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Adoption of AI-Supported Accounting Information Systems (AIS) and Work Efficiency of Bursary Personnel: Implications for Business Education Curriculum in Colleges of Education

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***Abstract* - Bursary offices in Nigerian Colleges of Education face growing pressure to modernise financial management, yet adoption of artificial intelligence-supported Accounting Information Systems (AI-AIS) in this setting remains underexplored. This study examined the drivers of AI-AIS adoption, the efficiency effects of adoption, and the moderating role of staff AI-specific skill. A convergent parallel mixed-methods design combined survey data from 167 bursary staff across five purposively selected Colleges of Education with semi-structured interviews, focus group discussions, system-log metrics, and document review. The Technology-Organisation-Environment (TOE) framework, extended by a Human Skill Drivers dimension and supplemented by the Technology Acceptance Model, guided the analysis. Six of seven hypotheses were supported. AI-AIS users processed substantially more transactions per day (M = 187.4 vs. 121.6; Cohen's d = 1.58), recorded lower error rates, and completed reports markedly faster than non-users. System integration quality ($\beta = .31$, $p < .001$), top management support ($\beta = .28$, $p < .001$), and staff AI-specific competency were the strongest predictors of adoption intention. Human skill significantly strengthened the association between adoption and efficiency ($\beta = .19$, $p = .004$), indicating that technology investment without concurrent competency development yields weaker returns. The findings point to the need for curriculum reform, targeted staff training, and stronger institutional AI governance to realise the operational benefits of AI-AIS in Nigerian higher education finance.**

Keywords: AI-supported accounting information systems; transaction throughput; bursary offices; Nigerian Colleges of Education; TOE framework; human skill drivers; digital literacy.

I. INTRODUCTION

Bursary offices in Nigerian Colleges of Education perform core financial functions, including student fee collection, payroll processing, procurement authorisation, statutory remittances, and regulatory reporting. The accuracy and timeliness of these processes affect institutional accountability and the continuity of educational services. Across Nigeria's 162 NCCE-accredited Colleges of Education, enrolment stands at approximately 430,000 students (NCCE, 2023), yet the financial systems supporting this population remain, in many institutions, largely manual or reliant on spreadsheet-based workflows that are poorly suited to the transaction volumes these functions demand.

Operational inefficiencies are common. Peak-period backlogs require staff overtime; errors surface at external audit rather than at point of entry; and reporting cycles extend well beyond the 24-to-72-hour benchmark that characterises comparable institutional environments (Ogbonna & Ebimobowei, 2012; Okeke *et al.*, 2023). A study of Akwanga College of Education confirmed this pattern, identifying fragmented system architecture, inadequate automation, and insufficient staff technical skills as the dominant constraints even where a basic Accounting Information System existed.

Against this background, the case for AI-supported AIS adoption is operational rather than merely technological. Machine learning, robotic process automation, and predictive analytics can reduce manual workload, improve transaction accuracy, and accelerate financial reporting. National policy reinforces this direction: the Federal Government's National Education Policy, TET Fund's ICT intervention programme, and the NCCE's revised Benchmark Minimum Academic Standards all signal that modernised financial administration is expected rather than optional.

Existing adoption studies in Nigeria concentrate mainly on commercial banking and private-sector manufacturing, leaving the bursary-office context in Colleges of Education underexplored (Iyoha *et al.*, 2020; CSEA, 2024). As a result, there is limited evidence on the efficiency consequences of AI-AIS adoption, the institutional factors that shape adoption, and the extent to which staff AI-specific skill determines whether adoption translates into performance gains. This study addresses all three gaps.

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1.1 Research Objectives and Hypotheses

The study pursues three integrated objectives.

i. First, it quantifies the efficiency effects of AI-AIS adoption by comparing transaction throughput, processing time, error rates, and report turnaround between users and non-users across five Colleges of Education.
ii. Second, it identifies the technological and organisational predictors of adoption intention within an expanded TOE framework.
iii. Third, it examines whether staff AI-specific skill moderates the relationship between adoption and efficiency.

Seven hypotheses operationalise these objectives.

H1 proposes that AI-AIS adoption is positively associated with transaction throughput.

H2a propose, respectively, that system integration quality, data quality.

H2b top management support are significant positive predictors of adoption intention.

H2c proposes that staff AI-specific skill significantly moderates the adoption-to-throughput relationship, such that higher skill amplifies throughput gains.

H4a and H4b propose that perceived usefulness and perceived ease of use are significant positive predictors of adoption intention.

H5 proposes that NDPA 2023 compliance readiness is positively associated with adoption intention.

1.2 Study Scope

The study is limited to the bursary offices of five purposively selected Colleges of Education representing federal, state, and private ownership across different geopolitical zones and ICT maturity levels. The primary efficiency indicator is transaction throughput, supplemented by processing time, error rates, report turnaround, and job satisfaction. The study is cross-sectional; longitudinal trends are outside its scope.

Table 1: Profile of Selected Nigerian Colleges of Education

Institution	Ownership	Zone	ICT Maturity	AI-AIS Status
FCT CoE, Zuba	Federal	North-Central	2 – Intermediate	Partial Adoption
LSCOE, Ijanikin	State	South-West	2 – Intermediate	Partial Adoption
OYSCOE, Lanlate	State	South-West	1 – Basic	Minimal/Manual
FCE (Tech), Asaba	Federal	South-South	2 – Intermediate	Partial Adoption
ABUAD CoE, Ekiti	Private	South-West	3 – Advanced	Full Adoption

Note: ICT Maturity rated 1 (Basic) to 3 (Advanced) from infrastructure audit items. CoE = College of Education.

II. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 AI-Supported Accounting Information Systems

An Accounting Information System collects, records, stores, and processes financial data to support organisational decision-making (Romney & Steinbart, 2021). When augmented by artificial intelligence, it can classify transactions, detect anomalies, generate narrative reports, and forecast budgetary variances. These capabilities are especially relevant in bursary offices, where workloads are high and errors carry regulatory consequences.

Global adoption has accelerated substantially since 2018. Evidence from large-scale accounting studies indicates that AI users close monthly books faster, allocate more time to high-value analytical tasks, and achieve better automation outcomes than non-users (Choi *et al.*, 2023). However, these gains are concentrated in higher-income private-sector environments; public educational institutions in Sub-Saharan Africa remain underrepresented in the empirical literature. In Nigeria, a national survey found that 74.1% of businesses had adopted AI in at least one domain, yet inadequate staff skills and limited IT infrastructure remained the primary barriers (CSEA, 2024). Within higher education, only 20% of a sample of state universities deployed genuinely intelligent AIS, with Colleges of Education lagging further still (Iyoha *et al.*, 2020).

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This places CoE bursary offices in a distinct position: facing the operational pressures that AI-AIS is designed to address, but starting from a lower baseline of digital infrastructure and human competency than the settings where adoption evidence has been generated.

2.2 Theoretical Framework

The study is grounded in the Technology-Organisation-Environment (TOE) framework (Tornatzky & Fleischer, 1990), which explains technology adoption through three jointly determined dimensions. The Technology dimension covers system integration quality, data quality, AI model performance, and implementation complexity. The Organisation dimension covers top management support, budget adequacy, and training provision. The Environment dimension covers regulatory requirements, NCCE directives, TET Fund conditions, and vendor dynamics. A review of 48 TOE studies confirmed robust explanatory power across industries (Oliveira & Martins, 2011), and Nigerian applications confirm its local relevance, with management support showing particularly strong effects (Awa *et al.*, 2015).

The Technology Acceptance Model (Davis, 1989) supplements the TOE framework at the individual level, with perceived usefulness and perceived ease of use jointly predicting adoption intention. Meta-analytic evidence confirms strong usefulness-to-intention (mean $r = .59$) and moderate ease-of-use-to-intention effects (mean $r = .46$; King & He, 2006).

The study's principal theoretical contribution is the elevation of staff competency from an organisational sub-variable to a standalone fourth dimension, termed Human Skill Drivers. Standard TOE and TAM formulations treat staff skill as incidental rather than structurally distinct. This study argues that in high-stakes, error-consequential financial environments, competency functions as a necessary condition for realising system capability rather than a supplementary facilitator. The argument draws on Skill-Biased Technical Change theory (Acemoglu, 2002), which holds that technological upgrading amplifies the productivity of skilled workers disproportionately, and on Human-Computer Interaction theory (Norman, 2013), which establishes that user competency and interface design jointly determine whether a system's technical capabilities are operationally realised. Three sub-constructs are operationalised: general digital literacy, AI-specific skills, and training provision. The conceptual logic, rather than the theoretical citations alone, does the work here: technology cannot deliver what its users are not equipped to extract.

2.3 Adoption Factors and Efficiency Evidence

System integration quality is a central predictor of adoption success because fragmented platforms increase duplication and manual reconciliation. In the Nigerian organisational context, Awa *et al.* (2015) returned a path coefficient of $\beta = .47$ in an enterprise resource planning adoption study. Federal Colleges of Education face a distinctive structural constraint: mandatory Government Integrated Financial Management Information System (GIFMIS) operation for statutory reporting limits their ability to deploy commercial AI-AIS modules without duplicative manual reconciliation, a barrier that has no parallel in most commercial-sector adoption research.

Data quality presents a parallel threshold problem. AI models trained on historically inconsistent or duplicate records produce unreliable outputs regardless of platform capability (Appelbaum *et al.*, 2017; DeLone & McLean, 2003). Top management support remains one of the most consistently replicated organisational enablers of IS adoption (Oliveira & Martins, 2011). In Nigerian CoEs, discretionary technology expenditure authority is concentrated in the Provost's office, meaning adoption trajectories depend substantially on individual executive disposition rather than institutionalised policy.

Regulatory requirements also matter. The Nigeria Data Protection Act 2023 creates obligations for institutions processing staff salaries, student fees, and supplier data, including requirements for data protection governance, risk assessment, and breach notification. In principle, these requirements should encourage better information-system practices, although compliance may remain largely procedural in some settings.

Efficiency evidence from comparable contexts is consistent. Throughput gains of 28–54% are documented in multi-country accounting studies (Choi *et al.*, 2023). Processing time reductions of 30–61% appear in banking and South African university finance (Al-Hakim, 2022; Sibanda & Ndebele, 2022). Error reductions of 15–67% arise from automated validation and anomaly flagging (Munoko *et al.*, 2020). These ranges provide the interpretive benchmarks for the present study.

2.4 Curriculum Implications

The NCCE Benchmark Minimum Academic Standards for Business Education (2022) confine technology content to basic ICT literacy and standard accounting software, with AI, machine learning, and data analytics absent. Evidence from Nigerian tertiary institutions indicates that only 19% of bursary staff possess adequate AI-specific competencies,

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while 73% have received no formal AI or data analytics training (Joshua, 2025). Moran (2026) argues that the scale of AI automation in professional accounting demands urgent curriculum revision globally. The present study advances this argument by identifying the specific competency deficits associated with AI-AIS use, providing an empirical basis for targeted curriculum investment rather than normative advocacy alone.

III. METHODOLOGY

3.1 Design

The study employed a convergent parallel mixed-methods design (Creswell & Plano Clark, 2018), in which quantitative and qualitative data were collected concurrently, analysed separately with strand-appropriate methods, and integrated at the interpretation stage through a joint display matrix. This design was chosen because the study's objectives require simultaneous quantitative precision for hypothesis testing and qualitative depth for mechanistic explanation. The five Colleges of Education served as bounded case units, enabling cross-institutional comparison by ownership type, ICT maturity, and AI-AIS adoption status (Yin, 2018).

The study is cross-sectional, which limits causal inference. To partially address this, the quantitative strand incorporates retrospective proxy measures from system-log records at institutions with traceable pre- and post-adoption transitions, following precedents in Al-Hakim (2022) and Sibanda and Ndebele (2022). Causal language has accordingly been moderated throughout the analysis and discussion.

3.2 Sample

The quantitative target population comprised all bursary staff in substantive financial processing roles across the five institutions, estimated at 320 to 380 individuals. Sample size was determined through G*Power 3.1 a priori power analysis (Faul *et al.*, 2009; effect size $f^2 = 0.15$, $\alpha = .05$, power = .80, five predictors), yielding a minimum $n = 161$. Of 220 questionnaires distributed, 179 were returned, representing an 81.4% response rate. After removing 12 cases for excessive missing data or outlier status by Mahalanobis distance ($p < .001$), the final analytic sample was $n = 167$. Harman's single-factor test assigned 34.2% of total variance to the first unrotated factor, below the 50% common method bias threshold, suggesting that common method bias is unlikely to substantially distort the findings, though it cannot be entirely excluded.

Qualitative participants were purposively selected for information richness (Patton, 2015). Five key-informant interviews per institution, targeting Bursars, senior accountants, IT officers, and business education lecturers, yielded approximately 25 interviews. Two focus groups of eight to ten participants each were convened: one with bursary clerks and junior accountants, one with business education lecturers. Saturation was monitored iteratively. Independence of normality and homogeneity of variance assumptions were checked for all comparative analyses; Levene's test confirmed variance equality before t-tests were interpreted.

3.3 Instruments and Validation

Four instruments served the convergent design. A structured questionnaire of 68 items across six sections used a 7-point Likert scale, consistent with Hair *et al.* (2019) PLS-SEM recommendations. Items were adapted from Davis (1989), DeLone and McLean (2003), and van Deursen et al. (2017), and contextualised for College of Education bursary operations. A semi-structured interview guide structured 45-to-60-minute key-informant sessions around five thematic clusters, with transcripts produced within 72 hours and member-checked within two weeks (Lincoln & Guba, 1985). A focus group protocol used a funnel design narrowing from broad technology experience to AI tools, competency gaps, and training needs (Morgan, 1997). A system-log and document observation checklist extracted mean daily transaction volume, processing time, error frequency, report turnaround, and NDPA 2023 compliance documentation from each institution's 30-day records.

All instruments underwent three validation stages: expert panel review for content validity (five-member panel; I-CVI $\geq .78$, S-CVI/Ave $\geq .90$), cognitive interviewing with five non-study bursary staff, and pilot testing on $n = 30$ non-study staff for internal consistency (Cronbach's $\alpha \geq .70$) and preliminary factor structure. Two constructs that were initially specified with two items were each expanded to three items following pilot testing feedback, in accordance with standard measurement guidance.

3.4 Analysis

Quantitative analysis proceeded in IBM SPSS 27 and SmartPLS 4 across four stages: data screening and common method bias assessment; measurement model evaluation (outer loadings $\geq .70$, AVE $\geq .50$, HTMT $< .85$ for reflective constructs; indicator weights and VIF < 3.3 for the formative Human Skill Drivers construct); structural model testing via bootstrapped path coefficients (5,000 subsamples, bias-corrected 95% confidence intervals); and one-way ANOVA with Tukey HSD and independent-samples t-tests for comparative efficiency analyses. Confidence intervals are reported alongside p-values throughout the results.

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Interview and focus group data were analysed through Braun and Clarke's (2006) six-phase reflexive thematic analysis in NVivo 14, with a second coder independently coding 20% of transcripts (Cohen's $\kappa \geq .70$). Disagreements were resolved through structured discussion. Quantitative and qualitative findings were then integrated through a joint display matrix (Guetterman *et al.*, 2015), examined for convergence, divergence, and complementarity.

IV. RESULTS

4.1 Sample Characteristics

Table 2 summarises the demographic and institutional profile of the 167 retained respondents. Accounting clerks and revenue clerks constituted the largest role groups, accounting collectively for 58.1% of the sample. The sample was slightly male-skewed at 57.5% and predominantly HND/BSc qualified. Service tenure was spread across all bands, indicating variation in experience levels that was controlled for in robustness analyses.

Table 2: Demographic and Institutional Profile of Respondents (N = 167)

Characteristic	Category	n	%
Institution	FCT CoE, Zuba	36	21.6
	LSCOE, Ijanikin	41	24.6
	OYSCOE, Lanlate	24	14.4
	FCE (Tech), Asaba	38	22.8
	ABUAD CoE, Ekiti	28	16.8
Role	Bursar	5	3.0
	Deputy/Assistant Bursar	12	7.2
	Principal/Senior Accountant	34	20.4
	Accounting Clerk	58	34.7
	Revenue Clerk	39	23.4
	IT/Systems Support Officer	19	11.4
Highest Qualification	OND/NCE	38	22.8
	HND/BSc	71	42.5
	PGD	18	10.8
	MSc/MBA	24	14.4
	Professional (ICAN/ANAN)	16	9.6

4.2 Measurement Model

All reflective construct outer loadings exceeded .70, with Cronbach's α and composite reliability values above .70 and AVE values above .50 for each construct (Table 3). Following reviewer feedback on measurement robustness, the two constructs initially specified with two items were each expanded to three items during pilot revision; reported psychometrics reflect the revised three-item versions. The Human Skill Drivers construct, specified as formative, showed indicator weights ranging from 0.08 to 0.22, with VIFs between 1.21 and 2.84, below the 3.3 collinearity threshold. Two indicators with non-significant weights were retained on content-validity grounds, consistent with formative measurement conventions (Hair *et al.*, 2019). All HTMT ratios fell below .85, ranging from .19 to .71, confirming discriminant validity.

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Table 3: Reliability and Convergent Validity of Reflective Constructs

Construct	Items	Loading Range	α	CR	AVE
System Integration Quality	3	0.78–0.85	.79	.88	.70
Data Quality	3	0.74–0.88	.81	.89	.73
Top Management Support	3	0.80–0.89	.83	.90	.76
Perceived Usefulness	4	0.76–0.91	.88	.92	.74
Perceived Ease of Use	4	0.73–0.87	.85	.90	.69
NDPA Compliance Readiness	3*	0.82–0.90	.80	.90	.75
Adoption Intention	3*	0.85–0.92	.83	.91	.77
Transaction Throughput	3	0.81–0.90	.84	.90	.76

Note: *Three-item versions following pilot revision. α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

4.3 Structural Model

The structural model demonstrated acceptable fit (SRMR = .061) and meaningful explanatory power, accounting for 58% of variance in adoption intention (R^2 = .58, 95% CI [.47, .68]) and 41% of variance in transaction throughput (R^2 = .41, 95% CI [.30, .52]). Blindfolding produced Q^2 values of .44 and .31, respectively, both above zero. Table 4 reports all path coefficients, bootstrap t-values, p-values, and hypothesis-testing outcomes. Confidence intervals for each path are available in the supplementary materials.

Table 4: Structural Path Coefficients and Hypothesis Testing Results

Hypotheses	Path	β	t-value	p-value	Decision
H2a	System Integration Quality → Adoption Intention	0.31	4.55	< .001	Supported
H2b	Data Quality → Adoption Intention	0.24	3.41	< .001	Supported
H2c	Top Management Support → Adoption Intention	0.28	3.98	< .001	Supported
H4a	Perceived Usefulness → Adoption Intention	0.22	3.15	.002	Supported
H4b	Perceived Ease of Use → Adoption Intention	0.14	2.04	.041	Supported
H5	NDPA Compliance Readiness → Adoption Intention	0.11	1.59	.112	Not Supported
H1	Adoption Intention → Transaction Throughput	0.46	6.82	< .001	Supported
H3	Adoption × Human Skill → Throughput (interaction)	0.19	2.87	.004	Supported

Note: All paths estimated via 5,000-subsample bootstrapping with bias-corrected 95% confidence intervals.

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4.4 Moderation Analysis (H3)

The interaction term between adoption intention and Human Skill Drivers on transaction throughput was positive and statistically significant ($\beta = .19$, 95% CI [.06, .32], $t = 2.87$, $p = .004$, $f^2 = .07$), supporting H3. Simple slopes analysis confirmed that the adoption-to-throughput association was markedly steeper among staff with above-median Human Skill Driver scores. A moderation plot with 95% confidence bands is provided in Figure 1 (see Appendix). The effect size corresponds to a small-to-medium effect by conventional benchmarks (Cohen, 1992), and is practically meaningful given the operational context.

4.5 Comparative Analyses

A one-way ANOVA comparing throughput across ownership types was significant, $F(2, 164) = 6.84$, $p = .001$, partial $\eta^2 = .077$. Tukey HSD post hoc comparisons indicated that the private institution reported significantly higher throughput than state institutions ($p = .002$); federal-versus-state and federal-versus-private comparisons did not reach significance. A second ANOVA by ICT maturity level was also significant, $F(2, 164) = 15.92$, $p < .001$, partial $\eta^2 = .163$, with each maturity level reporting significantly higher throughput than the level below it.

Independent-samples t-tests compared AI-AIS users ($n = 128$) against those without meaningful AI-AIS exposure ($n = 39$), the latter concentrated at OYSCOE Lanlate. Levene's test confirmed variance equality prior to interpretation. Table 5 summarises comparisons across four efficiency indicators and job satisfaction.

Table 5: AI-AIS Users versus Non-AI-AIS Users on Efficiency and Job Satisfaction Indicators

Indicator	AI-AIS Users M (SD)	Non-Users M (SD)	t	p	d
Daily throughput (transactions)	187.4 (42.1)	121.6 (33.8)	8.71	< .001	1.58
Processing time (min/transaction)	4.2 (1.3)	9.8 (2.6)	12.04	< .001	2.05
Error rate (per 100 transactions)	2.1 (0.9)	5.4 (1.7)	10.88	< .001	1.86
Report turnaround (hours)	41 (14)	187 (52)	14.22	< .001	2.41
Job satisfaction (7-pt scale)	5.6 (1.0)	4.3 (1.3)	6.05	< .001	1.05

Note: All differences favour AI-AIS users. Effect sizes are large by Cohen's (1992) criteria ($d > 0.8$). Observed values fall within the ranges reported in Al-Hakim (2022), Choi *et al.* (2023), Munoko *et al.* (2020), and Sibanda and Ndebele (2022).

4.6 Qualitative Findings

Thematic analysis of 25 key-informant interviews and two focus groups produced five interrelated themes. Participants described hybrid workflows in which digital data entry was still combined with manual cross-checking, especially during registration and payroll peaks. One senior accountant at FCT CoE, Zuba, observed that reconciling system outputs against physical registers during peak periods consumed the time savings that automation was meant to provide. Integration friction emerged as the primary technical barrier, particularly at federal institutions where mandatory GIFMIS use alongside commercial AIS platforms created a duplicative reconciliation burden with no equivalent in the private institutional context.

Executive support was characterised, consistently across interviews, as a near-binary adoption determinant. A deputy bursar at FCE (Tech), Asaba, noted that a proposal to expand AI-AIS coverage to procurement authorisation had remained unacted upon for over a year following a change in the Provost's office, despite available TETFund funding. Participants drew a clear distinction between general digital comfort, which most described as adequate, and AI-specific troubleshooting confidence, which most characterised as weak or absent. Peer-to-peer knowledge transfer was frequently identified as the primary mechanism through which any AI-AIS operating competency had been developed. Lecturers in both focus groups described curriculum technology content as lagging workplace practice by several years, with strong convergence on a preference for applied, hands-on training over conceptual AI coverage.

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NDPA 2023 compliance was characterised, particularly by participants outside senior leadership, as an audit-oriented documentation activity rather than an operationally embedded governance practice. Most junior and mid-level staff were unaware of their institution's Data Protection Officer appointment and had not encountered data protection obligations in any training context.

4.7 Integration: Joint Display Summary

Quantitative and qualitative findings converged across three central points. The 54% throughput advantage among AI-AIS users was mirrored in participant accounts of clearing transaction queues without overtime during peak registration periods. The prominence of system integration quality as an adoption predictor was elaborated qualitatively through detailed accounts of GIFMIS-to-commercial-AIS reconciliation burdens, adding mechanism to the structural path estimate. The moderation of throughput by human skill was complemented qualitatively by participant accounts distinguishing confident use of AI anomaly flags from sceptical manual override, the latter generating additional verification work that negated speed advantages. The null NDPA compliance finding represents a divergence that the qualitative strand resolves: operational decoupling of compliance from daily accounting practice explains why a theoretically grounded predictor produced no significant quantitative effect. The qualitative strand thus does not merely confirm quantitative results; it identifies the mechanism behind both the supported and the unsupported hypotheses.

V. DISCUSSION

5.1 AI-AIS Adoption and Transaction Throughput

The throughput difference between AI-AIS users and non-users is the study's most consequential operational finding. A mean of 187.4 transactions per day against 121.6 among non-users represents a 54% gap, with a Cohen's d of 1.58, a very large effect by conventional standards (Cohen, 1992). This figure sits at the upper boundary of the 28–54% range documented across multi-country accounting studies (Choi et al., 2023) and is consistent with Al-Hakim's (2022) findings from Iraqi commercial banks operating AI-AIS. The magnitude is plausible given the baseline: institutions without AI-AIS were not merely absent automation but were accumulating compounding inefficiencies through redundant manual posting, peak-period bottlenecks, and audit-stage error detection. The introduction of even partial AI-AIS automation addresses multiple inefficiencies simultaneously, generating gains that would not arise in settings where manual workflows were already rationalised. This finding should nonetheless be interpreted as an association rather than definitive causal evidence, given the cross-sectional design.

Report turnaround presents a complementary dimension of this picture. The mean of 41 hours for AI-AIS users against 187 hours for non-users brings the reporting cycle within the 24-to-72-hour benchmark. This is not merely an efficiency improvement in an abstract sense; it represents the operational difference between systemic non-compliance and adequate institutional accountability under NCCE and Accountant-General reporting obligations.

5.2 Technology and Organisational Predictors

System integration quality (β = .31, 95% CI [.18, .44]) was the strongest technical predictor of adoption intention, consistent with Awa et al. (2015) while falling somewhat below their commercial-sector estimate of β = .47. The gap is plausible given the structural GIFMIS constraint operating at federal institutions. Staff at these institutions described a workflow in which AI-generated outputs must be manually migrated between platforms, directly counteracting the time savings that automation would otherwise deliver. This regulatory integration barrier, largely absent from commercial-sector adoption literature, represents a contextual contribution of the present study to understanding AI adoption in African public institutions.

Data quality (β = .24, 95% CI [.10, .38]) confirmed that AI models cannot reliably classify transactions drawn from historically inconsistent records (Appelbaum et al., 2017; DeLone& McLean, 2003). Participants at three institutions described years of fragmented spreadsheet posting producing datasets characterised by duplicate entries and inconsistent account codes. Data quality thus functions less as a continuous predictor and more as a remediation threshold: institutions face a data-cleansing investment before AI-AIS platforms can deliver their intended capability.

Top management support (β = .28, 95% CI [.14, .42]) confirmed one of the most consistently replicated findings in IS adoption literature (Oliveira & Martins, 2011), but carries a CoE-specific nuance. The concentration of discretionary technology expenditure authority in the Provost's office, documented qualitatively as a near-binary adoption gate, implies adoption fragility specific to highly centralised governance structures. Where individual executive dispositions rather than institutionalised policy determine adoption trajectories, leadership turnover can reverse progress entirely, a systemic governance risk for the sector. Perceived usefulness (β = .22) and ease of use (β = .14) both reached significance, replicating the established meta-analytic pattern in which usefulness exerts the stronger influence (King & He, 2006).

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5.3 Human Skill as a Moderator

The moderation finding ($\beta = .19$, $p = .004$, $f^2 = .07$) is the study's most theoretically consequential result, because it instantiates the Skill-Biased Technical Change prediction (Acemoglu, 2002) in a public-sector African educational institution: technological upgrading amplifies the productivity of skilled workers, and adoption without skill development yields sub-optimal efficiency returns. This is a complementarity effect rather than simply a statistical interaction. The simple slopes analysis showed that the adoption-to-throughput association is substantially steeper among above-median skill scorers, consistent with Norman's (2013) complementarity principle: the usable capability of any information system is bounded by the competence of its user.

The qualitative data supply the mechanism with precision. Participants with higher AI competency acted on AI anomaly flags to accelerate reconciliation, whereas those with lower competency routed the same flags through redundant manual checking procedures that eliminated the speed advantage of automation. Under-skilled users experienced AI-AIS outputs as additional verification work rather than decision support, potentially increasing rather than reducing processing time. Standard TOE formulations that treat competency as an organisational sub-variable without modelling its moderating role produce adoption models that overestimate the direct efficiency effect while concealing this conditionality.

5.4 The NDPA Null Result

The non-significant effect of NDPA compliance readiness ($\beta = .11$, $p = .112$) is analytically informative rather than merely negative. The prior theoretical reasoning was substantively grounded: NDPA 2023 data governance investments materially overlap with those required for reliable AI-AIS operation. The qualitative explanation is that compliance activity at most study institutions was predominantly documentary and oriented to audit cycles rather than embedded in daily operational practice. Participants outside senior leadership were often unaware of their institution's Data Protection Officer appointment and had received no training on data protection obligations. What registers as compliance on institutional records does not map onto the operational awareness that would plausibly influence adoption intention. This compliance-decoupling account suggests that a stronger test of the theoretical relationship requires a composite compliance index drawing on both documentary evidence and perceptual measures of operationalised governance, rather than documentation awareness alone.

5.5 Curriculum and Practical Implications

The competency-gap data give empirical precision to what prior scholarship characterised normatively. Among respondents, 67% lacked AI anomaly-troubleshooting competence, 72% could not validate AI outputs confidently, and 81% had no API integration familiarity. These deficits identify the specific points at which curriculum investment yields the highest return. Three curriculum modules are proposed to address them in sequence: AIS Fundamentals and AI Ethics, targeting foundational concepts and data protection obligations (30 hours, 2 credits); AI-AIS Operations covering automation, anomaly troubleshooting, and workflow management (45 hours, 3 credits), targeting the two most acute operational deficits; and Data Governance, API Configuration, and AI Output Validation (30 hours, 2 credits), targeting advanced competencies currently absent from virtually all CoE bursary offices. These modules are designed to integrate with existing NCCE Benchmark Minimum Academic Standards elective slots rather than requiring wholesale curriculum redesign.

At the institutional level, the data quality and integration findings together recommend treating data remediation and system integration as prerequisite investments rather than concurrent activities. Deploying AI-AIS on historically inconsistent records generates unreliable outputs that erode staff trust and ultimately suppress adoption intention. At the sector governance level, the dependence of adoption trajectories on individual executive dispositions argues for embedding AI governance requirements in TETFund grant conditions and NCCE accreditation criteria, structural incentives that operate independently of any particular Provost's technology priorities.

5.6 Limitations and Future Research

This study has several limitations. The cross-sectional design is the most fundamental methodological constraint, precluding causal inference despite convergent support from retrospective log data and qualitative accounts. The purposive sample of five institutions, selected for heterogeneity rather than representativeness, does not support direct generalisation to Nigeria's 162 Colleges of Education, and the private-institution subsample is atypical in its resourcing. Some constructs were measured with limited item counts, though expanded versions were used following pilot feedback. The possibility of residual common method bias cannot be entirely ruled out despite the procedural and statistical checks applied. The compliance-readiness measure requires disaggregation into documentary and operational components in future instruments.

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Future research should pursue longitudinal tracking of efficiency metrics from AI-AIS adoption, to establish whether throughput gains persist and whether the human skill moderation effect strengthens as staff accumulate experience. A quasi-experimental evaluation comparing Colleges of Education that adopt the proposed curriculum modules against matched comparators would provide the evidentiary basis for NCCE-mandated curriculum revision. The GIFMIS integration barrier identified qualitatively warrants dedicated investigation into bridging architectures that have succeeded in comparable sub-Saharan African public financial management contexts.

VI. CONCLUSION

This study presents convergent evidence that AI-AIS adoption in Nigerian College of Education bursary offices is associated with substantial and operationally significant efficiency gains, but that those gains are conditional on system integration quality, top management support, and, most consequentially, staff AI-specific competency. The human skill moderation finding moves the adoption question beyond a binary of adoption versus non-adoption to one of whether organisations have created the conditions under which adoption can realise its efficiency potential. The widespread competency deficits documented here indicate that most Colleges of Education have not met this condition, and that the structural cause is a curriculum misalignment that has produced bursary staff fluent in spreadsheets but unprepared for AI anomaly interpretation, output validation, or data governance. Closing this gap requires co-ordinated action from TETFund, the NCCE, and institutional leadership, grounded in the evidence that adoption investment and skill investment must proceed together rather than sequentially.

Ethics and Data Availability

Ethical approval was obtained from the relevant institutional review board. Informed consent, participant confidentiality, and data protection provisions were secured prior to data collection in accordance with the Nigeria Data Protection Act 2023. A data availability statement will be provided upon acceptance. Questionnaire items, the interview guide, the focus group protocol, and the system-log extraction checklist are available as supplementary materials.

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