Artificial Intelligence-Driven Learning Systems and Training Efficiency: Evidence from the Nigerian Banking Sector

Mashood Mudashir
University of Abuja Business School, University of Abuja, FCT, Nigeria
ORCID: 0009-0002-2278-2536
mashoodmudashir66@gmail.com

ABSTRACT: Training and development (T&D) functions within financial institutions in emerging economies continue to grapple with the inefficiencies of uniform instructional models that fail to account for individual skill trajectories. This study examines the statistical association between AI-driven training and development and T&D process efficiency within the Nigerian banking sector, guided by the null hypothesis that AI-driven training and development is not significantly associated with training and development process efficiency ($H0_1$). Anchored in the Technology Acceptance Model (TAM) and the Ability-Motivation-Opportunity (AMO) framework, a quantitative cross-sectional survey design was employed. A multistage sampling procedure was used to draw a planned sample of 149 banking professionals from a population of 241 employees across four selected deposit money banks in Gwagwalada, Abuja; 124 usable questionnaires were obtained. Data were analyzed using multiple linear regression via SPSS. The four AI-driven training indicators were strongly associated with perceived process efficiency ($R = .878$, $R^2 = .770$). The four-predictor regression model was statistically significant, $F(4, 119) = 99.827$, $p < .001$. Competency Growth ($\beta = .807$, $p < .001$) and Learning Personalization ($\beta = .789$, $p < .001$) were the strongest unique predictors, while Training Cost reduction was also statistically significant ($\beta = .132$, $p = .018$); Skill Retention was not significant ($\beta = .091$, $p = .138$). The results indicate a strong predictive association within this cross-sectional, perception-based sample and should not be interpreted as evidence that AI training causes efficiency gains. The findings have implications for HRD practice in Nigerian banking, particularly where digital literacy, infrastructure reliability and employee acceptance influence the use of AI-enabled learning systems.

KEYWORDS: AI-Driven Training; Adaptive Learning Systems; Training Efficiency; Competency Development; Employee Upskilling; Human Resource Development; Digital Learning

I. INTRODUCTION

The intersection of artificial intelligence (AI) and human resource development (HRD) has emerged as one of the most consequential research frontiers in organizational scholarship. As institutions worldwide accelerate their digital transformation agendas, the training and development function is being fundamentally reconstituted by intelligent, adaptive technologies. Nowhere is this reconfiguration more consequential than in the banking sector, where rapid product innovation, regulatory complexity, and competitive pressure create persistent demands for workforce upskilling.Sub-Saharan Africa, and Nigeria in particular, represents a revealing setting for this development. Jaldi (2023) identified Nigeria as one of the leading African countries in organizational AI utilization, and institutions such as First Bank, UBA, GTBank, and Access Bank have invested in intelligent systems ranging from customer-facing chatbots to back-office process automation. Nigerian studies have nevertheless tended to examine AI adoption in broad relation to employee performance, administrative activity, recruitment, appraisal or customer service rather than isolate the learning and development function (Elegunde & Osagie, 2020; Ghedabna et al., 2024). Consequently, there is limited local evidence on whether learning personalization, skill

Volume 2, Issue 3, 2026
https://doi.org/10.5281/zenodo.

retention, training-cost reduction and competency growth are independently associated with the efficiency of the T&D process. The present study addresses this narrower gap among banking professionals in Gwagwalada, Abuja.

The gap is important because training efficiency is wider than a reduction in expenditure. It concerns the speed with which employees acquire required competencies, the durability of learning, the extent to which content responds to individual needs, and the resources used in the process. Conventional instructor-led sessions, static e-learning modules and calendar-based programmes often apply common content to employees with different skill needs (Chen, 2023; Veshne & Jamnani, 2024). AI-supported learning systems offer a different arrangement by using employee data, adaptive sequencing and feedback to tailor learning pathways. What remains uncertain in the Nigerian banking context is whether employees' reported experience of these AI-driven training features is systematically associated with greater T&D process efficiency when the main dimensions are considered together. This article therefore asks one focused question: Is AI-driven Training and Development significantly associated with Training and Development Process Efficiency in selected Nigerian deposit money banks? The study uses survey evidence from 124 banking professionals in Gwagwalada, Abuja, and applies multiple linear regression to examine the joint and unique predictive relationships of Learning Personalization, Skill Retention, Training Cost reduction and Competency Growth. In this respect, the article moves beyond broad measures of AI adoption and employee performance by concentrating on the internal training process and by separating the contribution of four specific learning-related indicators.

II. RELATED WORKS

A. Training and Development in the Banking Sector

Training and development occupy a structurally distinctive position within banking HRM. The sector's combination of regulatory scrutiny, technological volatility, and customer-facing complexity means that staff must continuously renew technical competencies from financial product knowledge and anti-money laundering protocols to data analytics and digital service tools. Chen (2023) characterizes training and development as a system of personalized and adaptable support that fosters professional growth according to the specific requests, needs, and learning capacities of individual employees. This definition signals a departure from the historical conception of training as a discrete, event-based intervention toward a continuous, individualized process. However, conventional training models have struggled to operationalize this aspiration. Ghedabna et al. (2024) observe that without AI-driven personalization, training retention remains low and logistical costs remain high, a criticism well-supported by evidence from Nigerian banks where high staff-to-instructor ratios and geographic dispersal compromise programme consistency. Veshne and Jamnani (2024) further document that traditional programmes generate adaptive learning pathways only in theory; in practice, curricula are standardized and fail to address the precise skill gaps that inhibit competency growth at the individual level. The shift toward digital learning environments, accelerated by the COVID-19 pandemic, introduced e-learning management (E-LM) systems into banking HR practice. Yet even E-LM platforms replicate the same one-size-fits-all limitation. The literature increasingly converges on the argument that true training efficiency requires AI integration: systems capable of diagnosing individual deficiencies, prescribing tailored content, delivering real-time feedback, and iterating content sequencing based on learner performance data (Wang et al., 2024; Jaiswal et al., 2022).

Volume 2, Issue 3, 2026
https://doi.org/10.5281/zenodo.22953489

B. AI-Driven Training and Development: Conceptual Dimensions

Scholarly conceptualization of AI-driven training and development has evolved rapidly, particularly since 2021. Mikalef and Gupta (2021) anchor the concept in the AI system's capacity to identify and learn from data inferences to achieve predetermined organizational goals such as closing competency gaps. This positions AI not merely as a delivery mechanism but as an active diagnostic and prescriptive agent within the learning ecosystem. Several distinct dimensions of AI-driven T&D have been identified in the recent literature. First, adaptive learning systems (ALS) represent the most extensively studied application. Veshne and Jamnani (2024) describe these as automated processes that generate adaptive learning pathways and provide real-time feedback to enable custom-made training programs that address precise skill gaps. Wang et al. (2024) demonstrate that ALS significantly improves learner outcomes by utilizing cognitive technology to enhance decision-making and information dissemination. The critical advance over static E-LM is the system's ability to modulate content difficulty, sequencing, and format in response to individual performance signals. Second, AI-driven skill gap analysis represents a proactive organizational capability that complements individual-level adaptation. Ghedabna et al. (2024) show that AI algorithms can detect deficiencies across an entire workforce and automatically suggest remedial courses, enabling HR functions to shift from reactive problem-solving to predictive capability management. The Accenture case, frequently cited in this literature, reportedly achieved a 40% reduction in identified skill gaps and a 50% increase in internal promotions through AI-driven development programmes (Ghedabna et al., 2024). Third, generative AI mentorship and virtual assistance have introduced a mechanism for continuous, on-demand developmental support. Park (2024) documents how generative AI mentorship provides tailored recommendations that ensure the effective application of learned skills in professional contexts. Ncube et al. (2025) elaborate that AI virtual advisors can map individual career aspirations to specific skill development pathways, creating alignment between personal growth goals and institutional human capital requirements. Fourth, the cost-efficiency dimension of AI-driven training deserves dedicated attention. Ghedabna et al. (2024) report a 33.3% reduction in training costs per employee following AI integration, attributing savings to the automation of administrative logistics, the elimination of physical facilities costs, and the reduction of dead time associated with instructor-led scheduling. Nawaz et al. (2024) similarly document that AI-driven talent intelligence reduces overall developmental expenditure while increasing the return on human capital investment.

C. Training Efficiency as an Organizational Outcome

Training efficiency is a multidimensional construct encompassing process-level and outcome-level components. At the process level, efficiency refers to the reduction of time and resource consumption required to deliver learning content and achieve defined competency benchmarks, the concept of time-to-competency that is increasingly used by HRD practitioners as a key performance indicator (Chen, 2023). At the outcome level, efficiency captures the durability of skill acquisition (retention), the degree of competency gain achieved relative to instructional investment, and the transferability of learning to job performance contexts. Benabou and Touhami (2025) note that AI fosters personalized and adaptable training according to the specific request, need, and learning capacity of each staff member, directly enhancing both process and outcome dimensions of efficiency. Empirical corroboration is emerging: Ghedabna et al. (2024) document a 133% return on investment for AI training implementations, a 37.5% reduction in mean training duration, and a 35% increase in knowledge retention rates compared to conventional methods. These figures, while drawn from global corporate settings, are increasingly cited in African banking scholarship as benchmarks for what the sector might achieve under accelerated AI adoption. Operationally, for the purposes of this study, Training and Development Process Efficiency is

Volume 2, Issue 3, 2026
https://doi.org/10.5281/zenodo.22953489

defined as the reduction in time and cost required to reach employee competency by utilizing targeted learning pathways instead of generic training programs, measured across four indicators: training acceleration, cost efficiency, skill improvement rate, and knowledge retention, all positioned as outcomes attributable to AI-driven T&D mechanisms.

III. THEORETICAL REVIEW

A. Technology Acceptance Model (TAM)

The Technology Acceptance Model, originally developed by Davis (1989), offers the primary theoretical lens through which this study interprets the adoption and effectiveness of AI-driven training systems. TAM posits that a technology's adoption is determined by two core perceptual constructs: Perceived Usefulness (PU) which is the degree to which users believe the technology will enhance job performance, and Perceived Ease of Use (PEOU) considered as the degree to which using the technology is expected to require minimal effort. In the training context, PU corresponds to employees' belief that AI-driven platforms will improve their skill acquisition and career development, while PEOU captures their assessment of the system's navigability and accessibility. The banking sector's AI adoption literature draws extensively on TAM to explain differential uptake across employee cohorts. Elegunde and Osagie (2020) find that willingness to migrate from familiar to AI-mediated training platforms is significantly shaped by perceived complementarity, which is whether the technology augments rather than displaces established professional practices. This framing anticipates the 'creative destruction' dynamic identified in later scholarship, where AI renders certain skills obsolete while creating demand for AI-complementary competencies (Jaiswal et al., 2022). Berg and Johnston (2025) extend TAM's relevance by noting the 'black box' paradox: even when AI training tools are perceived as useful and easy to use, insufficient explainability of algorithmic logic can undermine trust and long-term adoption. This concern has direct implications for the institutional design of AI learning systems in Nigerian banks, where building organizational trust in automated recommendations is still an emerging practice.

B. Ability-Motivation-Opportunity (AMO) Framework

Complementing the TAM perspective, the Ability-Motivation-Opportunity (AMO) framework provides a holistic HRD structure for understanding how AI-driven training translates into measurable efficiency outcomes. Ncube et al. (2025) summarize the theory's core proposition: individual performance is a function of three interacting components, Ability (possessing the knowledge and skills required for the role), Motivation (the drive to deploy those capabilities), and Opportunity (the organizational platform and conditions that allow application of abilities). In the AI-driven training context, each pillar is directly implicated. AI-driven skill gap analysis and adaptive learning systems serve the Ability dimension by identifying deficiencies and delivering targeted remediation faster and more precisely than traditional methods (Mikalef & Gupta, 2021). The Motivation dimension is served by the personalization of learning content and the alignment of development pathways with individual career aspirations considered by Ghedabna et al. (2024) as critical to learner engagement and sustained participation. Opportunity is addressed through the democratization of access to high-quality learning content via digital platforms, which reduces the geographic and scheduling barriers that historically limited training participation in dispersed banking networks (Ncube et al., 2025). The AMO framework also helps theorize the boundary conditions of AI effectiveness. O'Neill and Green (2021) caution that where digital literacy is low, the Opportunity dimension is effectively foreclosed making employees not to benefit from AI-driven personalization since they lack the foundational skills to navigate the platforms. This concern is particularly salient in the Nigerian context, where a documented digital divide exists between urban

Volume 2, Issue 3, 2026
https://doi.org/10.5281/zenodo.22953489

branch staff and those deployed in more peripheral locations. Zhai and Wibowo (2023) further warn that over-reliance on AI recommendations may gradually erode the Ability dimension by inhibiting the critical thinking and problem-solving competencies that AI systems cannot fully replicate.

C. Hypothesis Development

The theoretical architecture outlined above leads to a testable expectation. If AI-driven training and development systems diagnose skill gaps, tailor learning content, provide timely feedback and reduce administrative burdens as the literature suggests, higher levels of these practices should be associated with higher reported T&D process efficiency across the operational dimensions considered in this study. From the TAM perspective, employees who regard AI training platforms as useful and easy to use are more likely to adopt and engage with them. From the AMO perspective, AI-supported learning may strengthen Ability through targeted content, Motivation through personalized pathways, and Opportunity through digital access. These frameworks provide reasons to expect a positive association between AI-driven training practices and process efficiency, but the cross-sectional design does not establish the direction of causation. Existing empirical work broadly supports the expectation of a positive relationship. Ghedabna et al. (2024) report efficiency improvements associated with AI-supported employee development, while Jaiswal et al. (2022) show strong employee perceptions of AI's contribution to training effectiveness in multinational settings. Nigerian research has examined AI adoption and employee performance more generally (Elegunde & Osagie, 2020), but has not sufficiently separated the training function into learning personalization, skill retention, training cost and competency growth and tested their unique association with T&D process efficiency in deposit money banks. This is the specific empirical gap addressed here.
Accordingly, the study proposes:

H01: AI-Driven Training and Development is not significantly associated with Training and Development Process Efficiency in selected deposit money banks in Gwagwalada, Abuja.

IV. METHODOLOGY

A. Research Design

The study adopted a quantitative, cross-sectional survey research design. This design was appropriate for examining the strength and direction of the relationship between AI-driven T&D practices and process efficiency at a single point in time, using statistical inference to draw conclusions applicable to the broader banking population in the study area. The cross-sectional approach is well-established in HRM and HRD research for hypothesis testing in organizational contexts (Elegunde & Osagie, 2020; Ncube et al., 2025).

B. Population, Sample and Sampling Procedure

The study population comprised 241 banking professionals employed in four deposit money banks in Gwagwalada Area Council, Abuja: First Bank (68), United Bank for Africa (59), Guaranty Trust Bank (53), and Access Bank (61). A sample of 149 was determined at a 5% margin of error using the Raosoft sample-size procedure reported in the source dissertation. Selection followed a multistage procedure. The four banks were purposively retained because they had adopted AI-supported operational systems and granted access for the study. The sample was then allocated proportionately across the banks as follows: First Bank, 42; UBA, 36; GTBank, 33; and Access Bank, 38. Within each bank, respondents were selected by simple random sampling so that eligible employees had an equal opportunity of selection. Of the 149 questionnaires administered, 124 usable responses were obtained, representing 83.2% of the planned sample.

Volume 2, Issue 3, 2026
https://doi.org/10.5281/zenodo.22953489

C. Instrument and Measurement

Data were collected with the structured questionnaire used in the source dissertation. The article draws on eight five-point Likert items, anchored from 1 (Strongly Disagree) to 5 (Strongly Agree). AI-Driven Training and Development is represented by four items: AI provides personalized learning pathways; AI-driven training improves skill retention; AI reduces training cost; and AI enhances competency growth through adaptive learning. Training and Development Process Efficiency is represented by four outcome items covering training acceleration, cost efficiency, skill improvement and knowledge retention after training. The item content was developed from the study's operational definitions and the training literature, particularly Mikalef and Gupta (2021), Chen (2023), Ghedabna et al. (2024), Veshne and Jamnani (2024), and Benabou and Touhami (2025).

D. Validity and Reliability

Content and face validity were established through review by the project supervisor and management research experts before field administration. The source dissertation reports Cronbach's alpha coefficients of .780 for the overall Artificial Intelligence domain and .836 for the overall Enhanced Human Resource Functions domain. Both exceed the .70 benchmark used in the study. These coefficients are reported exactly as documented in the source dissertation; they are domain-level coefficients and are not presented as separate four-item subscale alphas for the narrower training measures used in this article. The measurement basis is summarized in Table 1. Ethical procedures included informed consent, anonymity and confidentiality.

Table 1: Measurement and Reliability Evidence

Scale/domain used in article	No of items	Indicators represented	Source basis	Cronbach α
AI-Driven Training and Development	4	Learning Personalization; Skill Retention; Training Cost; Competency Growth	Mikalef & Gupta (2021); Chen (2023); Ghedabna et al. (2024); Veshne & Jamnani (2024)	.780
Training and Development Process Efficiency	4	Training Acceleration; Cost Efficiency; Skill Improvement; Knowledge Retention	Chen (2023); Ghedabna et al. (2024); Benabou & Touhami (2025)	.836

Source: SPSS Output, 2026.

E. Analytical Technique

Descriptive statistics (frequencies and percentages) were used to summarize respondent perceptions across the measurement items. The hypothesis was examined with multiple linear regression in SPSS. The dependent variable was T&D Process Efficiency, while Learning Personalization, Skill Retention, Training Cost and Competency Growth were entered as four predictors. R and R^2 summarize the strength and proportion of sample variance associated with the predictor set, the F-test evaluates whether the model as a whole is statistically significant, and standardized beta coefficients indicate the unique predictive association of each indicator after the other predictors are held constant. Because the data are cross-sectional and perception-based, these statistics are interpreted as associations and predictions rather than causal effects.

Volume 2, Issue 3, 2026
https://doi.org/10.5281/zenodo.22953489

V. RESULTS AND DISCUSSION

A. Descriptive Analysis: AI-Driven Training and Development Indicators

Prior to regression analysis, descriptive analysis was conducted to assess respondent perceptions of AI-driven T&D practices. The results reveal strong positive perceptions across all four independent variable indicators. Regarding Learning Personalization (Table 4.15 in the source dissertation), 68.5% of respondents agreed or strongly agreed that AI provides personalized learning pathways for employees, with 41.9% agreeing and 26.6% strongly agreeing, while 22.6% were neutral. On Skill Retention (Table 4.16), the agreement rate increased to 72.6%, with 46.8% agreeing and 25.8% strongly agreeing, corroborating the proposition that AI-driven training improves the durability of acquired knowledge. Training Cost reduction (Table 4.17) attracted the highest agreement rate among the AI-driven T&D items, with 74.2% of respondents agreeing or strongly agreeing that AI reduces the overall cost of employee training programmes. Finally, Competency Growth through adaptive learning (Table 4.18) was endorsed by 73.4% of respondents, with 41.1% agreeing and 32.3% strongly agreeing that AI enhances competency advancement.

B. Descriptive Analysis: Training and Development Process Efficiency

On the dependent variable side, perceptions of actual T&D process efficiency were equally positive. Training Acceleration (Table 4.34) attracted agreement from 77.4% of respondents, with 42.7% strongly agreeing that AI accelerates the training process. Cost Efficiency improvement (Table 4.35) was endorsed by 81.5%, with a notably high proportion of strong agreement (47.6%). Skill Improvement Rate (Table 4.36) was affirmed by 82.2% of respondents, split evenly between agree (41.1%) and strongly agree (41.1%). Knowledge Retention enhancement (Table 4.37) was affirmed by 83.8% of respondents, with 42.7% strongly agreeing that AI increases employee knowledge retention after training. The high and consistent levels of endorsement across both variable sets are striking. In all instances, strong disagreement was minimal (under 7% for any item), and the neutral segment, while present, was systematically smaller than the agreement cohort. This pattern signals a broadly positive organizational perception of AI-driven training efficiency within these banks, providing a conducive data environment for regression modelling.

C. Regression Analysis: Test of Hypothesis

The hypothesis was tested using multiple linear regression with Training and Development Process Efficiency as the dependent variable and Learning Personalization, Skill Retention, Training Cost, and Competency Growth as predictors. The results are presented in Tables 1 through 3 below.

Table 2: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	F Statistic
1	.878	.770	.763	.23092	99.827

Source: SPSS Output, 2026.

Predictors: (Constant), Learning Personalization, Skill Retention, Training Cost, Competency Growth. Dependent Variable: T&D Process Efficiency.

The Model Summary (Table 2) shows a strong multiple correlation between the four AI-driven T&D indicators and reported training process efficiency (R = .878). The reported R^2 of .770 indicates that approximately 77% of the observed variance in process-efficiency scores is associated with the four predictors in this sample. Given the cross-sectional design and the use of respondents' perceptions, this

Volume 2, Issue 3, 2026
https://doi.org/10.5281/zenodo.22953489

statistic is not interpreted as evidence that AI-driven training causes 77% of training efficiency. The adjusted R^2 of .763 remains close to the unadjusted value, indicating that the model retains substantial predictive strength after adjustment for the number of predictors.

Table 3: **ANOVA**

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	26.841	4	6.710	99.827	.000
Residual	7.999	119	.067		
Total	34.840	123			

Source: Authors' recalculation from reported SPSS output, 2026.
Dependent Variable: T&D Process Efficiency.

With four predictors and 124 usable observations, the model has 4 regression degrees of freedom and 119 residual degrees of freedom. Using the reported sums of squares gives mean squares of 6.710 for regression and .067 for residual variation, producing $F(4, 119) = 99.827$, $p < .001$. The model is therefore statistically significant as a whole, indicating that the four AI-driven T&D indicators jointly provide a significant prediction of reported T&D process efficiency.

Table 4: Regression Coefficients

Predictor	B	Std. Error	Beta (β)	t-value	Sig.	Decision
Constant	.687	.204	-	3.376	.001	-
Learning Personalization	.132	.005	.789	15.892	.000	Significant
Skill Retention	.098	.066	.091	1.490	.138	Not Significant
Training Cost	.198	.089	.132	2.091	.018	Significant
Competency Growth	.140	.008	.807	17.183	.000	Significant

Dependent Variable: T&D Process Efficiency.
Source: SPSS Output, 2026.

The Coefficients table (Table 4) shows the unique predictive association of each AI-driven T&D indicator after the remaining indicators are controlled. Competency Growth has the largest standardized coefficient ($\beta = .807$, $p < .001$), followed by Learning Personalization ($\beta = .789$, $p < .001$). Training Cost reduction also has a positive statistically significant coefficient ($\beta = .132$, $p = .018$). Skill Retention is positively signed but is not statistically significant as a unique predictor ($\beta = .091$, $p = .138$). Accordingly, the present regression does not provide sufficient evidence that Skill Retention makes an independent contribution once the other indicators are included. The positive coefficients for the statistically significant predictors indicate that higher reported Learning Personalization, Training Cost reduction and Competency Growth are associated with higher reported T&D process efficiency, holding the other predictors constant. These coefficients describe relationships within the sample and should not be read as causal effects.

Volume 2, Issue 3, 2026
https://doi.org/10.5281/zenodo.22953489

D. Discussion

The findings show a strong statistical association between AI-driven training practices and reported T&D process efficiency in the selected banks. The model accounts for a large proportion of observed variation in efficiency scores, and the corrected overall test remains statistically significant. This pattern is consistent with international research that links AI-supported employee development with more individualized learning and lower administrative burdens. It should, however, be interpreted within the limits of a cross-sectional perception survey: the analysis does not establish that AI adoption caused the reported efficiency outcomes. Competency Growth ($\beta = .807$) has the largest unique coefficient in the model. This result suggests that respondents who report stronger competency advancement through adaptive learning also tend to report greater T&D process efficiency. The pattern is compatible with Jaiswal et al. (2022), who document the perceived contribution of AI to employee upskilling. In Nigerian banking, where digital products and regulatory requirements change quickly, an association between competency development and training efficiency is practically important, but the present design does not show that one produces the other. Learning Personalization ($\beta = .789$) is also strongly associated with process efficiency. This finding is consistent with Chen's (2023) view that AI-supported learning can respond to differences in employee needs and learning capacity. For banks, the implication is that the usefulness of an AI learning platform may depend less on the mere presence of automation than on whether employees experience the content as relevant to their actual skill requirements. Training Cost reduction has a smaller but statistically significant coefficient ($\beta = .132$). This finding adds some qualification to accounts that treat cost saving as the principal justification for AI investment in T&D (Ghedabna et al., 2024). In this sample, the stronger coefficients are attached to competency growth and learning personalization. Cost therefore appears to be one part of the reported efficiency relationship rather than its dominant feature.

Skill Retention is not statistically significant as a unique predictor ($\beta = .091$, $p = .138$). This result should be interpreted narrowly. It does not show that retention is unimportant to training, nor does it establish that the non-significance arises from multicollinearity. No VIF or tolerance diagnostics are reported in the available analysis, so a multicollinearity explanation would be speculative. The descriptive results show that respondents generally viewed AI favourably in relation to knowledge retention, but the multiple regression indicates that Skill Retention does not explain a statistically distinct portion of process-efficiency variation after the other three predictors are considered. Future work with diagnostic statistics and longitudinal data could examine this relationship more closely. The theoretical interpretation should likewise remain measured. TAM helps explain why employee acceptance may matter: perceived usefulness and ease of use can support engagement with AI learning platforms. The AMO framework provides a way of organizing the observed associations around Ability, Motivation and Opportunity. The present results are consistent with those perspectives, but they do not demonstrate the causal sequence proposed by either framework. The Nigerian setting also places practical limits on how these associations should be understood. Digital literacy is uneven across employees, reliable electricity and connectivity cannot be assumed in every branch, and the quality of local ICT support may differ between central and peripheral locations. Employee acceptance is equally important because staff may resist automated recommendations where systems are difficult to use or the basis of recommendations is unclear. These conditions mean that the same AI learning platform may be experienced differently across branches. For Nigerian banks, implementation therefore requires attention to basic infrastructure, digital-skills support, human oversight and clear communication about how training recommendations are generated.

Volume 2, Issue 3, 2026
https://doi.org/10.5281/zenodo.22953489

VI. IMPLICATIONS

A. Theoretical Implications

This study contributes to the literature on AI-driven HRD by documenting a strong association between AI-supported training practices and reported process efficiency in an African banking setting. The evidence extends a literature that has been dominated by North American, European and Asian corporate contexts, while also showing that the relative strength of the training indicators is not uniform. The results are therefore best read as evidence about how banking professionals perceive the relationship between AI-enabled learning arrangements and T&D efficiency rather than as a causal validation of AI effects. The comparatively large coefficients for Competency Growth and Learning Personalization, relative to Training Cost, suggest that capability development and relevance of learning content are central to employees' assessment of efficiency. This pattern is consistent with the Ability component of the AMO framework and with adaptive-learning arguments, although the cross-sectional design cannot establish the sequence through which these relationships arise.The non-significant coefficient for Skill Retention also calls for caution in refining the construct. The available evidence does not justify treating retention as a mediator, because mediation was not tested. A more appropriate conclusion is that retention did not make a statistically significant unique contribution in the present model. Future research may test direct and indirect relationships with designs and diagnostics suited to that purpose.

B. Managerial Implications

For banking HR executives and HRD practitioners, the findings support attention to competency-progression measures such as time-to-proficiency, post-training assessment and identified skill gaps when evaluating AI-supported training. These measures should complement, rather than replace, cost and completion indicators. The evidence from this study indicates that competency growth is strongly associated with employees' assessment of training-process efficiency. The strong association with Learning Personalization also suggests that uniform deployment of an AI platform may not be sufficient. Banks should configure learning systems around employee skill needs and should provide support for staff whose digital literacy is limited. Because infrastructure quality can vary between branches, implementation plans should also provide for connectivity, power reliability and local technical assistance rather than assume identical operating conditions across locations. Training Cost reduction is significant but comparatively modest. Cost saving should therefore not be the sole basis for communicating or evaluating AI-supported learning. Employee acceptance is more likely to be sustained where the system is useful, understandable and visibly connected to professional development. Clear human oversight is also important where employees are expected to rely on automated recommendations. Skill Retention was not a significant unique predictor, despite positive descriptive responses. Managers should therefore avoid assuming that AI adoption by itself guarantees durable retention of learning. Features such as spaced practice, reinforcement and on-the-job application may still be useful, but their effectiveness requires separate evaluation rather than inference from the present regression.

Volume 2, Issue 3, 2026
https://doi.org/10.5281/zenodo.22953489

VII. CONCLUSION

This study examined whether AI-driven training and development is associated with T&D process efficiency in selected deposit money banks in Gwagwalada, Abuja. The evidence indicates a strong predictive relationship. The four training indicators were jointly associated with a substantial proportion of variation in reported process efficiency ($R = .878$, $R^2 = .770$), and the four-predictor model was statistically significant, $F(4, 119) = 99.827$, $p < .001$. Competency Growth and Learning Personalization had the largest unique standardized coefficients, while Training Cost reduction was also significant. Skill Retention was not statistically significant as a unique predictor. The findings therefore support a practical case for carefully designed AI-supported learning in Nigerian banking, particularly where systems provide relevant learning pathways and assist employees in developing required competencies. They do not establish that AI causes training efficiency, because the study is cross-sectional and relies substantially on respondents' perceptions. Differences in digital literacy, infrastructure reliability, branch conditions and employee acceptance may also shape how AI learning systems are experienced in practice. For this reason, Nigerian banks should combine investment in learning technology with employee digital-skills development, reliable supporting infrastructure, human oversight and transparent communication about automated recommendations. Future studies should use longitudinal or experimental designs, extend coverage beyond Gwagwalada, and report regression diagnostics such as VIF and tolerance where relationships among training indicators are under consideration.

REFERENCES

Adiazmil, A., Hidayat, M., & Basuil, D. A. (2024). Strategic human resource planning in the era of digital transformation. Management Studies and Business Journal, 1(1), 130–137. https://doi.org/10.62207/q7158p72

Benabou, A., & Touhami, F. (2025). Integration of artificial intelligence in human resource management: Analyzing opportunities, challenges, and human-AI collaboration. Management and Accounting Review, 24(1), 405–430.

Berg, J., & Johnston, H. (2025). AI in human resource management: The limits of empiricism (ILO Working Paper 154). International Labour Organization. https://doi.org/10.54394/NMSH7611

Chen, Z. (2023). Artificial intelligence virtual trainer: Innovative didactics aimed at personalized training needs. Journal of the Knowledge Economy, 14, 2007–2025.

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. Human Resource Management Review, 33(1), 100899.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.

Elegunde, A. F., & Osagie, R. O. (2020). Artificial intelligence adoption and employee performance in the Nigerian banking industry. IAA Journal of Applied Sciences, 4(1), 105–111.

Ghedabna, L., Ghedabna, R., Imtiaz, Q., Faheem, M. A., Alkhayyat, A., & Hosen, M. S. (2024). Artificial intelligence in human resource management: Revolutionizing recruitment, performance, and employee development. Nanotechnology Perceptions, 20(S10), 52–68.

Jaiswal, A., Arun, C. J., & Varma, A. (2022). Rebooting employees: Upskilling for artificial intelligence in multinational corporations. The International Journal of Human Resource Management, 33(6), 1179–1208. https://doi.org/10.1080/09585192.2021.1891114

Jaldi, A. (2023). Artificial intelligence revolution in Africa: Economic opportunities and legal challenges. Policy Centre for the New South.

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. Information & Management, 58(3), 103434. https://doi.org/10.1016/j.im.2021.103434

Nawaz, N., Arunachalam, H., Pathi, B. K., & Gajenderan, V. (2024). The adoption of artificial intelligence in human resources management practices. International Journal of Information Management Data Insights, 4(1), 100208. https://doi.org/10.1016/j.jjimei.2023.100208

Ncube, T. R., Sishi, K. K., & Skinner, J. P. (2025). The impact of artificial intelligence on human resource management practices: An investigation. SA Journal of Human Resource Management, 23(0), a2960. https://doi.org/10.4102/sajhrm.v23i0.2960

O'Neill, M., & Green, W. (2021). Digital skills divide: Implications for artificial intelligence adoption in HRM. Journal of Organizational Behavior, 42(5), 611–625.

Olatunbosun, P. A., & Olatunbosun, O. M. (2025). Artificial intelligence in banking and financial institutions: Opportunities and challenges. Journal of Financial Innovation, 11(1), 45–67.

Park, J. (2024). Generative AI mentorship in corporate training: A new frontier. Journal of Workplace Learning, 36(2), 98–114.

Veshne, N., & Jamnani, A. (2024). AI-powered human resource management: Transforming talent acquisition, development, and retention. Journal of Emerging Technologies in Management, 9(1), 55–78.

Wang, Y., Li, X., & Zhang, H. (2024). AI-enabled adaptive learning systems and organizational performance: A cognitive technology perspective. Computers & Education: Artificial Intelligence, 6, 100180.

Zhai, X., & Wibowo, S. (2023). The risk of AI dependency in workplace training: Cognitive implications and design responses. Education and Information Technologies, 28(3), 3291–3312.