected auditors from Kinondoni and Ilala municipalities in Dar es Salaam. The pre-test was conducted to assess the clarity, comprehensibility and appropriateness of the questionnaire items before administration in the main study. Feedback obtained during the pre-test was used to refine unclear or ambiguous wording and improve the comprehensibility of the instrument. In addition, the reliability of the measurement scales was assessed using Cronbach's alpha (CA) and Composite Reliability (CR). As presented in Table 2, all values exceeded the adopted threshold of 0.70, indicating satisfactory internal consistency of the measurement scales. Also all factor loadings for the constructs were above 0.60, indicating adequate indicator reliability and satisfactory convergence of the measurement items on their respective constructs.

Table 2: Construct Reliability and Convergent Validity

Variable	CODE	Item	Factor loading	CA	CR	AVE
Complexity (CPX)	CPX 1	Learning curve	0.76	0.735	0.84	0.58
	CPX 2	Difficult in usage	0.74			
	CPX 3	Features Comprehension	0.72			
	CPX 4	Cognitive demand	0.8			
Incompatibility (ICPT)	ICPT 1	Misalignment with Processes	0.71	0.732	0.83	0.55
	ICPT 2	incompatible with current IT infrastructure	0.73			
	ICPT 3	Inconsistency with Values	0.8			
	ICPT 4	Resistance to Structures	0.7			
Relative Advantage (RA)	RA 1	Improvement in Efficiency	0.77	0.756	0.85	0.6
	RA 2	Better advantage	0.81			
	RA 3	Quality of Insights	0.75			
	RA 4	Cost Savings	0.74			
BDT Adoption Readiness	BDT1	Preparedness	0.82	0.752	0.83	0.62
	BDT2	Willingness	0.78			
	BDT3	Intention	0.77			

Furthermore, convergent and discriminant validity were assessed. Convergent validity was evaluated using the Average Variance Extracted (AVE). An AVE value of 0.50 or higher indicates that a construct explains at least half of the variance in its indicators and provides evidence of adequate convergent validity (Fornell & Larcker, 1981). As shown in Table 2, all constructs recorded AVE values above the recommended threshold of 0.50, providing evidence of satisfactory convergent validity.

Discriminant validity was assessed using the Fornell–Larcker criterion. According to this criterion, discriminant validity is supported when the square root of the AVE for each construct exceeds its correlations with the other constructs (Fornell & Larcker, 1981). As presented in Table 3, the square root of the AVE for each construct, shown by the diagonal values, exceeded its corresponding inter-construct correlations. The results therefore provided evidence of satisfactory discriminant validity among the constructs.

Table 3: Discriminant Validity (Fornell–Larcker Criterion)

Construct	CPX	ICPT	RA	BDT Readiness
CPX	**0.76**			
ICPT	0.42	**0.74**		
RA	0.46	0.44	**0.77**	
BDT Readiness	0.48	0.41	0.52	**0.79**

Note: Bold diagonal values represent the square root of AVE

To complement the traditional Fornell–Larcker criterion, the Heterotrait–Monotrait ratio of correlations (HTMT) was also employed, as presented in Table 4. The HTMT values ranged between 0.54 and 0.65, all of which fall below the conservative threshold of 0.85 (Henseler et al. 2015). These results provide further evidence that Complexity, Incompatibility, Relative Advantage, and BDT Adoption Readiness are empirically distinct constructs, each representing a unique dimension of the model.

Table 4: HTMT Matrix

Construct	CPX	ICPT	RA	BDT Readiness
Complexity (CPX)	–	0.62	0.58	0.65
Incompatibility (ICPT)	0.62	–	0.54	0.6
Relative Advantage (RA)	0.58	0.54	–	0.57
BDT Adoption Readiness	0.65	0.6	0.57	–

Data Analysis

Quantitative data were analysed using descriptive statistics and binary logistic regression. Descriptive statistics particularly means and standard deviations were used to assess the levels of the Innovation Traits examined in the study, namely Complexity, Incompatibility, and Relative Advantage. The analysis was conducted at both the item and construct levels. Item level descriptive statistics were used to examine respondents' assessments of the individual indicators measuring each Innovation Trait, while construct-level statistics summarized the overall levels of Complexity, Incompatibility, and Relative Advantage. For interpretation of the descriptive results, mean scores were classified into predetermined levels ranging from very low to very high. This enabled the study to establish the extent to which auditors perceived Complexity, Incompatibility, and Relative Advantage in relation to Big Data Technology. The descriptive analysis therefore provided an overall profile of the Innovation Traits before examining their statistical relationships with BDT Adoption Readiness.

Binary logistic regression was subsequently employed to examine associations of Complexity, Incompatibility, and Relative Advantage with BDT Adoption Readiness. The model was considered appropriate because the dependent variable was dichotomised into two categories, with high adoption readiness coded as 1 and low adoption readiness coded as 0. All constructs were entered into the regression model as composite means (range 1–5), calculated by averaging the respective items.

The binary logistic regression model was specified as:

$$ln\left(\frac{P}{1-P}\right) = \beta 0 + \beta 1CPX + \beta 2ICPT + \beta 3RA \ldots\ldots\ldots\ldots \text{(iii)}$$

P = probability of high Big Data Technology Adoption Readiness;
β0 = intercept;
β1, β2, β3 = regression coefficients;
CPX = Complexity;
ICPT = Incompatibility; and
RA = Relative Advantage.

The estimated regression coefficients, odds ratios Exp(β), 95% confidence intervals and significance levels were used to determine the direction and statistical significance of the relationships between the Innovation Traits and Big Data Technology Adoption Readiness.

Construct Operationalisation

Complexity, Incompatibility, and Relative Advantage were operationalised based on Diffusion of Innovation (DOI) Theory (Rogers, 2003). The measurement items for Complexity, Compatibility, and Relative Advantage were adapted from established measures used in previous Big Data Analytics adoption studies (Verma & Chaurasia, 2019; Lutfi et al., 2022) and contextualized to BDT in public sector auditing. Compatibility was operationalised inversely as Incompatibility to capture auditors' perceptions of the misalignment of BDT with existing audit practices, technological systems, and working arrangements.

Complexity and Incompatibility were each measured using four items on a five-point scale ranging from 1 = Very Low, 2 = Low, 3 = Neutral, 4 = High, and 5 = Very High, while Relative Advantage was measured using four items on a five-point agreement scale ranging from 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree. Consistent with the general approach to interpreting composite scores derived from Likert-type scales (Warmbrod, 2014), mean scores were used to describe the levels of the Innovation Traits. For this study, mean scores were interpreted as 1.00–1.99 = Very Low, 2.00–2.99 = Low, 3.00–3.49 = Neutral, 3.50–3.99 = High, and 4.00–5.00 = Very High. A measurement limitation exists in the study due to the use of different response anchors across constructs. Specifically, Complexity and Incompatibility items were measured on a 'Very Low–Very High' scale, while Relative Advantage and BDT Adoption Readiness employed agreement anchors

BDT Adoption Readiness, the dependent construct, was conceptualised with reference to the Theory of Planned Behaviour (TPB), which recognises behavioural intention as an important precursor to actual behaviour (Ajzen, 1991). Accordingly, BDT Adoption Readiness was measured using three questionnaire items. Preparedness was assessed with the statement, "I feel adequately prepared to adopt and use big data technologies in my auditing work." Willingness was measured with the item, "I am willing to adopt and use big data technologies in my auditing work." Intention was captured through the statement, "I intend to adopt and use big data technologies in my auditing work.". The construct was measured using three questionnaire items on a five-point agreement scale ranging from 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree. Following reliability and validity assessment, the items were aggregated to generate a composite score for construct-level analysis.

For the primary binary logistic regression analysis, the composite score was dichotomised using an operational criterion of ≥3.5 for high BDT Adoption Readiness and <3.5 for low BDT Adoption Readiness. The use of 3.5 was informed by previous applications and interpretations of five-point scales, including Spoth et al. (2015), Barton and Akin (2022), Yang et al. (2024), and Zumrawi and Macfadyen (2023). However, these studies did not validate 3.5 as a threshold specifically for technology readiness; they provide examples of the use or interpretation of scores around this level on five-point measures. The criterion was therefore adopted as an operational classification rule for the present study rather than as a validated or universal threshold for BDT Adoption Readiness. Because the readiness composite comprised three equally weighted items, the attainable mean scores immediately surrounding the specified cut-off were 3.33 and 3.67. Consequently, although the classification rule was specified as ≥3.5, its effective observed threshold was 3.67: respondents with composite scores of 3.67 or above were classified as having high BDT Adoption Readiness (coded 1), whereas those with scores of 3.33 or below were classified as having low BDT Adoption Readiness (coded 0).

Diagnostic tests

Before estimating the binary logistic regression model, diagnostic tests were conducted to assess multicollinearity, influential observations, and linearity-of-the-logit. Multicollinearity was assessed using the Variance Inflation Factor (VIF). The VIF values for Complexity 1.39, Incompatibility 1.35, and Relative Advantage 1.40 were all below the adopted threshold of 5, indicating that multicollinearity was not a concern among the predictor variables. Influential observations were assessed using Cook's Distance. The diagnostic results showed that Cook's Distance values remained below the adopted threshold of 1, indicating that no observation exerted undue influence on the estimated model. The linearity-of-the-logit was assessed for the continuous predictor variables using the Box–Tidwell procedure. The interaction terms between each predictor and its natural logarithmic transformation were statistically non-significant at the 5% significance level, indicating no evidence of violation of the linearity-of-the-logit assumption. Overall, the diagnostic tests indicated that the assessed assumptions for binary logistic regression were satisfactorily met.

Model Goodness of Fit

The goodness of fit of the binary logistic regression model was assessed using the Hosmer–Lemeshow test and the Nagelkerke pseudo- R^2. The Hosmer–Lemeshow test produced a p-value of 0.256, which was greater than the 0.05 significance level. The non-significant result indicated no evidence of a significant difference between the observed and model-predicted outcomes, suggesting that the model adequately fitted the data. The explanatory performance of the model was further assessed using the Nagelkerke pseudo- R^2. The calculated Nagelkerke R^2 is 0.12, consistent with the McKelvey–Zavoina R^2 of approximately 0.10. These results indicate modest explanatory power, with Complexity, Incompatibility, and Relative Advantage showing statistically significant associations with BDT Adoption Readiness.

Findings and Discussion

This section presents and discusses the descriptive and inferential findings on Innovation Traits and BDT Adoption Readiness. It first describes auditors' perceptions of Complexity, Incompatibility, and Relative Advantage, followed by the binary logistic regression findings on their associations with BDT Adoption Readiness.

Levels of Innovation Traits

The levels of Innovation Traits were assessed using descriptive statistics to determine the extent to which auditors perceived Complexity, Incompatibility, and Relative Advantage in relation to BDT. The analysis provided an overall understanding of auditors' perceptions and further identified the specific aspects contributing to the observed levels of each Innovation Trait. As indicated in table 5, the Complexity results further suggest that perceived difficulty was particularly associated with the practical use of BDT and the cognitive effort required working with the technology. Similarly, the Incompatibility findings indicate concerns regarding the alignment of BDT with existing audit processes, IT infrastructure, organisational practices, and established structures. In contrast, the high scores for Relative Advantage indicate that auditors perceived BDT as capable of improving audit efficiency, enhancing the quality of audit insights, and reducing costs associated with audit processes.

Table 5: Levels of innovation traits at item level

Construct	Code	Indicators	Mean ± SD	Description
Complexity (CPX)	CPX1	Using big data technology requires a steep learning curve	3.81±0.78	High
	CPX2	Big data technology is difficult to use in practice.	4.21 ±0.68	very high
	CPX3	The features of big data technology are difficult to comprehend	3.67 ±0.72	High
	CPX4	Using big data technology requires high cognitive effort.	4.12 ±0.56	very high
Incompatibility (ICPT)	ICPT1	Big data technology does not align well with existing auditing processes.	3.74 ±0.83	High
	ICPT2	Big data technology is not compatible with the current IT infrastructure.	3.64 ±0.75	High

	ICPT3	Big data technology is inconsistent with the values and practices of the organisation.	3.85 ±0.58	high
	ICPT4	Big data technology conflicts with established organisational structures.	3.75 ±0.85	High
Relative advantage (RA)	RA1	Using big data technology improves efficiency in auditing tasks.	4.42 ±0.76	Very high
	RA2	Big data technology provides a better advantage compared to current methods.	4.54 ±0.86	Very high
	RA3	Big data technology enhances the quality of insights generated during audits.	4.23 ±0.56	Very high
	RA4	Big data technology reduces costs associated with auditing processes.	4.12 ±0.78	Very high

The descriptive findings suggest favourable perceptions of the potential advantages of BDT may not automatically translate into high readiness when auditors simultaneously perceive the technology as difficult to use or incompatible with their existing audit environment. The subsequent binary logistic regression analysis therefore examined whether these Innovation Traits significantly related to the likelihood of high Big Data Technology Adoption Readiness.

Innovation Traits and Big Data Technology Adoption Readiness

Binary logistic regression was conducted to examine the associations of Complexity, Incompatibility, and Relative Advantage with BDT Adoption Readiness. The analysis was performed at the construct-level, whereby composite scores for each Innovation Trait were entered into the regression model rather than individual questionnaire items. The analysis assessed whether variations in these construct-level scores were associated with the likelihood of an auditor being classified as having high BDT Adoption Readiness relative to the reference category of low BDT Adoption Readiness.

Table 6: Binary logistic regression results

Construct	β	SE	Wald	p-value (Sig.)	Exp(β)	95% CI for Exp(β)
Complexity	−0.66	0.26	12	0.0005	0.52	[0.36, 0.75]
Incompatibility	−0.63	0.2	9.9	0.0017	0.54	[0.36, 0.79]
Relative Advantage	0.78	0.15	27	0.0001	2.18	[1.63, 2.91]
Constant (β_0)	−0.42	0.18	5.44	0.0197	0.66	[0.46, 0.94]

The regression results in table 6 shows that all three Innovation Traits are statistically significant predictors of Big Data Technology Adoption Readiness. Complexity and Incompatibility were negatively associated with the likelihood of high adoption readiness, whereas Relative Advantage was positively associated with high adoption readiness. The findings therefore supported the three hypotheses developed in the study.

Complexity had a statistically significant negative relationship with Big Data Technology Adoption Readiness ($\beta = -0.66$, OR = 0.52, p=.0005). The odds ratio indicates that, holding the other predictors constant, a one-unit increase in perceived Complexity was associated with approximately a 48% reduction in the odds of an auditor being classified as having high BDT Adoption Readiness. The finding therefore supports H1, which proposed that perceived Complexity is negatively associated with BDT Adoption Readiness. The finding suggests that greater perceived difficulty in understanding and using BDT is associated with lower BDT Adoption Readiness. This interpretation is particularly relevant given that the descriptive analysis also showed a high overall level of perceived Complexity. Auditors may recognise the potential value of BDT but remain less ready to engage with it when they anticipate steep learning requirements, difficulty in practical use, or substantial cognitive effort.

Incompatibility also had a statistically significant negative relationship with Big Data Technology Adoption Readiness ($\beta=-0.63$, OR = 0.54, p= .0019). Holding the other predictors constant, a one-unit increase in perceived Incompatibility was associated with approximately a 46% reduction in the odds of high BDT Adoption Readiness. The result therefore supports H2, which proposed that perceived Incompatibility is negatively associated with BDT Adoption Readiness. This finding indicates that auditors' readiness is associated not only with perceptions of BDT characteristics but also with its perceived fit within the existing audit environment. The descriptive results showed a high level of Incompatibility, suggesting that respondents perceived challenges concerning the alignment of BDT with existing audit processes, IT infrastructure, organisational practices, and established structures.

Relative Advantage had a statistically significant positive relationship with Big Data Technology Adoption Readiness ($\beta=0.78$, OR = 2.18, p= .0003). Holding Complexity and Incompatibility constant, a one-unit increase in perceived Relative Advantage was associated with approximately 2.18 times higher odds of an auditor being classified as having high BDT Adoption Readiness. This finding supports H3, which proposed that perceived Relative Advantage is positively associated with BDT Adoption Readiness. The positive relationship indicates that auditors are more likely to demonstrate high readiness when they perceive BDT as offering meaningful improvements over existing audit approaches. This finding is reinforced by the descriptive results, in which Relative Advantage recorded the highest overall mean among the three Innovation Traits. Respondents therefore appear to recognize considerable potential value in the application of BDT to public sector auditing.

These findings are consistent with the central proposition of DOI that perceptions of an innovation's Relative Advantage, Compatibility, and Complexity are relevant to adoption responses (Rogers, 2003). They are also broadly consistent with empirical BDA research identifying Relative Advantage, Complexity, and Compatibility as important technological characteristics associated with adoption decisions (Walker & Brown, 2019; Lutfi et al., 2022). In the present study, auditors recognised the potential advantages of BDT while their BDT Adoption Readiness was simultaneously associated with perceptions of its Complexity and fit with existing audit practices and technological arrangements. The findings therefore demonstrate the usefulness of DOI for examining BDT Adoption Readiness and apply established pre-adoption reasoning to the specific context of public sector auditing in Tanzania.

Conclusion

This study examined the associations of Complexity, Incompatibility, and Relative Advantage with BDT Adoption Readiness among auditors at the NAOT headquarters in Dodoma. The findings showed that Relative Advantage was associated with higher odds of high BDT Adoption Readiness, whereas Complexity and Incompatibility were associated with lower odds. The descriptive findings further revealed the coexistence of perceived benefits and barriers, with auditors reporting very high Relative Advantage alongside high levels of Complexity and Incompatibility. This suggests that auditors may recognise the potential value of BDT while simultaneously perceiving difficulties in its use and alignment with existing audit practices and technological systems. The study contributes to the application of Diffusion of Innovation Theory in public sector auditing by showing that BDT Adoption Readiness is associated with perceptions of the technology's benefits, complexity, and compatibility with the existing audit environment. Practically, the findings highlight the importance of considering both the perceived value of BDT and the challenges associated with its use and integration when planning future adoption initiatives.

NAOT should consider measures that enhance the perceived value of Big Data Technology (BDT) while addressing perceptions of its Complexity and Incompatibility. Such measures may include targeted capacity-building programmes, better alignment of BDT with existing audit workflows and technological systems, and clear demonstrations of its potential benefits for audit efficiency and insight generation. Since these measures were not directly examined in this study, their effectiveness in strengthening BDT Adoption Readiness should be empirically evaluated in future research.

References

Abulail, R. N., Badran, O. N., Shkoukani, M. A., & Omeish, F. (2025). Exploring the factors influencing AI adoption intentions in higher education: An integrated model of DOI, TOE, and TAM. *Computers, 14*(6), Article 230. https://doi.org/10.3390/computers14060230

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Babalghaith, R., & Aljarallah, A. (2024). Factors affecting big data analytics adoption in small and medium enterprises. *Information Systems Frontiers, 26*(6), 2165–2187. https://doi.org/10.1007/s10796-024-10538-2

Badshah, A., Daud, A., Alharbey, R., Banjar, A., Bukhari, A., & Alshemaimri, B. (2024). Big data applications: Overview, challenges and future. *Artificial Intelligence Review, 57*, Article 290. https://doi.org/10.1007/s10462-024-10938-5

Barton, J. L., & Akin, B. A. (2022). Implementation drivers as practical measures of data-driven decision-making: An initial validation study in early childhood programs. *Global Implementation Research and Applications, 2*, 141–152. https://doi.org/10.1007/s43477-022-00044-5

Che Hussain, N. H., Yin, C. W., Leng, L. W., Fong, L. S., & Wah, H. K. (2025). Exploring the adoption of audit data analytics among external auditors in Malaysia. *Information Management and Business Review, 17*(2(I)S), 84–95.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

e-Government Authority. (2022). *Electronic data sharing and exchange guidelines* (Version 1.1). President's Office, Public Service Management and Good Governance.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Han, X., Gstrein, O. J., & Andrikopoulos, V. (2024). When we talk about Big Data, what do we really mean? Toward a more precise definition of Big Data. *Frontiers in Big Data, 7*, Article 1441869. https://doi.org/10.3389/fdata.2024.1441869

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Kaine, G., & Wright, V. (2022). Relative advantage and complexity: Predicting the rate of adoption of agricultural innovations. *Frontiers in Agronomy, 4*, Article 967605. https://doi.org/10.3389/fagro.2022.967605

Karahanna, E., Straub, D. W., & Chervany, N. L. (1999). Information technology adoption across time: A cross-sectional comparison of pre-adoption and post-adoption beliefs. *MIS Quarterly, 23*(2), 183–213. https://doi.org/10.2307/249751

Lindell, M. K., & Whitney, D. J. (2001). Accounting for common method variance in cross-sectional research designs. *Journal of Applied Psychology, 86*(1), 114–121.

Lutfi, A., Alsyouf, A., Almaiah, M. A., Alrawad, M., Abdo, A. A. K., Al-Khasawneh, A. L., Ibrahim, N., & Saad, M. (2022). Factors influencing the adoption of big data analytics in the digital transformation era: Case study of Jordanian SMEs. *Sustainability, 14*(3), Article 1802. https://doi.org/10.3390/su14031802

Majengo, R., & Mbise, M. (2022). Determinants of software-as-a-service adoption by small and medium enterprises in Tanzania. *The African Journal of Information Systems, 14*(1), 23–43.

Maroufkhani, P., Iranmanesh, M., & Ghobakhloo, M. (2023). Determinants of big data analytics adoption in small and medium-sized enterprises (SMEs). *Industrial Management & Data Systems, 123*(1), 278–301. https://doi.org/10.1108/IMDS-11-2021-0695

Mertens, A., Kho, M., De Toni, F., & Parker, S. K. (2026). Why technology implementation fails: From adoption to dynamic technology integration. *European Journal of Work and Organizational Psychology*, 1–16. https://doi.org/10.1080/1359432X.2026.2684522

Mexhuani, B. (2025). Adopting digital tools in higher education: Opportunities, challenges and theoretical insights. *European Journal of Education, 60*(1), Article e12819. https://doi.org/10.1111/ejed.12819

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research, 2*(3), 192–222. https://doi.org/10.1287/isre.2.3.192

Mugobi, T., Mlozi, S., & Ngaruko, D. (2019). Testing mediation effects of information communication technology usage on technological, organizational and environmental factors and World Heritage Sites performance. *Huria: Journal of the Open University of Tanzania, 26*(2). https://doi.org/10.61538/huria.v26i2.788

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Ruhnke, K. (2023). Empirical research frameworks in a changing world: The case of audit data analytics. *Journal of International Accounting, Auditing and Taxation, 52*, Article 100545. https://doi.org/10.1016/j.intaccaudtax.2023.100545

Spoth, R., Schainker, L. M., Redmond, C., Ralston, E., Yeh, H.-C., & Perkins, D. F. (2015). Mixed picture of readiness for adoption of evidence-based prevention programs in communities: Exploratory surveys of state program delivery systems. *American Journal of Community Psychology, 55*(3–4), 253–265. https://doi.org/10.1007/s10464-015-9707-1

Tosi, D., Kokaj, R., & Roccetti, M. (2024). 15 years of Big Data: A systematic literature review. *Journal of Big Data, 11*, Article 73. https://doi.org/10.1186/s40537-024-00914-9

Vasarhelyi, M. A., Kogan, A., & Tuttle, B. M. (2015). Big data in accounting: An overview. *Accounting Horizons, 29*(2), 381–396. https://doi.org/10.2308/acch-51071

Verma, S., & Chaurasia, S. (2019). Understanding the determinants of big data analytics adoption. *Information Resources Management Journal, 32*(3), 1–26.

Walker, R. S., & Brown, I. (2019). Big data analytics adoption: A case study in a large South African telecommunications organisation. *South African Journal of Information Management, 21*(1), Article a1079. https://doi.org/10.4102/sajim.v21i1.1079

Warmbrod, J. R. (2014). Reporting and interpreting scores derived from Likert-type scales. *Journal of Agricultural Education, 55*(5), 30-47. https://doi.org/10.5032/jae.2014.05030

Werner, M., & Dayeh, J. (2025). A comprehensive review of factors limiting auditors' adoption of advanced audit data analytics. *Auditing: A Journal of Practice & Theory*. Advance online publication. 1–27. https://doi.org/10.2308/AJPT-2023-032

Yamane, T. (1967). *Statistics: An introductory analysis* (2nd ed.). Harper & Row.

Yang, J., Zhou, W. J., Zhou, S. C., Luo, D., Liu, Q., Wang, A.-L., Yu, S.-H., Zhu, X.-P., He, X. Y., Hu, F., Yang, B. X., & Chen, J. (2024). Integrated virtual simulation and face-to-face simulation for clinical judgment training among undergraduate nursing students: A mixed-methods study. *BMC Medical Education, 24*, Article 32. https://doi.org/10.1186/s12909-023-04988-6

Zumrawi, A. A., & Macfadyen, L. P. (2023). Proposed metrics for summarizing student evaluation of teaching data from balanced Likert scale surveys. *Cogent Education, 10*(2), Article 2254665. https://doi.org/10.1080/2331186X.2023.2254665

Kwilasa, T., & Koloseni, D. N. (2025). Driving innovation in data analytics adoption for auditing in Tanzania's banking sector. *International Research Journal of Business Studies, 18*(3), 317–330. https://doi.org/10.21632/irjbs.18.3.317-330