GPH-International Journal of Social Science and Humanities Research
(Online ISSN: 3050-9637)
Volume 9, Issue 10, October 2026
Publisher: Global Publication House
DOI: https://doi.org/10.5281/zenodo.24369196
Homepage: | https://gphjournal.org/index.php/ssh/index

Technological and Organisational Readiness for Artificial Intelligence Adoption and Organisational Innovation in Deposit Money Banks in Yenagoa, Bayelsa State, Nigeria

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Abstract

Banks in emerging economies are under pressure to deliver faster, more personalised and more efficient digital financial services, yet many struggle to convert investments in artificial intelligence (AI) into innovation. This study examined how two dimensions of AI adoption readiness, technological readiness and organisational readiness, relate to product innovation and process innovation in deposit money banks in Yenagoa, Bayelsa State, Nigeria. Anchored on the Technology Acceptance Model and the Resource-Based View, the study adopted a descriptive, cross-sectional, correlational survey of 400 employees and managers selected through stratified random sampling. Data were analysed with descriptive statistics, Pearson correlation and multiple regression. Respondents rated organisational readiness (M = 3.62), process innovation (M = 3.59), product innovation (M = 3.54) and technological readiness (M = 3.45) above the scale midpoint. Both readiness dimensions correlated strongly and positively with both innovation outcomes (r = .68 to .74, p < .001). In multiple regression, the two predictors jointly explained 57.5% of the variance in product innovation and 56.7% in process innovation, and organisational readiness had the larger standardised coefficient in both models (β = .535 and .444) compared with technological readiness (β = .263 and .353). The findings indicate that technology is necessary but not sufficient for AI-enabled innovation. Banks should pair investment in infrastructure and skills with leadership sponsorship, employee training, a supportive culture and strategic alignment.

Keywords:

Artificial intelligence adoption; technological readiness; organisational readiness; product innovation; process innovation; deposit money banks; Nigeria.

1. Introduction

Innovation is widely regarded as a determinant of organisational survival and competitiveness (Damanpour, 1991; Rogers, 2003). In banking, where products are intangible, switching costs are falling and customers increasingly expect fast, personalised and digital service, the capacity to introduce new services and to redesign internal processes has become central to competitive positioning. Artificial intelligence (AI) is now one of the most prominent technologies through which banks pursue these aims. Applications such as machine-learning credit scoring, real-time fraud monitoring, robotic process automation, chatbots and robo-advisory services have moved

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from experimentation into routine use in many institutions (Khandani et al., 2010; Huang & Rust, 2018; Davenport & Ronanki, 2018; Lazo & Ebardo, 2023).

There is evidence in Nigeria that customer-facing AI tools already exist in the digital service landscape for financial services, especially Chatbots (Abdulquadri et al., 2021). But getting an AI tool doesn't equate to innovating with it. Adopting the technology is hard because it needs to be integrated into data systems, workflows, decision rights and employee habits and many organisations report that the challenging aspect is in the surrounding environment, not the technology itself (Davenport & Ronanki, 2018). The literature on AI readiness in this context consequently focuses on the technological pillars of an organisation and on the organisational capacities to make use of these pillars (Alsheibani et al., 2018; Jöhnk et al., 2021).

The problem that inspired this study, is that although the deposit money banks in Yenagoa, like many banks in emerging markets, have constraints that can limit the translation of AI into new services and improved processes. These encompass legacy systems, a shortage of technical competencies, inconsistent employee training, resistance to change, and uncertainty regarding AI initiatives and strategic goals. The existing literature has focused on the adoption of AI at the national or developed country level, and to date, relatively few studies differentiate between technological readiness and organisational readiness and test these aspects against different types of innovations in the sub-national banking market, like Yenagoa, the capital of Bayelsa State, in the Niger Delta.

The study thus explores the relationship between the readiness for the use of artificial intelligence and the innovations of the deposit money banks in Yenagoa. In particular, it (i) considers the correlation between technological readiness and product innovation, (ii) considers the correlation between technological readiness and process innovation, (iii) considers the correlation between organisational readiness and product innovation and (iv) considers the correlation between organisational readiness and process innovation. The rest of the paper will review the literature and formulate the hypotheses, detail the method, present the results, interpret the results and their implications and conclude.

2. Literature Review and Hypotheses Development.

2.1 A.I Adoption and readiness

The AI is defined as the ability of computer systems to learn from data, recognise patterns, reason and make decisions-functions that normally need to be carried out by humans (Huang & Rust, 2018). The implementation of AI in an organisation is more than just acquiring these systems. It requires the surrounding conditions of the technology and is the embedding of AI in products, processes and decisions for consistent added value (Davenport & Ronanki, 2018).

Readiness is a condition that can be captured by reading. The technology readiness issues address the technical foundations and capabilities needed (Parasuraman, 2000). In the AI world they are reliable and secure digital infrastructure, integrated and usable data, access to appropriate AI tools and the technical skills to configure and operate them then monitor the results (Alsheibani et al., 2018). Organisational readiness is a shared willingness and ability to change (Weiner, 2009). In the case of AI, it involves leadership commitment, a learning and experimentation culture, employee preparation, change management and AI initiatives integration with strategy (Jöhnk et al., 2021). This separation between technological and organisational situations is similar to the technology and organisation contexts of the

technology–organisation–environment framework (Tornatzky & Fleischer, 1990) and provides two predictors for this study.

The typical set of challenges that are discussed in reviews of the use of AI in banking is as follows: implementation costs, limited technical expertise, legacy infrastructure and lack of data centralisation, security and privacy issues, and employee resistance (Lazo & Ebardo, 2023). These barriers relate to the two readiness dimensions. While much of the resistance, weak sponsorship and poor strategic alignment are organisational, much of the cost, infrastructure, data and skills are largely technological. It is helpful to look at the two dimensions in the same model, as they are interconnected: High tech costs may reduce training investment and training gaps, and in turn these training gaps will lead to further resistance.

2.2 Organisational Innovation-Product and Process

Organisational innovation is the development and application of novel ideas, products or practices that are new to the adopting organization (Damanpour, 1991). Product innovation refers to new or significantly improved goods or services, while process innovation involves new or improved methods of production or delivery (OECD/Eurostat, 2018; Utterback & Abernathy, 1975). In the banking sector, product innovation comprises features like personalised credit and savings products, AI-driven advisory and digital service channels. Process innovation refers to the automation of repetitive processes, automated fraud identification using artificial intelligence, quicker customer identification and verification, and data-driven decisions in credit assessment (Khandani et al., 2010; Davenport & Ronanki, 2018). The two are interdependent in that new services typically depend on a reorganization of the workflow and new processes, and in turn, new processes can provide the means for new services (Ettlie & Reza, 1992); they are not the same and the circumstances under which they are successful may also vary.

2.3 Theoretical Anchors

The study is presented in the light of two theories. The Technology Acceptance Model (TAM) is based on the premise that the acceptance and use of a technology is mediated by perceived usefulness and perceived ease of use (Davis, 1989; Venkatesh & Davis, 2000). TAM was developed at an individual level, but it can be applied in organisational AI adoption. The installed tools are only used when employees perceive them as useful and workable, all of which is influenced by leadership communication and supportive norms during AI deployment training. According to the Resource-based View (RBV), companies are able to create and sustain advantages by leveraging resources that are valuable, rare, difficult to imitate and effectively organized (Barney, 1991). Technological assets, like data, infrastructure, technical skills, as well as intangible organisational assets, like leadership capability, learning culture, and organisation routines of coordination, are resources in this sense. Also, intangible resources may play a larger role in ongoing innovation than purchased technology, where RBV suggests that competitors would have a more difficult time replicating these.

2.4 Prior Evidence and Research Gap.

Previous studies on the use of AI in banking have documented the applications and benefits of AI, such as enhancing credit-risk prediction (Khandani et al., 2010), a rise in the use of chatbots, analytics and automation (Lazo & Ebardo, 2023), and readiness frameworks based on conceptual work and interviews have identified technological, organisational and

environmental factors that influence the successful use of AI (Alsheibani et al., 2018; Jöhnk et al., 2021). However, much of this work is conceptual or qualitative or relates to large firms in developed economies. Previous research in Nigeria has concentrated on specific applications, like chatbots (Abdulquadri et al., 2021). The literature seems to have almost no study that estimates the individual impact of technological readiness and organisational readiness on product innovation and process innovation in a sub-national banking market, respectively. The present study seeks to bridge this void by testing the four hypotheses on the survey data collected in deposit money banks in Yenagoa.

2.5 Hypotheses

Technological readiness and innovation. Data pipelines, computing power and system integration, and skilled resources are all essential for AI applications. The implementation of digital tools and models of personalised offers, and automation and fraud monitoring, hinge on the availability of clean and interoperable customer data and models, respectively (Huang & Rust, 2021; Davenport & Ronanki, 2018). If the foundations are weak, banks will stay where they are – at the basic tools level. In an RBV perspective, technological resources are the platform for new services and redesigned processes. Accordingly:

> H1: Technological readiness has a significant positive relationship with product innovation in deposit money banks in Yenagoa.
>
> H2: Technological readiness has a significant positive relationship with process innovation in deposit money banks in Yenagoa.

Organisational readiness and innovation. Innovation research consistently finds that managerial attitude toward change and the availability of technical knowledge resources are positively associated with innovation (Damanpour, 1991). New AI-enabled services typically cut across information technology, operations, risk, compliance, marketing and customer service, so they require sponsorship, budget, coordination and tolerance of controlled experimentation (Jöhnk et al., 2021). Process change alters roles and routines, and its success depends on training, communication and the management of resistance (Weiner, 2009; Ettlie & Reza, 1992). TAM adds that perceptions of usefulness and ease of use are themselves shaped by organisational support. Accordingly:

> H3: Organisational readiness has a significant positive relationship with product innovation in deposit money banks in Yenagoa.
>
> H4: Organisational readiness has a significant positive relationship with process innovation in deposit money banks in Yenagoa.

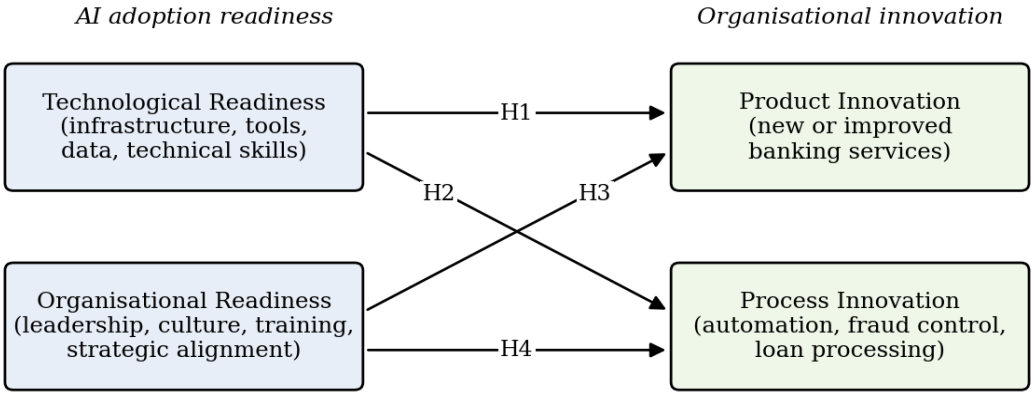

Figure 1. *Conceptual framework and hypothesised relationships*

3. Methodology

3.1 Research design

This research used descriptive, cross-sectional and correlational survey design. These descriptive survey designs are appropriate for the objective of describing the current state of AI readiness and innovation, the correlational element can be appropriate for the objective of estimating relationships among constructs, and the single-point-in-time cross-sectional design can be appropriate for conditions at a given time.

3.2 Study area, Population and Sample

The study was carried out in the capital of Bayelsa State in Nigeria, urban centre where deposit money banks are concentrated such as national banks and regional banks. The population consisted of about 1,000 employees and managers at about 10 deposit money banks in the city. Respondents ranged from frontline staff and back office staff to loan officers, IT staff, branch managers, and senior managers, whose jobs involve or rely on AI-enabled processes.

Stratified random sampling was used so that national and regional banks and both staff and managerial levels were represented. To get a sample of 400 respondents, Cochran's (1977) formula for large populations were used with a 95% level of confidence and 5% margin of error. The following results are based on these 400 cases.

3.3 Instrument and Measures

The data were gathered using a structured questionnaire, which was administered to the employees and managers. The questionnaire included questions regarding respondent profile, technological readiness (use of AI technologies, adequacy of IT infrastructure, access to AI tools and resources, and the training of staff), organisational readiness (leadership support, organisational culture towards technological change, investment in AI training, and perceived level of readiness for full AI integration), perceived impact of AI adoption on product and process innovation, and barriers to adoption. Construct scores are reported on a five-point scale with scores above 3.00 being a reflection of higher readiness or innovation. Also interviewed

were senior managers, IT staff and innovation officers using a semi-structured interview guide—this article only reports the quantitative survey part of that.

3.4 Validity and Reliability

Content and face validity was obtained by presentation of the questionnaire and interview guide to experts in AI, organisational innovation and banking to determine if items were representative of technological readiness, organisational readiness, product innovation and process innovation. Internal consistency was to be measured using the Cronbach alpha coefficient, between 0.70 and 0.80 was considered acceptable (Nunnally, 1978).

3.5 Data Analysis

Means and Standard Deviations were used for summarising responses. To explore bivariate relationship between the four constructs, Pearson product-moment correlation was used. Two multiple regression models were then estimated, and technological readiness and organisational readiness were included in the same model to determine the distinct effect of each, while holding the other constant. The hypotheses were tested at 5% level of significance. The phenomenon of multicollinearity was checked by tolerance and variance inflation factor (VIF), with the value of VIF less than 5 considered acceptable (Hair et al., 2019). The correlation matrix and descriptive statistics of the 400 cases were used to compute regression estimates, including the standardised and unstandardised coefficients, their standard errors, R^2 and F in a 2-predictor model (Cohen et al., 2003).

3.6 Ethical Considerations

Participation was voluntary. Respondents were informed about the purpose of the study, written informed consent was obtained, confidentiality and anonymity of any report were assured, and they were able to withdraw from the study at any time without penalty. Data were used solely for academic purposes.

4. Results

4.1 Descriptive statistics

The descriptive statistics are shown in Table 1. The mean scores of all four constructs were higher than the scale mid-point of 3.00. Organisational readiness recorded the highest mean (M = 3.62, SD = 0.74), followed by process innovation (M = 3.59, SD = 0.69), product innovation (M = 3.54, SD = 0.72) and technological readiness (M = 3.45, SD = 0.68). As a result, respondents' view of their banks' readiness in terms of AI-enabled process change and AI-enabled products is slightly behind in each of these areas. The mean standard deviations range from 0.68 to 0.74, which is considered moderate variability in perceptions between respondents and banks.

Table 1. *Descriptive statistics of the study variables*

Variable	N	M	SD	Interpretation
Technological readiness	400	3.45	0.68	Above midpoint
Organisational readiness	400	3.62	0.74	Above midpoint
Product innovation	400	3.54	0.72	Above midpoint
Process innovation	400	3.59	0.69	Above midpoint

Note. Scores are on a five-point metric; higher values indicate stronger readiness or innovation (midpoint = 3.00).

4.2 Correlation analysis

Table 2 shows that all correlations were positive and statistically significant ($p < .001$ for $N = 400$). Technological readiness correlated strongly with product innovation ($r = .68$) and process innovation ($r = .70$). Organisational readiness correlated strongly with product innovation ($r = .74$) and process innovation ($r = .72$). The two readiness dimensions were themselves strongly related ($r = .78$), although the correlation is well below unity, indicating that they are related but distinct constructs. Product and process innovation were very strongly correlated ($r = .85$), consistent with the view that the two types of innovation develop together.

Table 2. *Pearson correlation matrix (N = 400)*

Variable	1	2	3	4
1. Technological readiness	—			
2. Organisational readiness	.78	—		
3. Product innovation	.68	.74	—	
4. Process innovation	.70	.72	.85	—

Note. All coefficients are significant at $p < .001$ (two-tailed).

4.3 Multiple regression analysis

Table 3 reports the two regression models. Multicollinearity was not a serious concern. With a predictor intercorrelation of .78, tolerance was .392 and VIF was 2.55 for each predictor, below the threshold of 5 (Hair et al., 2019).

Product innovation. The model was significant, $F(2, 397) = 268.11$, $p < .001$, and the two predictors jointly explained 57.5% of the variance in product innovation (adjusted $R^2 = .572$). Both predictors made significant unique contributions, but organisational readiness ($\beta = .535$, $t = 10.23$) was a stronger predictor than technological readiness ($\beta = .263$, $t = 5.02$). Organisational readiness uniquely accounted for about 11.2% of the variance in product innovation, against about 2.7% for technological readiness; the remaining explained variance, about 43.6%, was shared between the two.

Process innovation. The model was also significant, $F(2, 397) = 260.26$, $p < .001$, explaining 56.7% of the variance (adjusted $R^2 = .565$). Organisational readiness ($\beta = .444$, $t = 8.42$) again had the larger standardised coefficient, but technological readiness ($\beta = .353$, $t = 6.70$) was closer behind than in the product model. Unique variance was about 7.7% for organisational readiness and 4.9% for technological readiness, with about 44.1% shared. By Cohen's (1988) conventions, both models represent large effects ($f^2 = 1.35$ and 1.31 respectively).

Table 3. *Multiple regression of innovation outcomes on readiness dimensions (N = 400)*

Predictor	B	SE B	β	t	p
Model 1: Product innovation					
Technological readiness	0.278	0.055	.263	5.02	< .001
Organisational readiness	0.521	0.051	.535	10.23	< .001
$R = .758$, $R^2 = .575$, adjusted $R^2 = .572$, $F(2, 397) = 268.11$, $p < .001$					
Model 2: Process innovation					
Technological readiness	0.359	0.054	.353	6.70	< .001
Organisational readiness	0.414	0.049	.444	8.42	< .001
$R = .753$, $R^2 = .567$, adjusted $R^2 = .565$, $F(2, 397) = 260.26$, $p < .001$					

Note. B = unstandardised coefficient; *SE B* = standard error of *B*; β = standardised coefficient. Degrees of freedom for each *t* test = 397.

4.4 Summary of hypothesis tests

Because every predictor remained significant at $p < .001$ in the multiple regression and every bivariate correlation was significant, all four hypotheses were supported (Table 4). Each relationship was positive.

Table 4. *Summary of hypothesis testing*

Hypothesis	Relationship	r	β	Decision (p < .001)
H1	Technological readiness → Product innovation	.68	.263	Supported
H2	Technological readiness → Process innovation	.70	.353	Supported
H3	Organisational readiness → Product innovation	.74	.535	Supported
H4	Organisational readiness → Process innovation	.72	.444	Supported

Note. r = Pearson correlation; β = standardised regression coefficient from the two-predictor model.

5. Discussion

5.1 Technological Readiness and Innovation (H1 and H2)

Project aims to advance the technology readiness of this product and provide innovation.

Even after controlling the organisational readiness, technological readiness was significantly and positively correlated with product and process innovation. It is consistent with the RBV argument, which considers technological resources as the basis for developing capabilities, and with the literature on AI-readiness that views infrastructure, data and skills as pre-conditions for use (Alsheibani et al., 2018; Davenport & Ronanki, 2018). The distribution of outcomes is informative. The unique coefficient for the technological readiness for process innovation was larger (β = .353) than the technological readiness for product innovation (β = .263). System integration, data quality, and computing reliability are directly dependent on process innovations like automated verification, transaction monitoring and workflow routing, which manifest early as operational constraints when the technical underpinnings are faulty. The result also sheds light on why the importance of process innovation was slighted higher than product innovation. While automated internal processes are a starting point for AI adoption in organizations, the need for richer data integration and analytical maturity arises in creating personalised products (Davenport & Ronanki, 2018; Huang & Rust, 2021).

However, the technological readiness construct was found to have the lowest mean of all the four constructs, but still above the midpoint, indicating that foundations were more constrained compared to technological readiness in Yenagoa. Skills, data and infrastructure are interdependent, and upgrading one without the other is not likely to take care of the constraint.

5.2 Organisational Preparedness and Innovation (H3 & H4)

The more powerful unique predictor of both outcomes was organisational readiness, particularly of product innovation (β = .535). This reinforces the idea of innovation as a process in an organisation and not merely an achievement. Establishing a new AI-powered service necessitates an executive sponsor, funding, cross-functional collaboration between technology, risk, compliance and customer-facing teams, and a culture that welcomes "controlled experimentation." These are the conditions identified by innovation research as important (Damanpour, 1991) and which the AI-readiness literature categorizes as strategy, resources, knowledge and culture (Jöhnk et al., 2021). In TAM, the perception of usefulness and ease of use of the installed tool is influenced by leadership communication and training, which ultimately influences the actual use of the tool during service delivery (Davis, 1989; Venkatesh & Davis, 2000).

The difference between the two predictors was smaller for process innovation (β = .444 vs .353). Process change also impacts on job content, as well as on approval paths and performance expectations; therefore it requires ability of the systems and people who understand, accept and govern them (Ettlie & Reza, 1992; Weiner, 2009). This implies that process innovation makes more use of technical and organisational conditions, and product innovation makes more use of organisational conditions.

5.3 Technology Required but not Sufficient.

All of this suggests that technology is the enabling but not the end factor in innovation with AI. This interpretation is supported by three characteristics of the results. First of all, both readiness dimensions had significant unique effects, leaving both to be taken seriously. Second, the organisational readiness factor appeared with the higher standardised coefficient in both models, corroborating the RBV tenet that intangible, hard-to-imitate components of the organisation may be more important in securing a sustainable advantage than may purchased technology (Barney, 1991). Leadership competence, learning culture and coordination routines can be developed by any competitor, while technology can be acquired by any competitor. Third, the proportionZ of the variance accounted for by the two predictors were relatively high, around 44% in each model. Their strong relationship ($r = .78$) implies that the two are coevolving in the development of banks and should be considered as a set of complementary, rather than conflicting, explanations.

The high correlation of product and process innovation ($r = .85$) further emphasizes the need to pursue the two together. Innovation in the processes of customer verification, credit assessment and risk monitoring, for example, is a prerequisite for a new AI-assisted lending product and the customer receives it as a faster and more responsive service.

6. Implications

6.1 Theoretical implications

The study extends TAM by showing that acceptance-related conditions, such as leadership support, training and culture, operate at the organisational level and are associated with innovation outcomes in addition to individual usage. It also supports the RBV by indicating that both technological and organisational resources contribute to innovation and that organisational resources appear to carry the larger unique weight. Methodologically, separating AI readiness into two dimensions and innovation into two types gives a more discriminating account than treating either as a single construct, and the different coefficient patterns across the two models show what would be lost by aggregation.

6.2 Managerial and policy implications

For bank managers, the results imply that AI adoption should be treated as a strategic change programme and not as an IT procurement exercise. Five practical implications follow.

- Assess readiness before committing capital. A diagnostic covering infrastructure, data quality, systems integration, cybersecurity, staff competence, leadership sponsorship and culture helps banks identify the binding constraint, which may be technical in one bank and organisational in another.
- Invest in people as well as platforms. Training should be continuous and role-specific, covering technical skills for specialists, data literacy for managers and practical competence for frontline staff.
- Establish clear executive sponsorship and governance for AI projects, including cross-functional teams and defined decision authority, so that product ideas can move from concept to launch.

- Implement in phases. Controlled pilots with predefined performance measures, followed by scaling and review, reduce the cost of failure and generate evidence that builds employee confidence.
- Evaluate product and process innovation together, using indicators of both efficiency and customer outcomes, and embed risk, compliance, privacy and fairness controls from the design stage.

Because the results show that the two readiness dimensions are complementary, the practical guidance can be summarised as a staged framework (Table 5). It begins with diagnosis because banks should understand their current capability before committing resources, and it ends with learning because the long-term objective is an organisational capability to identify, test, govern and improve AI-enabled innovation, and not a collection of isolated projects. Banks whose diagnosis shows weak infrastructure may sequence technical investment first, whereas technically advanced banks may obtain greater returns from culture, training and governance.

Table 5. *A readiness-based framework for AI-enabled innovation in deposit money banks*

Stage	Core activity	Expected output
1. Diagnose	Assess infrastructure, data, skills, culture, leadership sponsorship and current AI use	Readiness baseline
2. Prioritise	Select product and process problems with measurable value	AI project portfolio
3. Prepare	Build data, systems, skills, governance and change-management support together	Implementation capacity
4. Pilot	Test selected solutions at controlled scale with predefined measures	Evidence of feasibility
5. Implement	Integrate validated solutions into products and processes	Operational innovation
6. Monitor	Track performance, risk, fairness, security and customer outcomes	Performance evidence
7. Learn	Review results and update systems, training and governance	Continuous improvement

Note. Framework proposed by the authors from the study variables and findings; it has not been empirically tested.

For regulators and industry bodies, the findings point to the value of supporting reliable connectivity and power, expanding the supply of data and AI skills through collaboration among universities, professional bodies and banks, enforcing data-protection requirements, and providing guidance that allows responsible experimentation.

7. Limitations and Directions for Future Research

Several limitations should be noted. First, the cross-sectional design cannot establish causal order or show how readiness and innovation co-evolve; longitudinal designs would address

this. Second, the constructs were measured through self-reported perceptions, which are open to social-desirability and common-method bias (Podsakoff et al., 2003), and future studies could add objective indicators such as processing times, fraud-loss rates or the number of launched digital services. Third, the study covers one city, so generalisation to other Nigerian banking markets should be cautious. Fourth, respondents from the same bank may share perceptions, and the analysis does not model bank-level clustering; multilevel models would be appropriate with a larger number of banks. Fifth, the two predictors are strongly correlated, so the unique-effect estimates should be interpreted with care, although the VIF values were acceptable. Sixth, the interview component is not reported in this article. Future research could use structural equation modelling to test mediation, for example through employee acceptance or organisational learning, include moderators such as regulatory pressure and firm size, compare deposit money banks with fintech firms, and incorporate customer-level outcomes such as trust and satisfaction.

8. Conclusion

This study examined how technological and organisational readiness for AI relate to product and process innovation in deposit money banks in Yenagoa. Both dimensions of readiness were positively and significantly related to both forms of innovation, and together they explained more than half of the variance in each. Organisational readiness had the larger unique effect in both models, particularly for product innovation, while technological readiness remained an independent contributor, particularly for process innovation. The central conclusion is that banks should ask not only whether they possess AI technology but also whether they have the organisational capability to use it productively, responsibly and consistently. Banks that develop both forms of readiness are better placed to improve their services, automate their operations and compete in an increasingly digital financial sector.

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