© SEP 2026 | IRE Journals | Volume 10 Issue 3 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I3-1723462

Artificial Intelligence Adoption in the Nigerian Banking Industry: A Comparative Study of Bank Employees and Customers

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Abstract- Artificial intelligence (AI) is increasingly embedded in banking, but adoption depends on perceived value, trust, organizational readiness, and regulation. This quantitative study examined AI adoption in the Nigerian banking industry from bank employee and customer perspectives. Using a cross-sectional survey, data were collected from 102 respondents (43 employees and 59 customers). The study assessed awareness and current exposure, perceived benefits, trust and transparency, implementation and regulatory challenges, and future AI adoption orientation. Mann–Whitney U tests found no statistically significant employee–customer differences. Spearman correlations showed positive associations between four explanatory constructs and future adoption orientation, with perceived benefits showing the strongest association ($\rho = .662$, $p < .001$). Multiple regression explained 50.0% of the variance ($R^2 = .500$), with perceived benefits the only independent predictor ($B = .617$, $p < .001$). The findings highlight the importance of value, skills, infrastructure, security, transparency, and governance for responsible AI adoption in Nigerian banking.

Keywords - Artificial intelligence, AI adoption, Nigerian banking industry, technology acceptance, trust, explainability, banking customers, bank employees.

I. INTRODUCTION

Artificial intelligence (AI) has moved from a specialist technology to an increasingly important component of digital transformation in financial services. Banks use AI-related capabilities for activities such as fraud detection, customer support, risk analysis, process automation, personalization, and decision support. Research on AI-enabled banking shows that these applications can improve service performance and user experience, but acceptance is shaped by perceptions of usefulness, performance, trust, and risk (Alnaser et al., 2023).

The adoption question is therefore broader than whether a bank can technically deploy an AI system. Adoption also concerns whether employees and customers recognise its value, understand its role, trust its outputs, and consider the surrounding governance arrangements adequate. This is particularly relevant in financial services because AI can affect decisions involving money, identity, risk, and access to services. Explainability has become an important part of this discussion. A systematic review of AI in finance found that explainability is especially relevant in areas such as credit management, fraud detection, and risk-related decision making, where stakeholders may need to understand why a system produced a particular outcome (Černevičienė & Kabašinskas, 2024). Related work also shows that transparency is a major consideration in highly regulated financial applications (Weber et al., 2024).

The Nigerian banking industry provides a useful African context for examining these issues. Nigerian banks have continued to expand digital services while operating under requirements relating to cybersecurity, data protection, operational resilience, and regulatory compliance. Recent Nigerian studies have examined AI and bank performance, customer experience, employee performance, and specific applications such as fraud detection (Elegunde & Osagie, 2020; Ofuani et al., 2024; Alaba et al., 2025). These studies demonstrate growing interest in AI, but they do not fully address the combined perceptions of employees and customers across multiple adoption dimensions.

The present study addresses this gap by examining AI adoption from two stakeholder perspectives. The questionnaire measures awareness and current exposure, perceived benefits, trust and transparency, implementation and regulatory challenges, and future AI adoption orientation. The distinction is important: respondents may already interact with AI-enabled banking functions without necessarily recognising the technology as AI. The study therefore examines both existing exposure and orientation toward broader adoption.

This is a quantitative research paper. It has three objectives: to examine perceptions of AI adoption among bank employees and customers; to determine whether the two groups differ significantly; and to identify the factors associated with future AI adoption orientation. The study draws on the Technology Acceptance Model (TAM) and the Technology–Organisation–Environment (TOE) framework to interpret individual perceptions alongside organisational and environmental conditions.

1. Research Objectives

- To examine bank employees' and customers' perceptions of artificial intelligence adoption in the Nigerian banking industry.
- To determine whether significant differences exist between bank employees and customers in their perceptions of AI adoption.
- To identify the factors associated with future AI adoption orientation among the surveyed respondents.

II. CONCEPTUAL BACKGROUND AND LITERATURE REVIEW

1. Artificial Intelligence Adoption in Banking

AI adoption in banking can be understood as the organisational decision to accept, integrate, and expand AI capabilities within banking processes and services. It can include both customer-facing applications and internal operational systems. The concept is therefore wider than the adoption of a single chatbot, fraud-detection model, or automated decision tool.

Evidence from financial services indicates that the perceived value of AI is closely related to adoption. In a study of AI-enabled digital banking, Alnaser et al. (2023) found that user satisfaction and acceptance were associated with performance and other service characteristics. In South Africa, Hassan (2024) found that technological, organisational, and environmental factors significantly influenced the likelihood of AI adoption in financial services. These findings suggest that adoption is shaped by both perceived benefits and the conditions surrounding implementation.

Nigerian evidence is developing. Elegunde and Osagie (2020) found that AI could complement banking work processes and ease employee operations. Ofuani et al. (2024) examined AI integration at United Bank for Africa and reported significant effects for some AI-enabled banking applications on organisational performance. More recent Nigerian work has examined AI adoption for cybersecurity, fraud detection, customer experience, and financial inclusion, showing that infrastructure, competency, compliance, trust, and cost remain relevant issues (Alaba et al., 2025; Eke, 2026; Ibrahim et al., 2025).
Taken together, the literature suggests that AI adoption should be studied as a socio-technical process. Technical capability alone does not guarantee adoption. The perceived usefulness of the technology, organisational readiness, employee capability, customer confidence, data governance, and regulatory conditions can influence whether AI is accepted and expanded.

2. Technology Acceptance Model

The Technology Acceptance Model (TAM) explains technology acceptance primarily through perceived usefulness and perceived ease of use (Davis, 1989). Perceived usefulness is particularly relevant to the present study because respondents were asked whether AI improves efficiency, customer service, decision making, fraud detection, and other banking outcomes. TAM provides an individual-level explanation for why a stakeholder may support AI. If a customer believes that AI improves service or protects transactions, or an employee believes that it reduces routine work and improves decision support, the stakeholder may be more favourable toward wider adoption. The present study therefore treats perceived benefits as a central explanatory construct rather than assuming that awareness automatically leads to adoption.

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DOI: https://doi.org/10.64388/IREV10I3-1723462

3. Technology–Organisation–Environment Framework

The Technology–Organisation–Environment framework explains organisational technology adoption through technological, organisational, and environmental contexts (Tornatzky et al., 1990). The framework is useful for AI adoption because banking institutions must consider infrastructure, data, skills, leadership, investment, governance, competition, and regulation at the same time.

Recent financial-services evidence supports the relevance of TOE. Hassan (2024), for example, found that technological infrastructure, organisational leadership support, and regulatory clarity were important drivers of AI adoption in South Africa's financial services sector. The framework therefore complements TAM by moving beyond individual acceptance to the organisational environment in which AI adoption occurs.

4. Trust, Transparency, and Explainability

Trust is especially important when AI is used in financial services. Users may accept automation for routine activities but become more cautious when an AI system influences a consequential decision. Explainable AI seeks to make model outputs more understandable, supporting accountability and informed review.

The financial XAI literature shows that explainability is relevant to credit management, fraud detection, risk assessment, and other high-impact applications (Černevičienė & Kabašinskas, 2024; Weber et al., 2024). For Nigerian banks, this implies that adoption strategies should address not only model accuracy but also how decisions are communicated, challenged, monitored, and governed.

5. African and Nigerian Context

African banking environments have distinct institutional and infrastructural conditions that can shape AI adoption. Banks may need to integrate AI with legacy systems, manage uneven data quality, develop specialist skills, and comply with evolving data and cybersecurity requirements. These conditions make African evidence important rather than treating findings from other regions as automatically transferable.

Recent Nigerian studies show a similar pattern. A 2026 AJIS study of three Nigerian commercial banks similarly found that managerial support, data-professional skills, and technological infrastructure enabled AI use (Akobe et al., 2026). Research on AI-enabled cybersecurity identified skills and access to appropriate tools as continuing concerns (Eke, 2026). Research on AI-driven fraud detection identified infrastructure, staff competency, regulatory compliance, implementation cost, and perceived effectiveness as important adoption considerations (Alaba et al., 2025). The present study extends this literature by examining a broader set of adoption perceptions and comparing employees with customers.

6. Research Gap

Three gaps motivate the study. First, much of the established AI-adoption literature is based outside Nigeria, while Nigerian evidence is still fragmented across particular applications and organisational outcomes. Second, existing Nigerian studies frequently focus on employees, specific banks, or individual AI applications. Less attention has been given to the views of employees and customers within the same empirical framework. Third, adoption is sometimes discussed as a technical implementation issue without jointly considering perceived benefits, trust and transparency, and implementation challenges.

This study addresses these gaps through a stakeholder-comparative survey. Its contribution is not the claim that AI is simply present in Nigerian banking. Rather, it identifies which perceptions are most closely associated with respondents' orientation toward future AI adoption and whether employees and customers view the issue differently.

7. Conceptual Model

The model positions awareness/current exposure, perceived benefits, trust/transparency, and implementation/regulatory challenges as explanatory constructs associated with future AI adoption orientation. Employee and customer status provides

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DOI: https://doi.org/10.64388/IREV10I3-1723462

the comparative dimension of the study. The model is interpretive rather than a claim of causality because the research uses cross-sectional survey data.

Figure 1. Conceptual model of the study.

III. RESEARCH DESIGN

1. Research Design

The study adopted a cross-sectional quantitative survey design. A survey was appropriate because the research sought comparable measurements of perceptions among two respondent groups and required statistical tests of group differences and relationships among constructs.

2. Population, Sampling, and Data Collection

The target population comprised bank employees and bank customers with relevant exposure to banking services. A non-probability approach was used to reach accessible respondents who could provide information relevant to the research topic. The final dataset contained 102 valid responses, comprising 43 bank employees and 59 bank customers.

The use of non-probability sampling is a limitation because the sample cannot be assumed to represent all Nigerian bank employees or customers. However, the approach is suitable for an exploratory stakeholder comparison where the researcher needs access to respondents connected to the banking environment. The sampling limitation is therefore considered explicitly when interpreting the results.

3. Instrument and Measures

The questionnaire was structured around five substantive areas: awareness and current exposure, perceived benefits, trust and transparency, implementation and regulatory challenges, and future AI adoption orientation. The instrument also collected demographic information and included an optional open-ended question.

The awareness and exposure section was designed to distinguish general awareness from actual interaction with AI-enabled banking systems. This distinction is important because a customer may use fraud alerts, automated support, recommendation systems, or other intelligent features without knowing that AI is involved. The remaining sections used five-point Likert-type response scales.

4. Data Analysis

The analysis combined descriptive and inferential statistics. Descriptive statistics summarized respondent characteristics and construct-level responses. Cronbach's alpha assessed internal consistency; Mann–Whitney U tests examined employee–customer differences; Spearman rank-order correlations examined associations with future AI adoption orientation; and multiple linear regression assessed independent associations among the explanatory constructs. HC3 heteroscedasticity-consistent standard errors were applied. The open-ended responses were reviewed thematically to identify recurring implementation concerns. Because the design is cross-sectional and non-probability based, regression coefficients are interpreted as associations rather than causal effects.

5. Key statistical formulas

Construct mean: $\bar{X}_i = (x_i1 + x_i2 + \ldots + x_ik) / k$

where k is the number of items in a construct and $\bar{X}_i$ is the respondent-level construct score. The construct scores were then summarized across respondents.

Cronbach's alpha: $\alpha = [k/(k - 1)]\,[1 - \Sigma\sigma^2_i / \sigma^2_t]$

where k is the number of items, σ^2_i is the variance of each item, and σ^2_t is the variance of the total score.
Spearman rank correlation: $\rho = 1 - 6\Sigma d^2 / [n(n^2 - 1)]$
where d is the difference between paired ranks and n is the number of paired observations. Tied ranks were handled by the statistical software.

Mann–Whitney U: $U_1 = n_1n_2 + n_1(n_1 + 1)/2 - R_1$

where n_1 and n_2 are the two group sizes and R_1 is the sum of ranks for group 1. The smaller U statistic is used for inference.

Multiple linear regression: $Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \varepsilon$

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DOI: https://doi.org/10.64388/IREV10I3-1723462

Here, Y represents future AI adoption orientation; X_1–X_4 represent awareness/current exposure, perceived benefits, trust/transparency, and regulatory/implementation challenges. HC3 heteroscedasticity-consistent standard errors were used for inference.

Multiple linear regression was then used to assess the independent contribution of the explanatory constructs. Heteroscedasticity-consistent HC3 standard errors were applied. The open-ended responses were reviewed thematically to identify recurring implementation concerns. Because the design is cross-sectional and non-probability based, regression coefficients are interpreted as associations rather than causal effects.

6. Reliability of the Instrument

Table 1. Internal consistency of the study constructs.

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Construct	Cronbach's alpha
Awareness/current exposure	.757
Perceived benefits	.913
Trust/transparency	.840
Regulatory/implementation challenges	.739
Future AI adoption orientation	.920

The reliability coefficients indicate acceptable to excellent internal consistency across the constructs. Perceived benefits and future AI adoption orientation showed particularly strong internal consistency.

IV. ANALYSIS AND INTERPRETATION

1. Respondent Profile

Table 2. Characteristics of respondents (N = 102).

Characteristic	Category	n (%)
Respondent group	Bank employees	43 (42.2%)
	Bank customers	59 (57.8%)
Gender	Male	55 (53.9%)
	Female	46 (45.1%)
	Prefer not to say	1 (1.0%)
Age	18–25	14 (13.7%)
	26–35	60 (58.8%)
	36–45	23 (22.5%)
	46 years and above	5 (4.9%)

Customers represented 57.8% of the sample and employees represented 42.2%. The sample was also concentrated in the 26–35 age group, which accounted for 58.8% of respondents.

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DOI: https://doi.org/10.64388/IREV10I3-1723462

2. Construct-Level Results

Table 3. Construct-level descriptive results.

Construct	Mean
Awareness/current exposure	3.69
Perceived benefits	3.61
Trust/transparency	3.18
Regulatory/implementation challenges	3.52
Future AI adoption orientation	3.89

Future AI adoption orientation recorded the highest mean (M = 3.89), indicating a generally favourable orientation toward expanded AI adoption. Awareness/current exposure and perceived benefits were also above the scale midpoint.

Trust/transparency produced the lowest construct mean (M = 3.18). This is important because respondents could simultaneously recognise AI's potential benefits and remain uncertain about how AI-supported decisions are produced or explained. The pattern reinforces the need to treat trust as a distinct adoption condition rather than assuming that perceived usefulness automatically produces confidence.

3. Comparison of Employees and Customers

Table 4. Mann–Whitney U comparison of employees and customers.

Construct	Employees M	Customers M	p
Awareness/current exposure	3.74	3.66	.995
Perceived benefits	3.74	3.51	.178
Trust/transparency	3.38	2.99	.079
Regulatory/implementation challenges	3.71	3.38	.203
Future AI adoption orientation	3.90	3.89	.805

None of the employee–customer comparisons was statistically significant at the .05 level. The largest numerical difference was observed for trust/transparency, with employees reporting a higher mean than customers, but the difference did not reach statistical significance ($p = .079$). Future AI adoption orientation was almost identical between the groups (3.90 versus 3.89; $p = .805$).

4. Associations with Future AI Adoption Orientation

Table 5. Spearman correlations with future AI adoption orientation.

Predictor	Spearman rho	p
Awareness/current exposure	.468	< .001
Perceived benefits	.662	< .001
Trust/transparency	.433	< .001
Regulatory/implementation challenges	.385	< .001

All four constructs were positively associated with future AI adoption orientation. Perceived benefits showed the strongest association (rho = .662, $p < .001$), followed by awareness/current exposure (rho = .468, $p < .001$), trust/transparency (rho = .433, $p <$

.001), and regulatory/implementation challenges (rho = .385, p < .001).

5. Predictors of Future AI Adoption Orientation

Table 6. Multiple regression predicting future AI adoption orientation.

Predictor	B	HC3 p
Awareness/current exposure	.022	.817
Perceived benefits	.617	< .001
Trust/transparency	.033	.662
Regulatory/implementation challenges	.091	.487

The regression model explained 50.0% of the variance in future AI adoption orientation ($R^2 = .500$; adjusted $R^2 = .480$). Perceived benefits was the only statistically significant independent predictor (B = .617, p < .001; 95% CI [.386, .849]).

The difference between the correlation and regression results is informative. Awareness, trust/transparency, and implementation challenges were each positively correlated with future adoption orientation when considered separately. After the shared variance among all predictors was taken into account, only perceived benefits remained statistically significant. This suggests that perceived value may be the most direct adoption signal within this sample.

6. Open-Ended Responses

Forty-eight respondents provided additional comments. The responses repeatedly identified staff training and skilled personnel, cybersecurity and data protection, infrastructure investment, data quality and integration, AI governance, human oversight, automation, customer experience, and awareness.

These comments strengthen the quantitative findings because they show that respondents do not view AI adoption as a software-only issue. They repeatedly connected successful adoption with people, infrastructure, security, governance, and responsible oversight.

V. DISCUSSION AND IMPLICATIONS

The study found a generally favourable orientation toward future AI adoption in Nigerian banking. The highest construct mean was future AI adoption orientation, while perceived benefits also received a positive rating. This result is consistent with research showing that users are more likely to accept AI-enabled banking when they perceive improvements in performance and service value (Alnaser et al., 2023).

The strongest result was the relationship between perceived benefits and future AI adoption orientation. The correlation was moderate-to-strong (rho = .662), and perceived benefits remained the only significant predictor in the multivariable model. This provides empirical support for the usefulness logic of TAM: perceived value is not simply an attitude toward AI but an important signal of willingness to support broader adoption (Davis, 1989).

The finding also complements Nigerian evidence. Studies of AI in Nigerian banking have reported potential benefits for work processes and organisational performance (Elegunde & Osagie, 2020; Ofuani et al., 2024). The present study adds a stakeholder perspective by showing that perceived benefits are strongly related to respondents' orientation toward future adoption rather than only to a specific organisational performance measure.

Trust and transparency require a different interpretation. The construct had the lowest mean, yet it was positively correlated with future adoption orientation. This suggests that trust is relevant even when respondents remain cautious. The result is consistent with financial XAI research, which emphasises explainability and transparency in high-impact financial decisions (Černevičienė & Kabašinskas, 2024; Weber et al., 2024).

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DOI: https://doi.org/10.64388/IREV10I3-1723462

The absence of significant differences between employees and customers is also noteworthy. Employees may have more exposure to internal systems, policies, or AI-related discussions, while customers may experience AI indirectly through digital channels. Despite these different positions, the two groups showed similar overall orientations. The result suggests that AI adoption in banking may be understood as a shared stakeholder issue rather than a concern belonging only to internal technology users.

The positive correlation between implementation/regulatory challenges and future adoption orientation should not be read as evidence that challenges cause adoption. Respondents who are more aware of AI may also be more aware of its risks and implementation requirements. The relationship may therefore reflect greater engagement with the subject. A longitudinal or experimental design would be required to establish directionality.

The open-ended responses further support the TOE perspective. Participants repeatedly mentioned infrastructure, skilled personnel, data quality, cybersecurity, governance, and investment. Similar factors have been identified in African financial-services research. Hassan (2024), for example, found technological infrastructure, leadership support, and regulatory clarity to be important drivers of AI adoption in South Africa. Nigerian studies likewise identify competency, infrastructure, compliance, and implementation cost as relevant conditions (Alaba et al., 2025; Eke, 2026).

The combined TAM–TOE interpretation therefore provides a useful way of understanding the findings. TAM helps explain why perceived benefits matter at the stakeholder level, while TOE helps explain why adoption must also be supported by organisational capabilities and an enabling environment. The study does not claim to test the full causal structure of either framework; rather, the frameworks provide complementary theoretical lenses for interpreting the observed relationships.

1. THEORETICAL AND PRACTICAL CONTRIBUTION

The study makes three main contributions. First, it provides empirical evidence from Nigeria on AI adoption using both employee and customer perspectives. This responds to the tendency for adoption research to focus on a single stakeholder group or a specific AI application.

Second, the findings identify perceived benefits as the strongest explanatory factor among the constructs examined. This supports the continued relevance of usefulness-based technology acceptance explanations while showing that the effect remains when awareness, trust/transparency, and implementation challenges are considered together.

Third, the study connects adoption with responsible implementation. The open-ended responses and the lower trust/transparency score indicate that stakeholders want AI benefits without losing security, accountability, or human oversight. For banking institutions, this means AI strategies should combine business value with governance and risk controls.

2. IMPLICATIONS FOR PRACTICE

Banks should communicate the practical value of AI in terms that employees and customers can understand. Examples include faster service, stronger fraud detection, improved customer support, reduced routine workload, and better decision support. Demonstrating measurable value can strengthen the usefulness perceptions that were most strongly associated with future adoption in this study.

Banks should also strengthen AI literacy and specialist capability. Respondents repeatedly identified training and skilled personnel as priorities. Training should cover not only the use of AI tools but also data quality, cybersecurity, model limitations, responsible use, and escalation procedures.

Trust should be addressed through transparency and human oversight. Where AI affects important banking decisions, customers and employees should have appropriate information about the system's role and access to human review where necessary. This is consistent with the wider financial XAI literature, which links explainability with accountability and trustworthy AI deployment (Černevičienė & Kabašinskas, 2024).

Finally, AI adoption should be integrated with existing governance arrangements. Cybersecurity, data protection, model risk, vendor management, auditability, and regulatory compliance should be considered during AI planning rather than after deployment.

3. Ethical Considerations
Participation was voluntary, and the questionnaire stated that responses would be treated confidentially and used for research and professional analysis. The final dataset contains no respondent names or direct personal identifiers. No confidential bank information or individual respondent identities are reported.

4. LIMITATIONS AND FUTURE RESEARCH
The study has several limitations. First, the sample was obtained through non-probability sampling and therefore should not be treated as statistically representative of the entire Nigerian banking population. Second, the sample size of 102 limits the complexity of statistical modelling that can reasonably be supported. Third, the study relies on self-reported perceptions rather than direct observation of bank AI systems.

Fourth, the cross-sectional design does not establish causal relationships. The regression results should therefore be interpreted as associations. Future studies could use larger probability-based samples, longitudinal designs, and bank-level case studies. Research could also compare specific AI applications, such as fraud detection, customer-service chatbots, credit scoring, and cybersecurity systems.

Future research should also investigate the difference between actual AI interaction and perceived AI interaction. This is important because customers may interact with AI-enabled features without recognising them as AI. Combining survey data with scenario-based questions or verified system-use information could improve measurement accuracy.

VI. CONCLUSION

This study examined artificial intelligence adoption in the Nigerian banking industry from the perspectives of bank employees and customers. The findings show a generally positive orientation toward future AI adoption, but they also reveal continuing concerns about trust, transparency, implementation, skills, cybersecurity, data protection, and infrastructure.

Perceived benefits emerged as the strongest independent predictor of future AI adoption orientation. The finding suggests that stakeholders are more likely to support wider AI adoption when they can see clear and credible value in the technology. At the same time, the moderate trust/transparency result indicates that value alone is insufficient for responsible adoption.

The study contributes a stakeholder-based view of AI adoption in Nigerian banking and provides evidence that employees and customers in the sample hold broadly similar views. For Nigerian banks, the implication is clear: AI adoption should be pursued through a combination of demonstrable value, skilled people, reliable infrastructure, strong security, transparent governance, and appropriate human oversight.

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