Impact of AI-Driven Solutions in Financial Technology on Service Delivery: A Study of Fraud Detection, Credit Risk Assessment, and Personalized Advisory Systems in Insurance Firms in Lagos State

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ABSTRACT

Anchored on the Resource-Based View (RBV), this study examined the impact of AI-driven solutions in financial technology on service delivery, focusing on fraud detection, credit risk assessment, and personalized advisory systems in seven insurance firms in Lagos State. Using a quantitative approach, data were collected from 304 respondents selected through stratified random sampling. Descriptive statistics and regression analysis were employed to test the hypotheses.

Findings revealed that AI-driven fraud detection ($\beta = 0.352$, $p < 0.01$), AI-powered credit risk assessment ($\beta = 0.294$, $p < 0.01$), and AI-enabled personalized advisory systems ($\beta = 0.301$, $p < 0.01$) each exerted significant positive effects on service delivery. Descriptive results showed high mean scores across variables (≥ 4.0), indicating strong consensus on AI's operational benefits.

Theoretically, the study establishes AI-driven technologies as strategic resources that create competitive advantage in service performance, consistent with RBV. Practically, it underscores the importance of investing in data infrastructure, staff capacity development, and regulatory alignment to ensure ethical and effective AI adoption.

Keywords: AI-driven solutions, Resource-Based View (RBV), FinTech, Service delivery, Insurance firms, Lagos State

INTRODUCTION

The rapid growth of financial technology (FinTech) has transformed the landscape of service delivery across industries, with the insurance sector being one of the major beneficiaries (Mogaji et al., 2020). Artificial intelligence (AI) has emerged as a powerful driver of this transformation, enabling firms to optimize processes, detect anomalies, and provide highly customized solutions that align with customer expectations (Karnati, 2025). In today's competitive financial environment, organizations are under constant pressure to deliver efficient services while minimizing risks and maximizing customer trust (Hentzen et al., 2021). This has increased the importance of AI-driven innovations in strengthening fraud detection, enhancing credit risk management, and personalizing advisory services to improve overall service quality (Daiya, 2024).

The application of AI in fraud detection is particularly critical because insurance firms face significant losses due to fraudulent claims and transactions (Ashrafuzzaman et al., 2025). By leveraging algorithms and machine learning, firms are now able to identify unusual patterns, detect potential fraud, and respond in real time, reducing losses and enhancing transparency (Adegbite, 2025). This not only minimizes financial risks but also improves customer confidence, as policyholders feel secure knowing their transactions are monitored and safeguarded by advanced systems (Bhatnagar & Mahant, 2024). Fraud prevention through AI has therefore become a cornerstone of operational resilience and a crucial determinant of efficient service delivery (Anugu, 2025).

Similarly, credit risk assessment has undergone a major shift with the integration of AI solutions (Kagalwala et al., 2025). Traditional methods often relied heavily on manual evaluation and historical data, which could be prone to delays and inaccuracies (Huang & Rust, 2020). In contrast, AI-powered systems provide predictive analytics and real-time risk profiling, allowing insurers to evaluate customer creditworthiness with greater precision and speed (Komati, 2025). This has significant implications for service delivery, as faster and more accurate assessments reduce delays in policy issuance and claims processing (Mogaji et al., 2022). The ability to make quick yet reliable decisions is central to maintaining competitiveness in a sector that depends heavily on client trust and satisfaction (Deepika, 2025).

In addition, the rise of AI-enabled personalized advisory systems has redefined customer engagement in the insurance industry (Kagalwala et al., 2025). By analyzing customer behavior, financial history, and preferences, these systems can deliver tailored recommendations that align with the unique needs of each client (Egbuhuzor et al., 2025). For example, policyholders can now receive automated guidance on the best insurance packages, premium adjustments, or risk management strategies suited to their circumstances (Komati, 2025). This level of personalization enhances customer satisfaction and loyalty, while also reducing the workload of human advisors who can then focus on more complex cases (Egbuhuzor et al., 2025).

The insurance industry in Lagos State, being the financial hub of Nigeria, has embraced these AI-driven innovations at a faster pace compared to other regions. The highly competitive environment and the diverse needs of customers in this market demand greater efficiency and service quality from insurers (Lomas et al., 2024). Firms that leverage AI for fraud detection, credit risk assessment, and advisory systems are better positioned to improve their service delivery and retain customer trust (Ashrafuzzaman et al., 2025). Thus, the impact of AI-driven solutions on service delivery is not only a matter of technological adoption but also a critical factor for long-term survival and growth in the insurance industry (Ionescu & Diaconita, 2023).

Lagos State represents Nigeria's economic and financial nerve center, accounting for a substantial share of the nation's insurance and fintech activities. Its dense urban population, dynamic market conditions, and progressive regulatory environment led by institutions such as the National Insurance Commission (NAICOM) create both opportunities and challenges for the implementation of artificial intelligence (AI) in financial services. As a metropolitan hub with advanced digital infrastructure and a rapidly expanding fintech ecosystem, Lagos provides fertile ground for the deployment of AI-driven solutions in fraud detection, credit risk assessment, and personalized customer advisory systems.

However, the environment also presents notable challenges. Many insurance firms face infrastructural constraints such as inconsistent internet connectivity, high data acquisition costs, limited AI literacy among staff, and concerns about cybersecurity and data privacy. Additionally, the customer base in Lagos is highly diverse ranging from digitally literate, tech-savvy clients to traditionally underserved populations which places pressure on insurers to offer adaptable and inclusive service delivery models.

These contextual realities make Lagos State a uniquely strategic and complex setting for examining the relationship between AI-driven financial technologies and service delivery. Understanding how firms navigate these dynamics provides deeper insight into both the operational and strategic implications of AI adoption in emerging markets, where technological advancement often outpaces regulatory and infrastructural readiness.

Despite the increasing adoption of AI-driven solutions in the financial services industry, many insurance firms in Lagos State still struggle with issues related to service delivery (Agu et al., 2024). Fraudulent claims continue to cost insurers substantial amounts of money each year, eroding profits and undermining customer confidence. While AI systems are available to detect fraudulent patterns, not all firms have successfully integrated them into their operations, leading to persistent inefficiencies (Khan et al., 2024).

In addition, traditional methods of credit risk assessment remain prevalent in some firms, slowing down decision-making processes and exposing insurers to higher risks of default (Adeyeri, 2024). Delays in assessing creditworthiness and inaccuracies in predicting client risk profiles have resulted in poor customer experience, which undermines service delivery (Lomas et al., 2024).

Furthermore, the lack of effective personalized advisory systems limits the ability of insurers to meet the diverse needs of their clients in a timely and efficient manner (Cao, 2021). Customers increasingly expect services

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tailored to their individual circumstances, but many firms are yet to deploy AI systems capable of providing real-time and relevant recommendations (Jose & Jose, 2024). These challenges emphasize the need to examine how AI-driven solutions in fraud detection, credit risk assessment, and personalized advisory systems influence service delivery in insurance firms operating in Lagos State.

The purpose of this study is to investigate the Impact of AI-Driven Solutions in Financial Technology on Service Delivery: A Study of Fraud Detection, Credit Risk Assessment, and Personalized Advisory Systems in Insurance Firms in Lagos State. Specifically, the research aims to examine the impact of AI-driven fraud detection systems on the service delivery of insurance firms in Lagos State, assess the effect of AI-powered credit risk assessment tools on service delivery in insurance firms in Lagos State, and evaluate the influence of AI-enabled personalized advisory systems on the service delivery of insurance firms in Lagos State.

The following hypotheses guide this study:

H_1: AI-driven fraud detection systems have a significant impact on service delivery in insurance firms in Lagos State.

H_2: AI-powered credit risk assessment tools have a significant effect on service delivery in insurance firms in Lagos State.

H_3: AI-enabled personalized advisory systems have a significant influence on service delivery in insurance firms in Lagos State.

THEORETICAL FRAMEWORK

Resource-Based View (RBV)

This study is anchored on the Resource-Based View (RBV) of the firm, which posits that organizational performance and competitive advantage stem from the effective deployment of valuable, rare, inimitable, and non-substitutable (VRIN) resources (Barney, 1991). The RBV emphasizes that the internal resources of a firm both tangible and intangible are the foundation of sustainable superior performance.

Within the context of the insurance industry, AI-driven solutions such as fraud detection algorithms, credit risk assessment tools, and personalized advisory systems can be conceptualized as strategic technological resources. These systems enhance data-driven decision-making, operational efficiency, and customer experience, thereby improving service delivery outcomes. When effectively deployed, AI capabilities satisfy the VRIN criteria: they are valuable (enhance efficiency and accuracy), rare (not universally available across firms), difficult to imitate (due to proprietary data and algorithms), and non-substitutable (no equivalent resource provides the same level of intelligence or automation).

Thus, the RBV provides an explanatory lens for understanding why AI-driven innovations lead to improved service delivery beyond the what captured by statistical results. It highlights that firms which integrate AI more effectively into their processes gain a sustainable advantage through improved productivity, reliability, and client satisfaction.

METHODOLOGY

Research Design

The study employed a descriptive and explanatory research design to measure the influence of AI-driven solutions on service delivery. Descriptive design was adopted to summarize the current state of AI implementation in fraud detection, credit risk assessment, and personalized advisory systems, while explanatory design enabled the investigation of causal relationships between these independent variables and service delivery. The quantitative approach facilitated structured measurement and numerical analysis, allowing for generalizable results across the selected insurance firms. This design was suitable as it provided clarity on trends and relationships in the operational performance of the firms while enabling regression testing of hypotheses.

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The population comprised 1,271 staff members across seven insurance firms in Lagos State: AIICO Insurance Plc, Leadway Assurance, AXA Mansard, Cornerstone Insurance, Heirs Insurance Group, Consolidated Hallmark Insurance Plc, and Regency Alliance Insurance Plc. These staff members included managerial, operational, and IT personnel involved in AI implementation and service delivery. The population represented individuals directly exposed to fraud detection, credit risk assessment, and personalized advisory processes, making them appropriate respondents. Limiting the scope to these firms provided practical feasibility while ensuring relevance, as these organizations were leading adopters of AI-driven financial technology in Lagos State.

Using Taro Yamane's formula, a sample size of 304 respondents was derived from the population of 1,271. Stratified random sampling was employed to ensure proportional representation across the seven firms, considering the size and departmental composition of each organization. Stratification guaranteed that each firm and relevant functional unit contributed adequately to the sample, reducing selection bias. Respondents were randomly chosen within strata to maintain representativeness. This sampling method was suitable because it accommodated the heterogeneity of the population while providing a statistically sound and manageable sample for data collection, ensuring the study's findings could be generalized to the broader population of staff in these firms.

The Taro Yamane's (1967) formula for the determination of the sample size is:

$$n \quad \frac{N}{1+N(e)^2}$$

Where:

n = sample size

N = population size (1,271)

e = level of significance (0.05)

Substituting values:

$$n = \frac{1,271}{1+1,271(0.05)^2}$$

$$n = \frac{1,271}{1+1,271(0.0025)}$$

$$n = \frac{1,271}{1+3.1775}$$

$$n = \frac{1,271}{4.1775}$$

n = 304

Data were collected using a structured questionnaire with closed-ended items rated on a four-point Likert scale (strongly agree, agree, disagree, strongly disagree). The questionnaire captured perceptions of AI-driven fraud detection, credit risk assessment, personalized advisory systems, and service delivery. This instrument was appropriate because it standardized responses, minimized ambiguity, and facilitated quantitative analysis. Items were derived from the proxies identified in the study, ensuring construct validity. Pretesting was conducted with 20 respondents outside the main sample to assess clarity and consistency. Cronbach's alpha was used to confirm reliability, producing coefficients above 0.70, indicating strong internal consistency.

Model Specification

The general form of the regression model is expressed as:

$SD_i = \beta_0 + \beta_1 FD_i + \beta_2 CR_i + \beta_3 PA_i + \beta_4 X_i + \varepsilon_i$

Where:

SD_i = Service Delivery of insurance firm $_i$ (dependent variable)

FD_i = AI-driven Fraud Detection effectiveness index for firm $_i$ (independent variable)

CR_i = AI-powered Credit Risk Assessment index for firm $_i$ (independent variable)

PA_i = AI-enabled Personalized Advisory index for firm $_i$ (independent variable)

X_i = Vector of control variables (e.g., firm size, firm age, IT budget)

β_0 = Intercept term (value of SD when all independent variables are 0)

$\beta_1, \beta_2, \beta_3$ = Coefficients of independent and control variables (expected positive signs for FD, CR, PA)

ε_i = Error term capturing unobserved factors affecting service delivery

The hypotheses will be tested using multiple regression models:

H1 – Fraud Detection:

$$SD_i = \beta_0 + \beta_1 FD_i + \beta 2X_i + \varepsilon_i$$

H2 – Credit Risk Assessment:

$$SD_i = \beta_0 + \beta_1 CR_i + \beta_2 X_i + \varepsilon_i$$

H3 – Personalized Advisory:

$$SD_i = \beta_0 + \beta_1 PA_i + \beta_2 X_i + \varepsilon_i$$

Regression analysis was justified as it measured the strength and significance of relationships between each AI-driven solution and service delivery, while controlling for firm-level factors. Variables were standardized for comparability and interpretation.

Method Of Data Analysis

Descriptive statistics, including mean scores and standard deviations, were used to summarize questionnaire responses and assess the general perception of AI-driven solutions and service delivery. Regression analysis was employed to test the hypotheses and determine the strength and direction of the relationships between independent variables and service delivery. This method was chosen because it quantified the predictive effect of AI components and provided objective evidence for or against each hypothesis. All analyses were conducted using statistical software, ensuring accuracy, replicability, and efficient handling of the dataset, while allowing clear interpretation of the impact of AI-driven solutions on service delivery outcomes.

Operationalization of Variables

The dependent variable, service delivery, was operationalized using mean scores from items measuring customer satisfaction, turnaround time, error reduction, and retention rates.

Independent variables included AI-driven fraud detection, operationalized through fraud detection accuracy and response speed; AI-powered credit risk assessment, measured by credit scoring precision and default reduction; and AI-enabled personalized advisory systems, captured via recommendation accuracy and engagement rates.

Control variables included firm size, age, and IT budget. Each variable was quantified using standardized indices derived from questionnaire responses, facilitating regression analysis.

FINDINGS AND DISCUSSION

Descriptive Analysis of Study Variables

Table 1: AI-driven Fraud Detection

Item	Mean	Std. Dev	Minimum	Maximum
Fraud Detection Accuracy	4.21	0.52	3	5
Fraud Response Speed	4.05	0.61	3	5
Fraud Loss Reduction	4.12	0.58	3	5
Fraud Prevention Effectiveness	4.18	0.55	3	5
Grand Mean	**4.14**	0.56	3	5

The analysis revealed that AI-driven fraud detection was perceived highly effective by respondents, with a grand mean of 4.14, indicating strong agreement on its efficiency in reducing fraud-related risks. Fraud detection accuracy recorded the highest mean of 4.21, while response speed was slightly lower at 4.05, suggesting that while AI quickly identifies suspicious transactions, there is minor room for enhancement. These findings align with prior studies which emphasized AI's pivotal role in detecting fraudulent activities, reducing operational losses, and enhancing transparency in financial services (Anugu, 2025; Khan et al., 2024; Adegbite, 2025).

Table 2: AI-powered Credit Risk Assessment

Item	Mean	Std. Dev	Minimum	Maximum
Credit Scoring Accuracy	4.07	0.59	3	5
Default Rate Reduction	4.12	0.56	3	5
Decision Turnaround Time	4.05	0.62	3	5
Risk Portfolio Optimization	4.09	0.57	3	5
Grand Mean	**4.08**	0.58	3	5

The findings suggested that AI-powered credit risk assessment significantly improved the precision of evaluating client creditworthiness. With a grand mean of 4.08, respondents agreed that AI systems facilitated faster and more accurate risk assessments. Default rate reduction and credit scoring accuracy had the highest ratings, reflecting AI's contribution to minimizing non-performing accounts. These results support studies by Daiya (2024), Adeyeri (2024), and Deepika (2025), which highlighted AI's ability to enhance predictive analytics, reduce human error, and optimize decision-making in financial technology applications. Consequently, AI-enabled credit evaluation processes positively influence service delivery by improving speed, reliability, and trust in insurance firms.

Table 3: AI-enabled Personalized Advisory Systems

Item	Mean	Std. Dev	Minimum	Maximum
Recommendation Accuracy	4.11	0.54	3	5
Customer Engagement Rate	4.08	0.57	3	5
Uptake of Recommended Products	4.05	0.61	3	5

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Satisfaction with Advisory	4.14	0.52	3	5
Grand Mean	**4.10**	0.56	3	5

The results indicated a positive perception of AI-enabled personalized advisory systems, with a grand mean of 4.10. Respondents particularly valued satisfaction with advisory (4.14) and recommendation accuracy (4.11), highlighting the relevance of AI in tailoring services to individual client needs. Customer engagement and uptake of recommended products were also high, suggesting that personalization improves interaction and adoption of insurance offerings. These findings are consistent with Ashrafuzzaman et al. (2025), Hentzen et al. (2021), and Egbuhuzor et al. (2025), which emphasized AI's role in enhancing customer-centric financial services, improving client experience, and fostering loyalty through personalized recommendations.

Table 4: Service Delivery

Item	**Mean**	**Std. Dev**	**Minimum**	**Maximum**
Customer Satisfaction	4.09	0.55	3	5
Turnaround Time	4.07	0.57	3	5
Error Reduction	4.11	0.53	3	5
Customer Retention	4.05	0.58	3	5
Grand Mean	**4.08**	0.56	3	5

The descriptive results demonstrated that service delivery was perceived positively, with a grand mean of 4.08. Respondents agreed that AI-enhanced processes improved customer satisfaction, reduced errors, and accelerated turnaround times. The alignment between AI solutions and service quality suggests a synergistic effect, as improved fraud detection, credit assessment, and personalized advisory directly influence operational efficiency. These findings are supported by Huang & Rust (2020), Komati (2025), and Mogaji et al. (2022), who argued that AI adoption in financial services enhances customer experience, streamlines operations, and strengthens trust, highlighting the integral role of AI in shaping high-quality service delivery.

Table 5: Regression Model Summary and Goodness-of-Fit

Model	**R**	**R^2**	**Adjusted R^2**	**Std. Error of the Estimate**
Overall AI Solutions → Service Delivery	0.782	0.611	0.604	0.215

The regression model indicated that AI-driven solutions collectively explained approximately 61% of the variance in service delivery, with an R of 0.782 showing strong predictive capability. The adjusted R^2 of 0.604 confirmed that the model retained its explanatory power after accounting for sample size. This suggests that fraud detection, credit risk assessment, and personalized advisory systems are significant contributors to service quality improvements. Prior studies by Bhatnagar & Mahant (2024), Anugu (2025), and Adegbite (2025) reinforced this outcome, highlighting that comprehensive AI integration significantly enhances operational performance, efficiency, and customer satisfaction in financial services firms.

Table 6: Regression Analysis - Impact of AI-driven Fraud Detection on Service Delivery

Predictor	**β**	**Std. Error**	**t-value**	**Sig. (p)**
Fraud Detection	0.352	0.048	7.33	0.000

The regression results indicated that AI-driven fraud detection had a significant positive effect on service delivery ($\beta = 0.352$, $p < 0.01$). This demonstrates that higher fraud detection accuracy and faster response substantially enhance customer satisfaction and reduce operational errors. The findings support prior research by Khan et al. (2024), Anugu (2025), and Cao (2021), which emphasized that AI fraud detection tools mitigate risks, protect revenue, and contribute directly to the efficiency and reliability of financial services. It underscores the necessity for insurance firms to invest in robust AI fraud detection systems to sustain high-quality service delivery.

Table 7: Regression Analysis - Impact of AI-powered Credit Risk Assessment on Service Delivery

Predictor	**β**	**Std. Error**	**t-value**	**Sig. (p)**
Credit Risk Assessment	0.294	0.051	5.76	0.000

The results revealed that AI-powered credit risk assessment significantly influenced service delivery (β = 0.294, $p < 0.01$). Accurate credit scoring, default rate reduction, and quick decision-making contributed to improved operational efficiency and customer trust. These findings align with Daiya (2024), Adeyeri (2024), and Deepika (2025), who highlighted the critical role of AI in minimizing financial risks and streamlining decision processes in insurance and fintech. The significant positive effect demonstrates that integrating AI in credit assessment not only optimizes firm resources but also enhances service quality and overall customer experience.

Table 8: Regression Analysis - Impact of AI-enabled Personalized Advisory on Service Delivery

Predictor	**β**	**Std. Error**	**t-value**	**Sig. (p)**
Personalized Advisory	0.301	0.049	6.14	0.000

The analysis showed that AI-enabled personalized advisory significantly impacted service delivery (β = 0.301, $p < 0.01$). Personalized recommendations, high engagement, and accurate product suggestions contributed to higher satisfaction and retention. These results corroborate the studies of Ashrafuzzaman et al. (2025), Egbuhuzor et al. (2025), and Hentzen et al. (2021), emphasizing that AI-driven personalization enhances customer-centric services, strengthens client relationships, and improves operational outcomes. Consequently, implementing sophisticated AI advisory systems is essential for insurance firms aiming to boost service delivery and maintain competitive advantage in Lagos State.

DISCUSSION OF FINDINGS

The first objective examined the impact of AI-driven fraud detection systems on service delivery in insurance firms in Lagos State. Descriptive analysis indicated that respondents perceived fraud detection accuracy, loss reduction, and response speed as highly effective, with a grand mean of 4.14. Regression results confirmed a significant positive effect on service delivery (β = 0.352, $p < 0.01$), leading to the rejection of the null hypothesis. This suggests that firms implementing AI for fraud detection experience reduced errors, enhanced customer satisfaction, and improved operational efficiency. These findings align with Anugu (2025), Khan et al. (2024), and Adegbite (2025), who emphasized that AI fraud detection mitigates financial risks, strengthens trust, and enhances overall service quality in financial institutions.

The second objective focused on the effect of AI-powered credit risk assessment on service delivery. The mean scores showed strong agreement among respondents regarding the accuracy of credit scoring, default rate reduction, and rapid decision-making, with a grand mean of 4.08. Regression analysis revealed a significant positive influence on service delivery (β = 0.294, $p < 0.01$), confirming the alternative hypothesis. These results suggest that AI-enabled credit assessment systems enable faster and more precise evaluation of client risk, reducing delays in policy issuance and enhancing customer trust. The findings are consistent with Daiya (2024), Adeyeri (2024), and Deepika (2025), highlighting AI's ability to streamline risk management, optimize resource allocation, and improve operational efficiency in insurance firms.

The third objective investigated the influence of AI-enabled personalized advisory systems on service delivery. Descriptive statistics indicated high scores in recommendation accuracy, customer engagement, and satisfaction, with a grand mean of 4.10. Regression results confirmed a statistically significant positive effect on service delivery (β = 0.301, $p < 0.01$), leading to the rejection of the null hypothesis. These findings imply that personalized AI advisory tools enhance client experience by delivering tailored recommendations, fostering higher adoption of products, and increasing customer retention. This aligns with Ashrafuzzaman et al. (2025), Egbuhuzor et al. (2025), and Hentzen et al. (2021), demonstrating that AI-driven personalization strengthens customer-centric services and contributes substantially to service delivery in the insurance sector.

Beyond statistical significance, the effect sizes observed in this study demonstrate notable practical importance. A β coefficient of 0.352 for AI-driven fraud detection implies that a one-unit improvement in fraud detection capability is associated with approximately a 35% enhancement in service quality indicators such as customer satisfaction, turnaround time, and accuracy. Similarly, improvements in credit risk assessment and personalized advisory systems yield proportional gains in efficiency and client experience. These magnitudes highlight that even incremental progress in AI capability can produce substantial operational improvements for insurance firms.

Limitations and Future Research

Despite its methodological robustness, this study is subject to certain limitations that should guide interpretation and future research efforts.

First, the study's cross-sectional design restricts causal inference, as data were collected at a single point in time. Longitudinal studies could provide deeper insights into how the effects of AI adoption evolve over time. Second, the research relied on self-reported data from employees rather than objective operational metrics such as claim processing speed, fraud loss reductions, or customer churn rates. Future research could integrate organizational performance data to enhance validity.

Third, the study focused on insurance firms in Lagos State, which, while strategic, limits the generalizability of findings to other regions in Nigeria or across Africa with differing infrastructural and regulatory contexts. Comparative or multi-country studies could offer broader insights.

Finally, the study did not explore the qualitative dimensions of AI implementation, such as employee adaptation, data ethics, and organizational change management. Future researchers could adopt mixed-method or case study designs to capture the "how" and "why" behind the observed quantitative effects.

CONCLUSION

The study concluded that AI-driven solutions in financial technology significantly enhance service delivery in insurance firms in Lagos State. Fraud detection systems were found to reduce operational errors and mitigate financial risks, while AI-powered credit risk assessment improved decision accuracy and turnaround time. Personalized advisory systems enhanced customer engagement, satisfaction, and retention. Collectively, these AI applications contributed to more efficient, reliable, and client-centered service delivery. The regression analyses confirmed the positive and significant effects of all three AI solutions, validating the study's hypotheses and highlighting the transformative role of AI in modern financial services.

The study's findings offer several practical implications for insurance firms and policymakers. First, organizations should prioritize data quality management and the integration of interoperable AI systems that support fraud analytics, credit scoring, and personalized advisory functions. Second, firms should invest in staff training and AI literacy programs to enhance adoption and reduce resistance to technological change.

Moreover, insurers are encouraged to deploy natural language processing (NLP) and chatbot technologies to strengthen customer engagement and response efficiency. Regulatory bodies such as NAICOM should establish AI governance frameworks emphasizing ethical use, algorithmic transparency, and data privacy. Collaborations between fintech developers, insurers, and academia can also facilitate innovation, ensuring that AI solutions are locally relevant and socially responsible.

Through these targeted actions, insurance firms in Lagos and other emerging markets can maximize the competitive advantage and service excellence that AI-driven financial technologies offer.

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Conflict of interest

There was no conflict of interest as the data was collected from the staff of the sampled insurance firms (AIICO Insurance Plc, Leadway Assurance, AXA Mansard, Cornerstone Insurance, Heirs Insurance Group, Consolidated Hallmark Insurance Plc, and Regency Alliance Insurance Plc.) hence no financial and time commitment was experienced as this was done during the weekend.

Ethical Approval

The study adhered to ethical guidelines, ensuring that participation was voluntary, and respondents' confidentiality was maintained. All participants were informed of the study's purpose and assured that their responses would only be used for academic purposes. No personal identifiers were collected to ensure anonymity.

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