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FROM FORENSIC KNOWLEDGE TO FRAUD DETECTION PERFORMANCE: MEDIATING ROLE OF BIG DATA ANALYTICS SKILLS IN THE PUBLIC SECTOR

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Abstract

This study examines how forensic accounting knowledge (FAKR) influences fraud detection performance (TPFPD) in the public sector, with big data analytics skills (BDASR) as a mediating factor. Drawing on the Theory of Planned Behaviour and Competency Theory (CT), we surveyed 305 forensic accountants and auditors in Nigeria's federal institutions. Using Partial Least Squares Structural Equation Modelling (PLS-SEM), outcome reveal that FAKR significantly predicts TPFPD both directly and indirectly through BDASR. Professionals with higher forensic expertise are more likely to develop analytics capabilities, which enhance fraud detection effectiveness in digitized financial management systems like TSA, GIFMIS, and IPPIS. The model demonstrates moderate explanatory power ($R^2 = 0.339$) and predictive relevance ($Q^2 = 0.183$). Findings underscore the need for governments to integrate analytics training into recruitment and professional development, embed hybrid competencies in curricula, and invest in technology to strengthen fraud prevention. By providing empirical evidence from an emerging economy, this study contributes to accounting information systems and forensic accounting literature while offering practical and policy guidance for enhancing public sector accountability.

Keywords: Forensic accounting knowledge, big data analytics skills, fraud detection, task performance, public sector, PLS-SEM

JEL Classification Code: M41, M49

1. Introduction

The rapid shift toward data-driven governance has transformed the expectations placed on public sector institutions to detect, prevent, and respond to financial fraud with speed and precision. In emerging economies such as Nigeria, the adoption of advanced public financial management systems — including the Integrated Payroll and Personnel Information System (IPPIS), Government Integrated Financial Management Information System (GIFMIS), and Treasury Single Account (TSA) — has enhanced fiscal transparency and operational efficiency. However, these digitized platforms have also introduced complex, data-intensive

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environments that sophisticated fraud actors can exploit. The consequences of such misconduct are severe, draining public resources, destabilizing budgets, and eroding citizens' trust in government.

Despite institutional reforms and anti-corruption frameworks, persistent financial irregularities reveal a critical weakness in the incorporation of forensic accounting knowledge (FAKR) and big data analytics skills (BDASR) within fraud detection practices. Traditional detection techniques, which rely heavily on manual audits and compliance-based reporting, are increasingly inadequate in digital contexts. Forensic accountants and auditors may possess deep domain expertise but often lack the technical capacity to navigate and interpret large, complex datasets — a gap that limits timely anomaly detection and the proactive prevention of fraud.

Existing research in accounting information systems and forensic accounting typically examines domain expertise and technological skills in isolation, overlooking how these competencies can work together to enhance task performance in fraud prevention and detection (TPFPD). Moreover, empirical evidence from public sector environments in developing countries remains limited, even though these contexts face acute governance and accountability challenges. Addressing this gap is critical not only for improving investigative effectiveness but also for safeguarding economic stability and ensuring equitable allocation of public funds.

This study responds to these challenges by modelling how BDASR mediates the relationship between FAKR and TPFPD in Nigeria's federal public sector. By integrating the Theory of Planned Behaviour and Competency Theory (CT), it advances a hybrid competency framework that reflects the realities of digitized financial systems. The study aims to inform policy, guide curriculum development, and support institutional reforms that strengthen fraud detection capacity, promote public sector accountability, and contribute to sustainable economic governance.

1.1. Problem Statement

Despite extensive reforms in public financial management, fraud remains a persistent challenge in many emerging economies. In Nigeria, digital platforms like the TSA, GIFMIS, and Integrated Payroll and IPPIS have modernized fiscal operations but also introduced complex, data-intensive environments that can be exploited for financial misconduct. Traditional fraud detection approaches, reliant on manual audits and compliance-based checks, are increasingly inadequate for identifying sophisticated, technology-enabled schemes. While FAKR is critical for investigating irregularities, the absence of complementary BDASR limits the ability to detect and respond to anomalies in real time. Existing research often treats domain expertise and technological capability in isolation, overlooking their combined potential to enhance task performance in TPFPD. Furthermore, empirical studies integrating hybrid competencies within public sector contexts, particularly in developing countries, remain scarce. This gap in the accounting information systems and forensic accounting literature necessitates an investigation into whether BDASR mediates the

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relationship between FAKR and TPFPD, offering insights that could inform policy, curriculum development, and institutional strategies for strengthening public accountability systems.

1.2. Significance of the Paper

This research offers theoretical, methodological, and practical contributions. Theoretically, it extends the Theory of Planned Behaviour and CT by demonstrating how hybrid competencies shape fraud detection performance in digitized governance systems. Methodologically, it employs PLS-SEM to validate a mediation model within a public sector context, a relatively underexplored setting in accounting information systems research. Practically, the results guide policymakers in embedding analytics literacy into recruitment and promotion criteria, inform universities on curriculum reform to integrate forensic and analytics training, and assist professional bodies in developing certification programs that reflect hybrid skill needs. Societally, the study supports efforts to reduce financial leakages, improve fiscal responsibility, and restore public trust in governance.

1.3. Scope of the Study

The study focuses on federal-level forensic accountants and government auditors in Nigeria who are directly involved in fraud detection and investigation within digitized financial management systems. It does not include state-level, local government, or private sector professionals. The scope is limited to assessing FAKR, BDASR, and TPFPD using cross-sectional survey data, without longitudinal tracking or experimental interventions.

1.4. Research Questions

1. To what extent does FAKR influence task performance in TPFPD in the public sector?
2. How does FAKR relate to BDASR among public sector professionals?
3. What is the direct effect of BDASR on TPFPD in the public sector?
4. Does BDASR mediate the relationship between FAKR and TPFPD?

1.5. Research Objectives

1. To determine the extent to which FAKR influences TPFPD among public sector professionals.
2. To examine the relationship between FAKR and BDASR to identify knowledge-driven antecedents of analytics competence.
3. To evaluate the direct effect of BDASR on TPFPD in fraud-related tasks.
4. To test the mediating role of BDASR in the relationship between FAKR and TPFPD.

1.6. Hypotheses Development

This study empirically tests four hypotheses derived from the Theory of Planned Behaviour and CT, examining the direct and mediated relationships between forensic accounting knowledge, big data analytics skills, and fraud detection performance in the public sector.

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1.7. Structure of the Paper

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on FAKR, BDASR, and task performance in fraud detection, and presents the conceptual framework and underpinning theories. Section 3 describes the research methodology, such as the sample, measurement instruments, and data analysis procedures. Section 4 reports the results, while Section 5 discusses the findings, implications, and limitations. Section 6 concludes the paper with recommendations for policy, practice, and future research.

2. Literature Review

2.1. Conceptual framework

The study examines the impact of BDASR on FAKR and TPFPD of forensic accountants and auditors in the Nigerian public sector. The model developed by Baron and Kenny (1986) and amplified by MacKinnon 2007 is shown in Figure 1, Conceptual framework of the study.

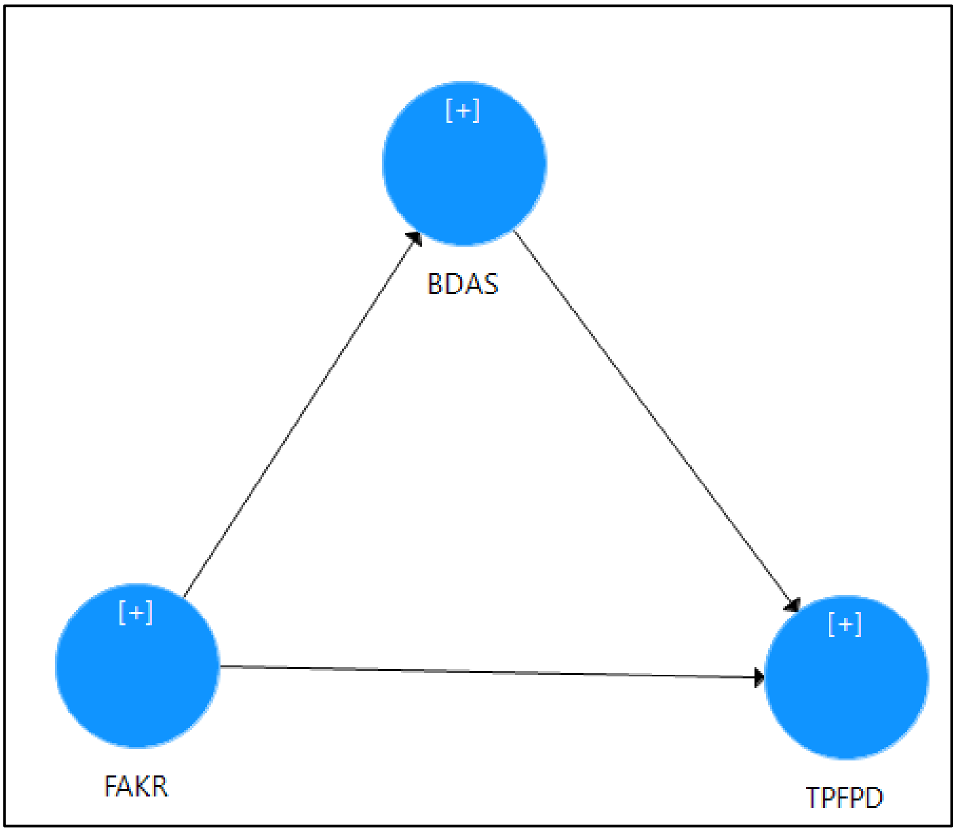

Figure 1. Conceptual framework of the study

2.2. Forensic Accounting Knowledge Requirement (FAKR)

FAKR refers to the set of technical, investigative, and legal competencies necessary to identify, examine, and document evidence of financial fraud. It extends beyond traditional accounting to encompass litigation support, fraud scheme typologies, and the interpretation of regulatory frameworks. In the public sector, FAKR demands familiarity with statutory audit procedures, procurement processes, and anti-corruption mandates such as Nigeria’s Public Procurement Act and the Economic and Financial Crimes Commission Act. Previous studies

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affirm the value of forensic expertise in strengthening fraud risk assessment and investigative precision (Rezaee & Burton, 1997; Popoola et al., 2014). However, recent scholarship has begun to question whether knowledge alone can meet the challenges posed by large, complex, and fast-moving datasets generated by modern public finance systems (Akinbowale et al., 2023a). Without complementary digital competencies, even highly knowledgeable professionals may be limited to reactive, rather than proactive, fraud detection.

2.3. Big Data Analytics Skills Requirement (BDASR)

BDASR involves the ability to harness computational tools and statistical models to detect irregularities in large and heterogeneous datasets. In the context of fraud detection, BDASR includes data mining, anomaly detection, predictive analytics, and advanced visualization techniques that enable real-time identification of suspicious transactions (Appelbaum et al., 2017; Gepp et al., 2018). Particularly, these skills are valuable in environments involving TSA, GIFMIS, and IPPIS, where transaction volumes are high and traditional audit sampling methods are insufficient. Empirical evidence from private sector studies suggests that analytics-enabled fraud detection can significantly improve detection speed and reduce false positives (Mittal et al., 2021), but integration within public sector forensic functions remains limited. This underutilization is often attributed to budgetary constraints, inadequate training, and organizational resistance to technological adoption. Addressing this gap requires a deeper understanding of how BDASR interacts with domain expertise to produce measurable improvements in task performance.

2.4. Task Performance in Fraud Prevention and Detection (TPFPD)

TPFPD reflects the consistent application of investigative strategies to uncover and address fraudulent activities. It includes anomaly recognition, evidence gathering, structured reporting, and communication of findings to stakeholders (Dzomira, 2015; Hassink et al., 2010). In the public sector, high TPFPD contributes to safeguarding public funds, improving fiscal discipline, and enhancing citizens' trust in governance. While traditional determinants of TPFPD include professional experience, ethical orientation, and subject-matter knowledge, the increasing reliance on digitized systems means that technical proficiency — particularly in big data analytics — is becoming an equally important predictor of performance. Previous studies (Popoola et al., 2015; Akinbowale et al., 2023b) call for hybrid competency frameworks that merge investigative knowledge with technological capability to meet contemporary fraud detection demands.

2.5. Theoretical Framework

The conceptual framework (Figure 2) models the hypothesised relationships between FAKR, BDASR, and TPFPD. It proposes that FAKR has both a direct impact on TPFPD and an indirect impact through BDASR, positioning BDASR as a mediating competency that transforms domain expertise into enhanced fraud detection performance.

The framework is grounded in the Theory of Planned Behaviour (Ajzen, 1991), which conceptualises knowledge as a driver of attitudes and intentions, and analytics skills as a

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factor enhancing perceived behavioural control. It also draws on CT (McClelland, 1961), which emphasises that superior performance emerges from the integration of knowledge, skills, and abilities.

In this model:

H1: FAKR → TPFPD (direct effect)

H2: FAKR → BDASR (direct effect)

H3: BDASR → TPFPD (direct effect)

H4: BDASR mediates the FAKR–TPFPD relationship

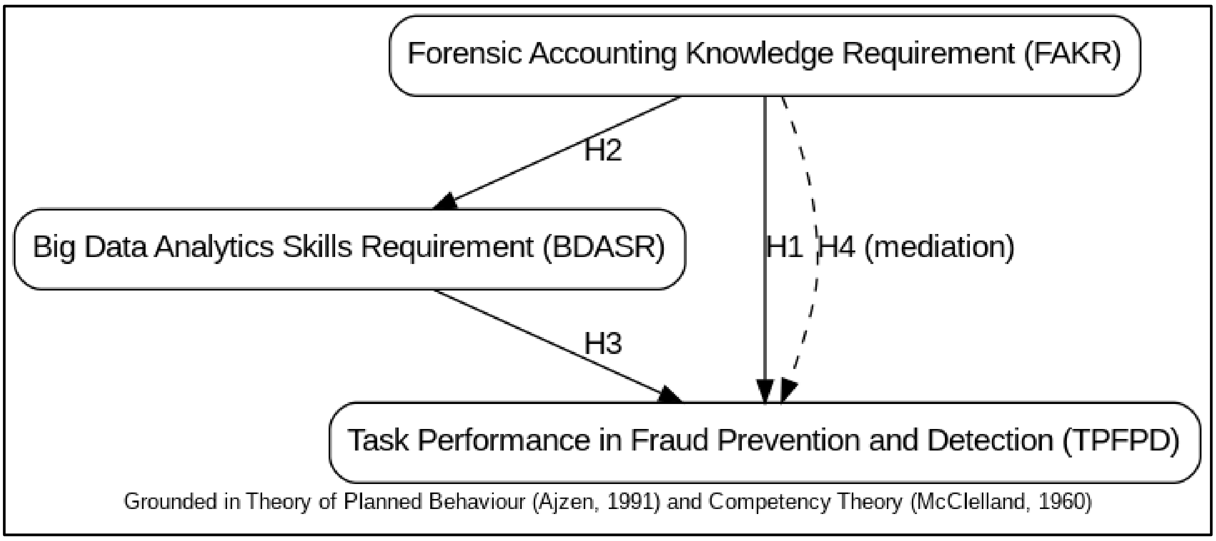

Figure 2. Theoretical Framework of the Study

2.6. Underpinning Theories

Theory of Planned Behaviour (Ajzen, 1991):

In this context, FAKR informs the attitudinal and normative beliefs driving professionals' intention to detect fraud, while BDASR contributes to perceived behavioural control, enabling effective action.

Competency Theory (McClelland, 1961):

CT posits that performance is maximized when relevant knowledge and skills are synergistically applied. Here, FAKR represents the knowledge dimension and BDASR the skill dimension, jointly influencing TPFPD.

These theoretical perspectives jointly underpin the hypothesis that BDASR acts as a mediating mechanism through which FAKR is transformed into tangible improvements in fraud detection performance, especially in the resource-constrained and politically sensitive environment of the public sector.

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3. Research Methodology

3.1. Research Design

This study adopted a quantitative, cross-sectional research design to investigate the direct and mediated relationships between FAKR, BDASR, and TPFPD in Nigeria's federal public sector. The design is appropriate for examining latent constructs and complex mediation pathways using survey data. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used owing to its suitability for predictive models, small-to-moderate sample sizes, and non-normal data distributions (Hair et al., 2022).

3.2. Population and Sampling

The target population comprised forensic accountants and government auditors employed in federal public sector institutions, including the Offices of the Accountant General and Auditor General, as well as anti-corruption agencies. Respondents were selected using purposive sampling to ensure inclusion of professionals with direct fraud detection responsibilities. Following the distribution of 364 questionnaires, 305 valid responses were obtained after data screening. This exceeds the least sample size requirement for mediation analysis in PLS-SEM, which is guided by the ten-times rule and statistical power considerations.

3.3. Measurement Instruments

The study utilised structured questionnaires containing validated multi-item scales measured on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

FAKR items captured investigative techniques, legal knowledge, and fraud identification capabilities, adapted from Popoola (2014) and DiGabriele (2008).

BDASR items assessed competencies in data mining, anomaly detection, statistical modelling, and visualisation tools, adapted from Appelbaum et al. (2017) and Imjai et al. (2024).

TPFPD items measured fraud detection consistency, reporting accuracy, and contributions to anti-fraud systems, based on Dzomira (2015) and the AICPA (2008) framework.

Content validity was confirmed through expert review and a pilot test with 20 respondents, resulting in minor wording adjustments for clarity.

3.4. Data Collection

Data were collected over a six-week period through both physical delivery and encrypted digital forms. Respondents were briefed on the study's objective and assured of anonymity and voluntary participation. Ethical protocols were observed, and only professionals with direct fraud investigation experience were invited to participate.

3.5. Data Analysis Procedures

PLS-SEM analysis was carried out by using SmartPLS 4.0, following a two-stage approach:

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Measurement Model Evaluation: Assessed indicator reliability (outer loadings ≥ 0.70), internal consistency (Cronbach's Alpha, Composite Reliability, rho_A ≥ 0.70), convergent validity (AVE ≥ 0.50), and discriminant validity (Fornell–Larcker criterion, HTMT ratio, and cross-loadings).

Structural Model Evaluation: Tested for multicollinearity (VIF < 3.3), evaluated path coefficients, effect sizes (f^2), coefficient of determination (R^2), predictive relevance (Q^2), and performed mediation analysis using bias-corrected bootstrapping (5,000 resamples). The selection of PLS-SEM was motivated by its ability to handle complex models and its robustness in prediction-focused research within emerging economy contexts.

3.6. Ethical Considerations

The study was conducted in compliance with established research ethics standards. Approval was fetched from the relevant institutional ethics committee. Participation was voluntary, informed consent was secured, and confidentiality was maintained throughout the research process.

4. Results

4.1. Descriptive Statistics

Table 1 demonstrates the descriptive statistics for FAKR, BDASR, and TPFPD. The results show high mean scores for all constructs (FAKR: 4.45; BDASR: 4.29; TPFPD: 4.32), indicating strong self-reported competence among respondents. Standard deviations were relatively low (≤ 0.535), suggesting consistency in responses across the sample.

Table 1. Descriptive Statistics of the Study

Constructs	N	Minimum	Maximum	Mean	Std. Deviation
FAKR	305	2	5	4.45	0.514
BDASR	305	3	5	4.29	0.535
TPFPD	305	2	5	4.32	0.504
Valid N (listwise)	305				

4.2. Measurement Model Assessment

The paper assesses observed indicators that reliably and validly measure the latent constructs FAKR, BDASR, and TPFPD in terms of discriminant validity, internal consistency, and convergent validity.

Assessment of Internal Consistency and Convergent Validity

This subsection assesses the validity and reliability of the latent constructs by assessing internal consistency reliability (Cronbach's alpha, composite reliability, rho_A) and convergent validity (indicator reliability and average variance extracted (AVE)) of FAKR, BDASR, and TPFPD.

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First, we conduct outer loading relevance testing (OLRT) as recommended by Hair et al. (2014; 2017:114) in arriving at the measurement model results.

As per Hair et al. (2014; 2017) and Popoola (2014), the essentials in the determination of reflective measurement models are the estimates for the relationship between the latent variables (unobserved) and the manifest variables (observed). These crucial estimates are represented in Table 2.

Table 2. Key Evaluation Summary Results for Reflective Measurement Model

Construct	Indicators	Outer Loadings	Indicator Reliability	AVE	Cronbach's Alpha	CR	Rho_A
BDASR	BDASR3	0.734	0.539	0.564	0.746	0.838	0.751
	BDASR6	0.740	0.548				
	BDASR7	0.738	0.545				
	BDASR8	0.791	0.626				
FAKR	FAKR3	0.716	0.513	0.544	0.723	0.827	0.723
	FAKR4	0.746	0.557				
	FAKR6	0.763	0.582				
	FAKR7	0.725	0.526				
TPFPD	TPFPD11	0.757	0.573	0.581	0.819	0.874	0.819
	TPFPD12	0.791	0.625				
	TPFPD13	0.786	0.618				
	TPFPD14	0.756	0.572				
	TPFPD6	0.719	0.517				

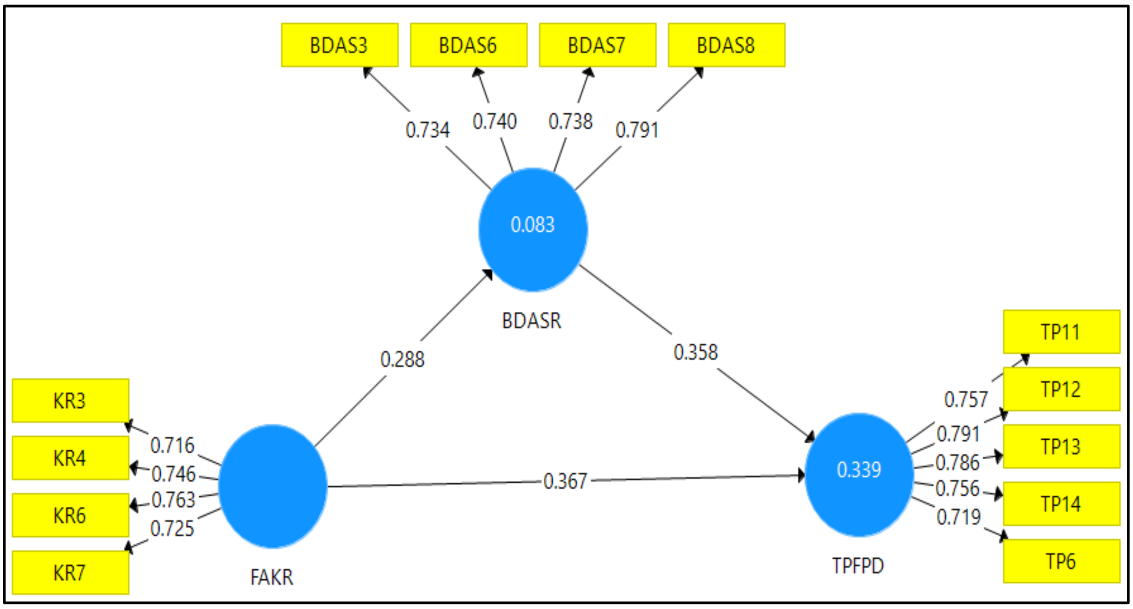

Figure 3. Key Evaluation Summary Results for Reflective Measurement Model and R^2 Assessment

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All outer loadings for the reflective indicators exceeded the recommended threshold of 0.70, confirming strong indicator reliability. Composite reliability (CR) and rho_A values for FAKR, BDASR, and TPFPD were all above 0.70, demonstrating internal consistency.

AVE values ranged from 0.544 to 0.581, exceeding the 0.50 threshold, thus confirming convergent validity for each construct and that the constructs are conceptually distinct regarding their reliability and validity. Table 2 illustrates the key quality criterion of the measurement model.

Assessment of Discriminant Validity

Discriminant validity was verified through three methods:

Indicator Cross-Loadings Analysis Method

Establishing discriminant validity, an indicator's loading on its allocated construct must be greater than all its cross-loadings with other constructs. The loadings and cross-loadings for every indicator is shown in Table 3. Each indicator loaded maximum on its intended construct, with no problematic cross-loading observed. For instance, the indicator TPfra1 has the highest value for the loading with its corresponding construct TPFPD11 (0.757), while all cross-loadings with other constructs are much lesser (e.g., TPFPD11 on BDASR: 0.335; TPFPD11 on FAKR: 0.373).

Table 3. Assessment of Discriminant Validity: Indicator Cross-loadings Analysis

Constructs	Indicators	BDASR	FAKR	TPFPD
BDASR	BDAS3	**0.734**	0.210	0.431
	BDAS6	**0.740**	0.247	0.282
	BDAS7	**0.738**	0.172	0.275
	BDAS8	**0.791**	0.231	0.371
FAKR	KR3	0.196	**0.716**	0.383
	KR4	0.198	**0.746**	0.309
	KR6	0.123	**0.763**	0.312
	KR7	0.300	**0.725**	0.366
TPFPD	TP11	0.335	0.373	**0.757**
	TP12	0.360	0.366	**0.791**
	TP13	0.358	0.338	**0.786**
	TP14	0.378	0.321	**0.756**
	TP6	0.338	0.391	**0.719**

The same finding holds for the other indicators of TPFPD6 (i.e., TPFPD: 0.719) as well as the indicators measuring BDASR and FAKR on the same row. Similarly, the indication BDASR8 maintains the maximum value for the loading with its corresponding construct BDASR (0.791), while all cross-loadings with other constructs are considerably lower (see FAKR on TPFPD: 0.371; BDASR on FAKR: 0.231).

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Based on the indicator cross-loadings assessments, as demonstrated in Table 3, there is better discriminant validity in the study.

Fornell-Larcker Criterion Method

We also evaluate the discriminant validity based on the Fornell-Larcker criterion. The logic of the Fornell-Larcker method is based on the concept that a construct, BDASR, shares more variance with its related indicators than with any other construct (i.e., FAKR or TPFPD). The Fornell-Larcker criterion comes with two possibilities, such as

(a) compare the square root of the AVE values with the latent variable correlations, and

(b) determines whether the AVE is larger than the squared correlation with other constructs.

Table 4. Assessment of Discriminant Validity: Fornell-Larcker Criterion Analysis

Construct	BDASR	FAKR	TPFPD)
BDASR	**0.751**		
FAKR	0.288	**0.738**	
TPFPD	0.464	0.471	**0.762**

This study adopted method (a), which compares the square root of the AVE values with the latent variable correlations to establish discriminant validity. In essence, the square root of each construct's AVE must be higher than its maximum correlation with other constructs. In this paper, the square root of AVE for each construct was higher than its correlations with other constructs.

For example, for TPFPD in Table 4, we compare all correlations in the row and column of TPFPD with its square root of the AVE. Therefore, discriminant validity is established as the TPFPD (0.762), BDASR (0.751), and FAKR (0.738) recorded highest values than their highest corresponding row and column values of a latent correlation. Reading from Table 4, the BDASR (0.751) achieves the highest corresponding value of TPFPD (0.288) in a row and FAKR (0.464) in a column, thus justifying the criterion for better discriminant validity.

Heterotrait-Monotrait (HTMT) Ratio of Correlations Method

This study employed HTMT, which is one of the useful criteria to assess discriminant validity (Nitzl 2016). Also, Henseler et al. (2015) propose the superior performance of the HTMT through Monte Carlo simulation and find that it achieves higher specificity and sensitivity rates of 97% to 99% as compared to the indicator cross-loadings and Fornell-Larcker criterion (20.82%).

Table 5. HTMT Ratio of Correlations Method

Constructs	BDASR	FAKR	TPFPD
BDASR	[redacted]		

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FAKR	**0.374**		
TPFPD	**0.577**	**0.601**	

The benchmark for evaluating HTMT value < 1 shows better discriminant validity, and a value > 1 reflects the existence of a lack of discriminant validity. Prior studies by Kline (2011) and Clark and Watson (1995) suggest a cut-off, though stringent, of 0.85. In like manner, Henseler et al. (2015), Teo et al. (2008), and Gold et al. (2001) suggest a threshold value of 0.90 to establish discriminant validity between a given pair of reflective constructs. In our study, all HTMT values were below 0.90, further confirming discriminant validity. The results marked in bold (i.e., TPFPD in FAKR, 0.601; TPFPD in BDASR, 0.577; and FAKR in BDASR, 0.374) indicate the existence of good discriminant validity because the HTMT values meet the threshold cut-off of below 0.90, as demonstrated in Table 5.

4.3. Structural Model Evaluation

4.3.1 Multicollinearity Diagnostics

One of the vital steps in assessing the structural model is to conduct VIF statistics, which are essential for the reflective inner model and formative outer (measurement) models. Collinearity occurs when multiple independent variables are intercorrelated. Since our study is situated on reflective measures, we use only the inner model VIF. Considering the PLS-SEM context, a VIF value of 5 and a value > 5 pose a potential collinearity issue (Hair et al., 2011), while the generally accepted threshold of VIF value is < 3.3 (Diamantopoulos and Siguaw, 2006).

This study examines collinearity using VIF values, as shown in Table 6, all of which were between 1.00 and 1.09, which are well below the threshold of 10 (Hair et al., 2014). The implication of the result is an indication of the absence of multicollinearity issues in the model.

Table 6. Assessment of Collinearity Issue (VIF) for a Reflective Measurement Model

Construct	BDASR	FAKR	TPFPD
BDASR			1.09
FAKR	1.0		1.09
TPFPD			

Model Predictive Power: Coefficient of Determination (R^2)

The R-square (R^2) value is a measure of the model's predictive power. It signifies the exogenous latent variables' (FAKR and BDASR) cumulative impacts on the endogenous latent variable, TPFPD. In essence, it highlights the amount of variance in the endogenous construct, TPFPD, explained by all the exogenous constructs (i.e., FAKR and BDASR) linked

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to it. The R^2 ranges from zero to one and characterizes a measure of in-sample predictive power (Rigdon, 2012; Sarstedt et al., 2014).

Table 7. Coefficient of Determination (R^2)

Construct	R Square	R Square Adjusted
BDASR	0.083	0.080
TPFPD	0.339	0.335

The model's explanatory power was evaluated using R^2 values for TPFPD = 0.339, indicating that FAKR and BDASR jointly explain 33.9% of the variance in TPFPD. Likewise, the R^2 for BDASR = 0.083, demonstrating that FAKR accounts for 8.3% of the variance in BDAS. These R^2 values suggest moderate explanatory power, particularly for TPFPD, as demonstrated in Table 7 and Figure 3.

Model Predictive Relevance: Effect Size f^2

The f-square effect size measures how effectively one exogenous construct contributes to explaining a specific endogenous construct in terms of R-square (R^2), as shown in Table VIII of this study.

Table 8. Effect Size (f^2)

Construct	BDASR	FAKR	TPFPD
BDASR			0.178
FAKR	0.090		0.188
TPFPD			

As noted in Table 8, we confirm that the f^2 values showed:

- FAKR → TPFPD: $f^2 = 0.188$ (medium effect)
- BDASR → TPFPD: $f^2 = 0.178$ (medium effect)
- FAKR → BDASR: $f^2 = 0.090$ (small-to-medium effect)

This conclusion is based on Cohen's (1988) threshold criteria of 0.02, 0.15, and 0.35 that represented small, medium, and substantial effects. However, previous literature indicates that values of less than 0.02 suggest no effect size (Hair et al., 2017).

Model Out-of-Sample Predictive Power: Effect Size Q^2

Having assessed the R^2 value of TPFPD and BDASR, there is a need to consider the change in R^2 value when a specified exogenous construct, say FAKR, is omitted from the model. This is because of the impact the omitted construct could have on the endogenous construct, TPFPD.

Also, we note that assessing the magnitude of the R^2 values as a criterion of predictive accuracy is not enough. Hence, our study explores further to examine Stone-Geiser's Q^2 value (Geisser, 1974; Stone, 1974). This measure represents the model's out-of-sample predictive

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power. According to Hair et al. (2017), when a PLS-SEM path model exhibits predictive relevance, it accurately predicts data not used in the model estimation. In the structural model, Q^2 values greater than 0 for a TPFPD specify the path model's predictive relevance for the TPFPD.

Table 9. Model Predictive Significance Value Effect Size (q^2)

Construct	SSO	SSE	Q^2 (=1-SSE/SSO)
BDASR	1,220.00	1169.214	0.042
FAKR	1,220.00	1220.000	
TPFPD	1,525.00	1246.540	0.183

In this study, we obtain the sum of the squared observations (SS0) and the sum of prediction errors (SSE) through the blindfolding technique of the PLS path model at omission distance (D7) of data points per blindfolding round as recommended by Apel and Wold (1982) and Hair et al. (2012).

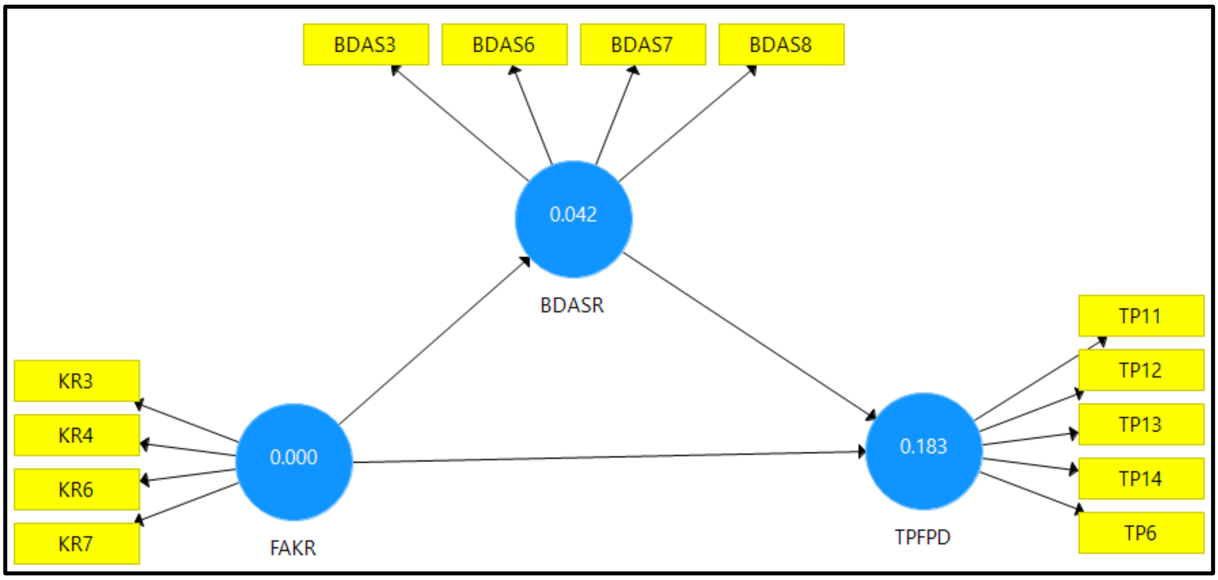

Figure 4. Model Out-of-Sample Predictive Relevance - Effect Size Q^2

This study adopts cross-validated redundancy as a measure of Q^2 because it contains the structural model, the critical element of the path model, to predict removed data points. The results in the last column (i.e., 1 – SSE/SSO) revealed the predictive significance of the Q^2 of TPFPD (0.183) and BDASR (0.042) values as reflected in Table 9 and Figure 4, Model Out-of-Sample Predictive Relevance - Effect Size Q^2, which present moderate predictive importance, while q^2 statistics reflected small to medium predictive accuracy in consideration of Cohen's (1988) criterion of 0.02, 0.15, and 0.35 that represented small, medium, and substantial effects. Thus, the model of BDASR on the relationship with FAKR and TPFPD has confirmed adequate explanatory and predictive quality for SEM analysis.

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4.3.2 Hypothesis Testing

Bootstrapping results (5,000 subsamples) of the hypotheses testing are illustrated in Table 10.

Table 10. Structural Model Hypothesis Testing for Direct and Indirect Effects with Confidence Intervals (Lower and Upper Levels)

Hypothesis	Relationship	Std Beta	Std Error	T-Stats	P-Values	Decision	f2	q2	5% CILL	95% CIUL
H1	BDASR -> TPFPD	0.358	0.047	7.690	0.000	Supported	0.178	0.042	0.278	0.432
H2	FAKR -> BDASR	0.288	0.061	4.758	0.000	Supported	0.090		0.167	0.374
H3	FAKR -> TPFPD	0.367	0.055	6.683	0.000	Supported	0.188	0.183	0.262	0.448
H4	FAKR -> BDASR -> TPFPD	0.103	0.028	3.752	0.000	Supported			0.06	0.149

Note:
** p 0.01; * p   0.05
R-Square = BDASR 0.083; TPFPD, 0.339
Effect size impact indicator according to Cohen (1988), f2 values: 0.35 (large), 0.15 (medium), and 0.02 (small)
Q-square (BDASR = 0.042), TPFPD = 0.183)
Predictive relevance (q2) of Predictor exogenous latent variables as according to Henseler et al. (2009), q2 values: 0.35 (large), 0.15 (medium), and 0.02 (small).

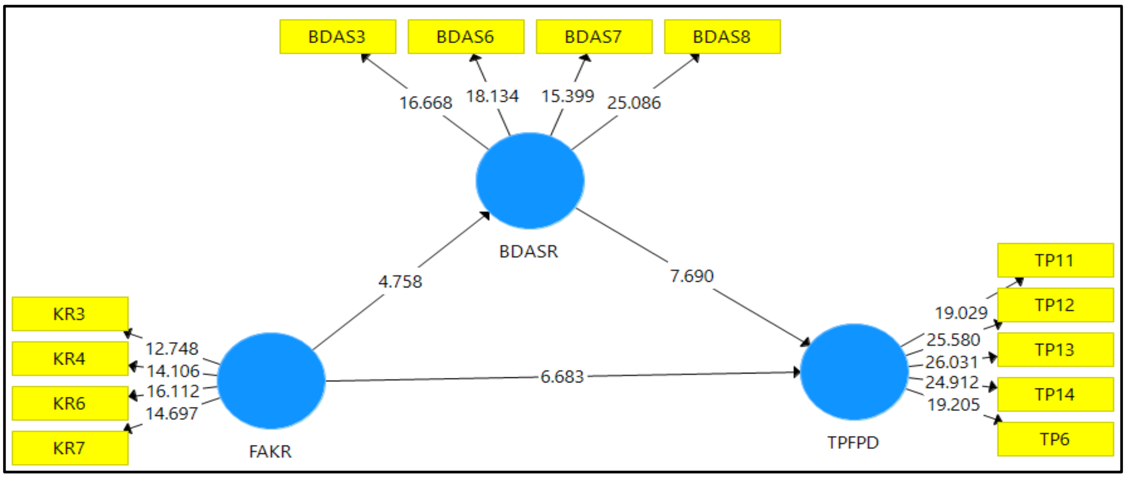

Figure 5. Structural Model Hypothesis Testing for Direct and Indirect Effects with Confidence Intervals (Lower and Upper Levels)

H1: FAKR → TPFPD ($\beta = 0.367$, $t = 6.683$, $p < 0.001$) — Supported.

H2: FAKR → BDASR ($\beta = 0.288$, $t = 4.758$, $p < 0.001$) — Supported.

H3: BDASR → TPFPD ($\beta = 0.358$, $t = 7.690$, $p < 0.001$) — Supported.

H4: FAKR → BDASR → TPFPD ($\beta = 0.103$, $t = 3.752$, $p < 0.001$) — Supported.

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Interpretation:

All four hypotheses were supported, confirming both the direct influence of FAKR on TPFPD and the mediating role of BDASR.

4.4. Summary of Key Findings

- The measurement model met all reliability (Cronbach's alpha, outer loadings, CR) and validity (AVE, Fornell–Larcker, HTMT) thresholds.
- Structural model results showed moderate explanatory power for TPFPD and small-to-moderate explanatory power for BDASR.
- Effect sizes indicate that both knowledge and analytics skills play meaningful roles in predicting fraud detection performance.
- Mediation analysis confirmed BDASR as a significant pathway linking FAKR to TPFPD, supporting the hybrid competency model.

5. Discussion

5.1. Overview of Key Findings

This research examined the direct and mediated effects of FAKR and BDASR on TPFPD in Nigeria's federal public sector. The results provide strong empirical support for a hybrid competency model, demonstrating that:

a) FAKR significantly and positively influences TPFPD both directly and indirectly through BDASR.
b) FAKR significantly predicts BDASR, suggesting knowledge-driven adoption of analytics competencies.
c) BDASR significantly predicts TPFPD, underscoring the strategic importance of technical analytics skills in fraud detection.
d) BDASR partially mediates the FAKR–TPFPD relationship, validating the proposed conceptual framework grounded in the Theory of Planned Behaviour (TPB) and Competency Theory (CT).

These results have important theoretical, methodological, and practical implications for public sector fraud detection in emerging economies.

5.2. Discussion by Research Questions, Research Objectives and Hypothesis

RQ1. To what extent does FAKR influence TPFPD in the public sector?

RO1. To define the extent to which FAKR influences TPFPD among public sector professionals.

H1: FAKR has a significant positive effect on TPFPD (FAKR → TPFPD).

The significant positive effect of FAKR on TPFPD ($\beta = 0.367$, $t = 6.683$, $p < 0.001$) supports the proposition that domain-specific knowledge is a critical determinant of fraud detection performance. This aligns with prior studies (Popoola et al., 2014; DiGabriele, 2008) which found that forensic expertise enhances professional judgment, investigative accuracy, and

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decision quality in fraud-related tasks. In the context of TPB, FAKR represents cognitive preparedness that shapes attitudes toward fraud investigation and increases the perceived capability to perform such tasks. From the perspective of CT, FAKR is a foundational component of competence, enabling professionals to understand fraud typologies, identify anomalies, and interpret financial evidence.

However, the outcomes also demonstrate that while FAKR is a stronger predictor, its influence on TPFPD is amplified when coupled with analytics skills, suggesting that knowledge alone is no longer sufficient in digitised environments.

RQ2: How does FAKR relate to BDASR among public sector professionals?

RO2: To evaluate the relationship between FAKR and BDASR to identify knowledge-driven antecedents of analytics competence.

H2: FAKR positively influences BDASR (FAKR → BDASR)

The positive effect of FAKR on BDASR ($\beta = 0.288$, $p < 0.001$) confirms that professionals with strong forensic knowledge are more inclined to develop technical analytics skills. This supports the notion that domain knowledge drives skill acquisition, as individuals seek tools that enhance their ability to operationalise their expertise. Prior research in AIS and forensic accounting (Appelbaum et al., 2017; Mittal et al., 2021) similarly suggests that awareness of complex fraud schemes motivates adoption of data analytics tools.

In TPB terms, FAKR enhances perceived behavioural control over analytics adoption by providing the conceptual foundation to understand what to look for in large datasets. Under CT, this finding reflects the interplay between knowledge and skill in achieving high-level competence.

RQ3: What is the direct impact of BDASR on TPFPD in the public sector?

RO3: To assess the direct impact of BDASR on TPFPD in fraud-related tasks.

H3: BDASR has a significant positive effect on TPFPD (BDASR → TPFPD).

BDASR's significant positive effect on TPFPD ($\beta = 0.358$, $p < 0.001$) underscores the role of analytics skills as a strategic enabler of performance. Professionals proficient in data mining, anomaly detection, and visualisation tools are better able to detect subtle fraud indicators, process large transaction volumes, and produce timely, accurate investigative reports. These results corroborate findings by Gepp et al. (2018) and Imjai et al. (2024) that analytics-driven approaches enhance detection speed and reduce false positives.

This finding is especially important in the Nigerian public sector, where digitised financial systems such as TSA, GIFMIS, and IPPIS generate large, complex datasets. Without BDASR, the potential of these systems to support proactive fraud detection remains underutilised.

RQ4: Does BDASR mediate the relationship between FAKR and TPFPD?

RO4: To test the mediating role of BDASR in the relationship between FAKR and TPFPD.

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H4: BDASR mediates the relationship between FAKR and TPFPD (BDASR in the FAKR–TPFPD Relationship)

The mediation analysis confirms that BDASR partially mediates the relationship between FAKR and TPFPD ($\beta = 0.103$, $p < 0.001$). This validates the hybrid competency model, where technical analytics skills serve as a bridge between domain knowledge and performance outcomes.

This result aligns with recent calls in the forensic accounting literature to integrate technological skills into professional competency frameworks (Akinbowale et al., 2023b; Fairchild and Mackinnon, 2009). It also extends TPB by illustrating how perceived behavioural control (analytics skills) interacts with cognitive preparedness (knowledge) to influence actual behaviour (fraud detection performance). From a CT perspective, the finding affirms that superior performance emerges when knowledge and skills are synergistically applied.

6. Implications

The results of this study carry major impact across theoretical, practical, policy, educational, and technological domains.

Theoretically, the findings extend the Theory of Planned Behaviour by empirically demonstrating that technical analytics skills operate as a mediating mechanism between cognitive preparedness, represented by FAKR, and actual TPFPD. This integration enriches CT by showing that superior performance emerges when domain knowledge and technical skills are applied in synergy, particularly in high-stakes, digitised environments.

From a practical perspective, the study underscores the necessity for public sector forensic professionals to cultivate a hybrid skill set. While forensic knowledge remains fundamental, the capacity to analyse large and complex datasets—through BDASR—is now indispensable for timely and effective fraud detection. For policy makers, the evidence suggests that recruitment, training, and promotion systems within the public sector should explicitly integrate analytics competencies into competency frameworks, ensuring that investigative roles are staffed by professionals capable of operating in data-intensive contexts.

In the educational sphere, the findings support curriculum reform in accounting, auditing, and forensic science programmes. Higher education institutions and professional bodies should embed data analytics modules, simulation-based training, and cross-disciplinary learning opportunities into their offerings, preparing graduates for the realities of modern fraud investigation. Technologically, the results provide justification for increased investment in analytics infrastructure—such as anomaly detection software, real-time dashboards, and predictive modelling tools—paired with capacity building to ensure these resources are fully utilised. In combination, these implications provide a roadmap for enhancing public sector fraud detection capacity in Nigeria and comparable contexts.

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7. Limitations and Future Research Signposts

While the study makes valuable contributions, specific limitations should be acknowledged. First, the cross-sectional design limits causal inference, capturing relationships at a single point in time. Future research may adopt experimental or longitudinal designs to observe how the integration of forensic knowledge and analytics skills evolves and influences performance over time. Second, reliance on self-reported measures can introduce perceptual bias, as participants could overstate their competencies or performance. Incorporating objective performance metrics—such as detection rates or case resolution times—would strengthen the validity of future findings.

Third, the study focuses exclusively on federal-level public sector professionals in Nigeria, which may limit generalisability to state-level agencies, local governments, or private sector contexts. Comparative studies across multiple tiers of government or across countries with similar digital governance initiatives could provide broader insights. Fourth, the model could be extended to examine additional mediators or moderators, such as organisational support, ethical climate, or technology readiness, which may shape the knowledge–skill–performance relationship. Finally, qualitative approaches, including in-depth interviews or case studies, could complement the quantitative results by providing richer contextual understanding of how hybrid competencies are applied in real-world investigations.

8. Conclusion

This study examine how FAKR translates into TPFPD within Nigeria's digitised public sector, with BDASR serving as a mediating competency. Through PLS-SEM analysis on data from 305 forensic accountants and auditors, the outcomes confirmed that both knowledge and analytics skills are significant predictors of performance, with BDASR partially mediating the FAKR–TPFPD relationship. These results empirically validate a hybrid competency model grounded in the Theory of Planned Behaviour and CT, offering new theoretical and practical insights into public sector fraud detection.

By demonstrating that hybrid competencies enhance performance in data-intensive environments, this research provides a foundation for policy reforms, curriculum development, and technology investments aimed at strengthening public financial accountability. Although limited by its design and scope, the study opens avenues for further inquiry into the integration of knowledge and technology in fraud detection across diverse institutional and geographic contexts. In an era where financial misconduct increasingly exploits digital systems, the ability to combine investigative expertise with analytics capability will remain central to protecting public resources and sustaining public trust.

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Conflict of Interest

The author declares that there is no conflict of interest.

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