



Artificial intelligence and customer satisfaction in the Nigerian banking sector

Oluwayomi Omotayo Olota*

PhD in Business Administration
University of Ilorin
240003, 1 University Rd., Ilorin, Nigeria
<https://orcid.org/0009-0008-6633-9919>

Olatunde Nathaniel Akinkunmi

Master of Sciences in Business Administration
University of Ilorin
240003, 1 University Rd., Ilorin, Nigeria
<https://orcid.org/0009-0005-3414-1236>

Ebenezer Oluwadamilare Balogun

Master of Sciences in Business Administration
University of Ilorin
240003, 1 University Rd., Ilorin, Nigeria
<https://orcid.org/0000-0003-0419-188X>

Abstract. The integration of artificial intelligence (AI) into the banking sector has transformed customer satisfaction, particularly through innovations such as digital payment services and smart banking solutions. Hence, this study aimed to examine the effect of artificial intelligence on customer satisfaction in the banking sector. The specific objectives were to investigate the effect of digital payment systems on service reliability in the banking sector and the impact of smart banking solutions on digital support responsiveness within the banking sector. A descriptive survey research design was employed for the study, and a simple random sampling technique was adopted. The sample size was determined using T. Yamane's sample size determination formula. Data obtained through a questionnaire were analysed using PLS-SEM through SmartPLS. The findings revealed that digital payment systems positively and significantly affect service reliability in the banking sector – secure fund transfer ($\beta = 0.379$, $T = 6.962$, $p = 0.000$) and instant payment confirmation ($\beta = 0.367$, $T = 1.942$, $p = 0.057$). Smart banking solutions positively and partially significantly affect digital support responsiveness in the banking sector – automated account management ($\beta = 0.965$, $T = 41.759$, $p = 0.000$) and personalised financial insights ($\beta = -0.104$, $T = 1.209$, $p = 0.084$). It was concluded that artificial intelligence positively influences customer satisfaction in selected banks across Nigeria. The findings of this study hold practical value for the Nigerian banking sector, as they highlight how AI technologies can be effectively applied to enhance customer satisfaction and loyalty. Bank executives, digital strategy developers, and customer service managers can use these insights to guide investments in personalised AI solutions, real-time support systems, and intelligent service automation, thereby strengthening long-term customer relationships

Keywords: digital payment system; smart banking solution; digital support responsiveness; service reliability; customer loyalty

INTRODUCTION

The study of artificial intelligence and customer satisfaction in the Nigerian banking sector is justified by the growing reliance on digital technologies to enhance service delivery

and strengthen competitiveness. Nigerian banks increasingly integrate AI-driven solutions such as chatbots, roboadvisers, fraud detection systems, and personalised financial

Suggested Citation:

Olota, O.O., Akinkunmi, O.N., & Balogun, E.O. (2025). Artificial intelligence and customer satisfaction in the Nigerian banking sector. *University Economic Bulletin*, 20(2), 44-56. doi: 10.69587/ueb/2.2025.44.

*Corresponding author



recommendations to improve efficiency and meet evolving customer expectations. In a market characterised by rising customer demands, financial inclusion goals, and intense competition, AI offers banks the ability to deliver faster, more accurate, and more tailored services that directly influence satisfaction levels. Furthermore, in the context of rapid digital transformation across Africa, examining the link between AI adoption and customer satisfaction provides valuable insights into how banks can leverage technology to build trust, loyalty, and long-term customer relationships.

The application of state-of-the-art technologies in service delivery has redefined the interaction between financial institutions and their clientele, especially in emerging economies. In Nigeria, the drive for innovation has become a strategic response to rising customer expectations and operational challenges. The author C. Gabriel-Okwuchi (2025) concluded that technological innovation in banking plays a pivotal role in enhancing customer experience, improving efficiency, and maintaining a competitive advantage. He also argued that modern technologies help to address long-standing challenges such as transaction delays, limited accessibility, and ineffective grievance mechanisms. Supporting this view, N. Dhiman *et al.* (2023) found that the integration of digital tools into banking operations enhances client experiences, particularly in terms of faster resolution of queries and overall service quality. Collectively, these studies emphasise that technology is no longer optional for Nigerian banks but a necessity for survival and growth.

This digitalisation trend has been accelerated by the growing penetration of smartphones and increased internet access across Nigeria. E. Ukpé (2025) concluded that the use of intelligent algorithms enables banks to predict customer needs and proactively offer relevant solutions, creating a more personalised banking experience. In addition, S. Akinepalli (2024) highlighted that automation reduces human error, a common source of frustration in traditional banking. Together, these findings illustrate how AI-based solutions are not only enhancing convenience but also addressing financial inclusivity in the Nigerian banking landscape.

Client expectations continue to evolve, pushing financial institutions to view loyalty and engagement as dynamic rather than static. M. Katragadda (2025) concluded that predictive analytics allow banks to anticipate client needs even before they are expressed, thereby strengthening customer satisfaction. Similarly, S. Agarwal *et al.* (2022) found that chatbots and virtual assistants have become increasingly popular because they efficiently manage routine enquiries and deliver instant responses. Reinforcing this perspective, Y. Chikaipa *et al.* (2025) observed that customers engaging with automated systems reported higher satisfaction levels due to the immediacy and consistency of support. However, J. Blümel *et al.* (2024) cautioned that excessive dependence on automation can result in impersonal experiences when addressing complex issues, indicating that banks must balance efficiency with empathy.

On the one hand, smart banking solutions employ AI and automation to gain efficiency; on the other hand,

inefficiencies in digital support often cause customer dissatisfaction. A. Uzoka *et al.* (2024) concluded that although AI-powered chatbots and helpdesks enhance efficiency, they struggle to resolve complex issues, leading to prolonged grievance processes. Similarly, J.-C. Lee & X. Chen (2022) found that over 40% of smart banking app users reported delayed resolutions due to ineffective AI responses, which had a direct negative effect on satisfaction. To address this gap, V. Nagubathula (2025) argued for hybrid support models that combine AI efficiency with human oversight, ensuring responsiveness, empathy, and overall customer trust.

Specifically, the objectives of this study were: to determine the effect of digital payment systems on service reliability and to investigate the influence of smart banking solutions on digital support responsiveness. This study aimed to examine how artificial intelligence, through digital payment systems and smart banking solutions, influences service reliability and digital support responsiveness in the Nigerian banking sector.

LITERATURE REVIEW

Artificial intelligence (AI) is the simulation of human intelligence in machines that are programmed to think, learn, and perform tasks typically carried out by humans. This includes natural language processing, pattern recognition, decision-making, and visual perception (Enholm *et al.*, 2022). AI can generally be categorised into narrow AI, which focuses on solving specific tasks such as voice assistants or recommendation systems, and general AI, which seeks to emulate broader human cognitive capabilities (Fjelland, 2020). However, general AI remains largely theoretical. Narrow AI has gained wide-ranging applications across industries such as banking, healthcare, and retail, where it performs functions including fraud detection, customer personalisation, and predictive analytics (Jan *et al.*, 2023). With advancements in AI, the faster an AI system learns and adapts to new data, the more efficient and useful it becomes, leading to an expansion of its applications across multiple sectors.

With its rapid growth and widespread application, AI poses certain ethical dilemmas that require attention. Issues of transparency, job displacement, and data privacy have become increasingly significant as AI becomes embedded in daily life and business operations (Al-Kfairy *et al.*, 2024). AI holds great promise for transforming industries through process automation, improved decision-making, and optimised performance, yet its social implications must be carefully considered. In sectors such as education, healthcare, and finance, AI has already revolutionised service delivery and enhanced operational efficiency. However, the ethical concerns associated with large-scale AI adoption require ongoing research and a focus on responsible implementation for societal benefit (Huang *et al.*, 2022).

Customer satisfaction (CS) is defined as the degree to which customers' expectations of a product, service, or brand experience are met or exceeded. N. Rane *et al.* (2023)

state that CS is a key determinant of customer retention, loyalty, and the long-term success of any business, as it reflects how effectively a company's offerings meet customer needs. Customer satisfaction involves both rational evaluations of product or service quality and emotional responses that contribute to overall fulfilment. It is dynamic rather than static and evolves with factors such as product and service quality, after-sales support, and brand interaction (D. Lestari *et al.*, 2025). A. Aziz (2025) emphasises the importance of post-purchase satisfaction, noting that events occurring after purchasing – from delivery time to customer support – play a crucial role in shaping customer perceptions. Furthermore, according to expectancy-disconfirmation theory, customer satisfaction occurs when actual performance exceeds expectations. In the current era of intense market competition, systematic monitoring through customer feedback and CS surveys supports data-driven decision-making. The relationship between CS and organisational performance has been extensively researched; studies have shown that satisfied customers are more likely to repurchase and recommend brands to others, reflecting both their positive experiences and sustained loyalty (Otto *et al.*, 2020).

The integration of AI into customer service is reshaping interactions between businesses and consumers, thereby enhancing customer satisfaction. Artificial intelligence employs methods such as machine learning, natural language processing, and predictive analytics to improve customer interaction, expedite service delivery, and anticipate customer needs. AI-driven systems are efficient, responsive, and personalised in nature (Huang *et al.*, 2022; Lestari *et al.*, 2025). Consequently, customer satisfaction results directly from the deliberate use of these intelligent systems. The speed, personalisation, and accuracy of AI-enabled services contribute to customers' perceptions of value and service quality (Alkairy *et al.*, 2024; Aziz, 2025).

AI is crucial in improving service speed and precision, ultimately enhancing customer satisfaction. A chatbot, for example, can provide round-the-clock assistance with minimal waiting time for customers. Handling queries in this way results in greater client satisfaction and retention (Fjelland, 2020; Rane *et al.*, 2023). Predictive analytics further enhances satisfaction by enabling companies to foresee customer preferences through AI and address potential issues proactively to provide a seamless experience and anticipate client needs. The ability to personalise interactions through AI-client data networks in product recommending fosters a more engaging and fulfilling experience, which, in turn, strengthens trust and confidence (Otto *et al.*, 2020; Enholm *et al.*, 2022).

The adoption of digital payment systems has considerably enhanced service reliability by reducing delays associated with manual processing and minimising human error. Studies indicate that digital payment platforms meet the transactional demand for faster and more secure financial operations, thereby instilling greater confidence and satisfaction among customers (Khiaonarong *et al.*, 2021). These

systems are distinguished by their use of robust encryption and fraud detection mechanisms that prevent payment fraud, thus enhancing the overall reliability of financial services (Odio *et al.*, 2025). Further research shows that organisations implementing digital payment systems experience fewer service interruptions than their cash-based counterparts, as cash transactions face physical limitations such as shortages or restricted availability (Sravan *et al.*, 2024). This shift towards digital payments has been a major advantage in emerging markets, where banking infrastructure has traditionally faced obstacles that hindered financial inclusion (Dutta *et al.*, 2024). Consequently, financial service availability and consistency have improved significantly.

Smart banking solutions, driven by machine learning and artificial intelligence, have transformed digital support responsiveness by offering real-time customer service and predictive problem resolution. These technologies enable banks to review customer queries in real time and provide timely, accurate feedback, thereby improving the user experience (Epstein & Quinn, 2020). For instance, AI-powered chatbots and virtual assistants have reduced customer waiting times by up to 70%, making service delivery highly efficient (Lee & Chen, 2022). Smart banking systems also use big data to predict customer requirements and act proactively before issues arise, thereby eliminating service delays (Nagubathula, 2025). Empirical evidence shows higher customer retention among financial institutions that adopt such technologies, owing to improved interaction quality and faster issue resolution (Agustiawan, 2024). These technologies have also enabled 24/7 customer support, removing traditional banking-hour restrictions and ensuring uninterrupted access to financial services (Uzoka *et al.*, 2024).

The expectancy-disconfirmation theory (EDT) proposed by R. Oliver (1977) defines customer satisfaction as a comparison between expected and perceived performance before and after purchase. The theory assumes that satisfaction results from positive disconfirmation (better-than-expected performance) and dissatisfaction from negative disconfirmation (worse-than-expected performance). It suggests that customers consciously set expectations and rationally compare their service experiences against them. A criticism of EDT is that it oversimplifies satisfaction by excluding emotional and cultural factors (Lilliengren *et al.*, 2016).

EDT accurately explains the application of AI in customer satisfaction within the Nigerian banking sector, where AI technologies (e.g. chatbots and fraud detection applications) must meet users' expectations to enhance satisfaction. Evidence shows that when expectations are met by AI services – such as faster transactions and continuous availability – customer satisfaction increases, whereas performance gaps lead to dissatisfaction (Prentice *et al.*, 2020). Research by F. Alnaser *et al.* (2023) demonstrates that integrating AI features into digital banking applications, including problem-solving capabilities, visual appeal, innovation, communication quality, and customisation, positively influences customer satisfaction through expectation confirmation. This aligns well with EDT's focus on

expectation-performance evaluation and supports its application in analysing AI-driven satisfaction dynamics in Nigeria's banking sector through a systematic comparison of expectation-performance gaps.

MATERIALS AND METHODS

The study employed a descriptive survey design to assess the impact of artificial intelligence on customer satisfaction within Nigeria's banking sector. The design was appropriate, as it enabled the researcher to describe and quantify existing service delivery processes supported by AI technologies within the banking system. The study focused on five major commercial banks in Nigeria – Zenith Bank, Access Bank, First Bank, GTBank, and UBA – due to their extensive customer bases, high levels of digital adoption, and early integration of artificial intelligence in service delivery. These banks represented a balanced mix of innovation leadership, customer interaction points, and nationwide presence, making them suitable cases for assessing AI's role in enhancing customer satisfaction.

The target population comprised active customers of the principal branches of the five banks in Kwara State. Their estimated combined customer base was 20,000 across the principal branches in Ilorin, Offa, and Omu-Aran. A sample size of 377 respondents was determined using T. Yamane's (1967) formula for a known population, with a margin of error of less than 5%, ensuring statistical representativeness and generalisability of the results. The study was conducted in 2025 to capture recent trends in AI adoption and customer satisfaction in the Nigerian banking industry. It adhered to established ethical standards, including informed consent from all participants, voluntary participation without coercion, and confidentiality and anonymity of respondents' data. Ethical approval was obtained in accordance with the American Sociological Association's Code of Ethics (2018) to ensure compliance throughout the data collection process.

Participants were selected using purposive-proportional sampling, ensuring proportional representation across the selected banks relative to customer population size and digital service usage. Data were collected using a structured questionnaire. The validity of the instrument was confirmed through expert review and construct validation, while reliability was assessed using Cronbach's alpha and composite reliability (CR) in SmartPLS version 3.2.2, with thresholds of 0.6 and above. Descriptive

statistics (mean and standard deviation) and inferential statistics were employed, with partial least squares structural equation modelling (PLS-SEM) used to analyse the structural relationship between artificial intelligence deployment and customer satisfaction among the sampled banks.

Hypothesis I

Ho₁: The digital payment system did not have a significant effect on service reliability.

A multivariate regression model was used to relate the independent variables to the dependent variable as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3$$

$$Y = \beta_0 + \beta_1 + \beta_2 + \beta_3,$$

where Y is the dependent variable (service reliability); X₁, X₂ and X₃ are the independent variables; X₁ is the secure fund transfer; X₂ is the instant payment confirmation; B₀ is the constant.

Hypothesis II

Ho₂: Smart banking solutions had no significant effect on digital support responsiveness.

A multivariate regression model was used to relate the independent variables to the dependent variable as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3$$

$$Y = \beta_0 + \beta_1 + \beta_2 + \beta_3,$$

where Y is the dependent variable (digital support responsiveness); X₁, X₂ and X₃ are the independent variables; X₁ is the personalised financial insights; X₂ is the automated account management; B₀ is the constant.

This methodology combined representative sampling of 377 banking customers, validated and reliable instruments, adherence to ethical standards, and the application of PLS-SEM to examine AI's impact on customer satisfaction in the Nigerian banking sector through multivariate regression analysis.

RESULTS AND DISCUSSION

In this study, 391 questionnaires were administered to obtain the required data from the selected respondents. A total of 321 valid responses were received and considered suitable for analysis. This indicates that 70 questionnaires were discarded due to incomplete responses, failure to meet the criteria set by the researcher, or non-response. Hence, the 321 valid questionnaires were used for subsequent analysis. Descriptive statistics and the normality test relating to Research Question One are presented in Table 1.

Table 1. Descriptive analysis and normality test

	Mean	Standard deviation	Excess kurtosis	Skewness	Number of observations used
Fund security	2.931	1.057	-0.717	-0.260	321.000
Fund transfer	3.109	0.881	-0.284	0.005	321.000
Instant payment	3.445	1.049	-0.294	-0.449	321.000
Payment confirmation	3.156	1.071	-0.646	-0.329	321.000
Service quality	2.533	1.026	-0.858	-0.028	321.000
Service standard	3.754	1.085	-0.036	-0.794	321.000

Source: calculated by the authors based on SmartPLS output

Descriptive statistics in Table 1 reveal that service standard recorded the highest mean value (3.754), indicating that customers place the greatest value on consistent service delivery, while service quality had the lowest mean (2.533), highlighting a perceived quality gap. All variables exhibited normal distributions, with skewness values ranging between -0.794 and 0.005 and kurtosis values between -0.858 and -0.036, confirming the suitability of the data for further analysis. The moderate standard deviations (0.881-1.085) suggest reasonable consistency in respondents' perceptions,

implying that expectations regarding digital payment systems among banking customers are relatively aligned, which banks can leverage to enhance service reliability.

Objective and hypothesis one restatement. Objective one: To determine the effect of the digital payment system on service reliability. H_{01} : The digital payment system does not have a significant effect on service reliability. Figure 1 illustrates the direct relationship between digital payment system attributes – instant payment confirmation and secure fund transfer – and service reliability.

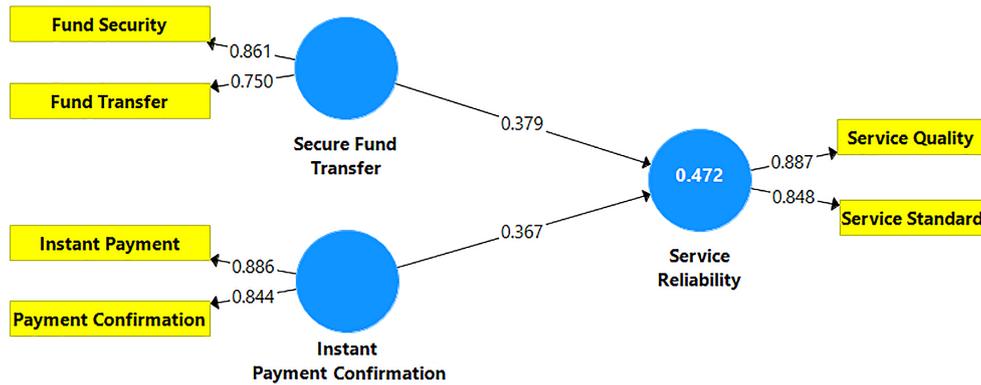


Figure 1. Path model of digital payment system and service reliability

Source: calculated by the authors based on SmartPLS output

Figure 1 shows the direct relationship between the digital payment system attributes (instant payment confirmation and secure fund transfer) and service reliability. Both independent variables exhibit strong factor loadings and positive path coefficients with the dependent variable.

This finding confirms that secure payments and prompt payment confirmation enhance customers' perception of service reliability in online banking. Consequently, banks should prioritise investments in both areas to improve overall customer satisfaction.

Table 2. Construct reliability and validity

	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
Instant payment confirmation	0.765	0.856	0.748
Secure fund transfer	0.772	0.788	0.652
Service reliability	0.773	0.859	0.753

Source: calculated by the authors based on SmartPLS output

Table 2 indicates that all constructs demonstrate high reliability, with Cronbach's alpha values exceeding 0.7 (instant payment confirmation: 0.765; secure fund transfer: 0.772; service reliability: 0.773), confirming internal consistency. Composite reliability values (0.788-0.859) confirm construct reliability, while average variance extracted (AVE) values exceeding 0.5 (0.652-0.753) confirm high

convergent validity. These strong psychometric properties affirm the reliability and validity of the measurement model, providing a sound basis for banks to develop digital payment strategies that enhance customer satisfaction. Table 3 presents the inter-construct correlations and the square roots of AVE values, demonstrating discriminant validity among the examined variables.

Table 3. Discriminant validity

	Instant payment confirmation	Secure fund transfer	Service reliability
Instant payment confirmation	0.865		
Secure fund transfer	0.700	0.807	
Service reliability	0.632	0.635	0.868

Source: calculated by the authors based on SmartPLS output

Square roots of AVE values (bold diagonal: instant payment confirmation – 0.865, secure fund transfer – 0.807,

service reliability – 0.868) are greater than the inter-construct correlations in Table 3, thereby confirming discriminant

validity. Strong moderate-to-high correlations between instant payment confirmation and secure fund transfer (0.700), instant payment confirmation and service reliability (0.632), and secure fund transfer and service reliability (0.635) reflect significant relationships without evidence of multicollinearity. This verifies that each construct represents

a distinct yet complementary concept, indicating that banks should address them as separate but mutually reinforcing variables when developing digital payment systems to enhance customer satisfaction. Table 4 presents the variance inflation factor (VIF) values, which confirm that the digital payment system variables are free from multicollinearity.

Table 4. Inner variance inflation factor values

	Instant payment confirmation	Secure fund transfer	Service reliability
Instant payment confirmation			1.959
Secure fund transfer			1.959
Service reliability			

Source: calculated by the authors based on SmartPLS output

The VIF values for instant payment confirmation and secure fund transfer are 1.959 each, well below the critical threshold of 5.0. This indicates the absence of multicollinearity, confirming that these digital payment components are independent predictors of service reliability. The lack of such problematic correlations implies that each variable can be effectively assessed to determine its individual

contribution, enabling banks to identify the specific digital payment factors that most influence service reliability and customer satisfaction, and to design more targeted improvement strategies. The bootstrapping results further demonstrate that secure fund transfer significantly influences service reliability, whereas instant payment confirmation does not (Table 5).

Table 5. Bootstrapping results showing path coefficients for the structural model

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Instant payment confirmation -> Service reliability	0.367	0.367	0.189	1.942	0.057
Secure fund transfer -> Service reliability	0.379	0.380	0.054	6.962	0.000

Source: calculated by the authors based on SmartPLS output

Bootstrapping outcomes in Table 5 indicate that secure fund transfer has a significant positive effect on service reliability ($\beta = 0.379$, $t = 6.962$, $p < 0.001$), whereas instant payment confirmation is not statistically significant ($\beta = 0.367$, $t = 1.942$, $p = 0.057$). This suggests that customers place greater importance on the security of fund transfers than on confirmation speed when assessing the reliability of digital banking services. Although both variables display

comparable beta coefficients, the greater statistical significance of secure fund transfer underscores its critical role in fostering trust and satisfaction in online banking. Consequently, banks should prioritise strengthening payment security mechanisms to reinforce customer confidence and loyalty. Digital payment features collectively explain a substantial proportion of the variance in service reliability, as shown in Table 6.

Table 6. Coefficient of determination score

	R-square	R-square adjusted
Service reliability	0.472	0.469

Source: calculated by the authors based on SmartPLS output

In Table 6, the R-square value of 0.472 indicates that instant payment confirmation and secure fund transfer collectively explain 47.2% of the variance in service reliability, with an adjusted R-square of 0.469, which prevents overestimation of the finding due to multiple predictors. The moderate explanatory power confirms the significant influence of digital payment features on customers'

perception of service reliability. Nevertheless, the remaining unexplained variance suggests that additional factors influence service reliability, highlighting the need for a holistic approach to service quality in banking. Table 7 presents the effect sizes (f^2), showing that both instant payment confirmation and secure fund transfer have moderate effects on service reliability.

Table 7. Assessment of the effect size (f^2)

	Instant payment confirmation	Secure fund transfer	Service reliability
Instant payment confirmation			0.130
Secure fund transfer			0.139
Service reliability			

Source: calculated by the authors based on SmartPLS output

According to Table 7, the effect sizes (f^2) for instant payment confirmation (0.130) and secure fund transfer (0.139) both fall within Cohen’s medium effect size range, indicating that both contribute comparably to service reliability. This suggests that banks should invest equally in secure transaction platforms and effective payment confirmation systems to enhance service reliability and customer satisfaction, rather than focusing on one element over the other in digital transformation. Descriptive statistics for responses related to research question two and the normality test are shown in Table 8. As shown in Table 8, the descriptive statistics demonstrate that personalised offers and account digitalisation receive the highest

ratings among customers, indicating that customers place the greatest value on personalised experiences and digitalised account management. Response accuracy ranks lowest, marking it as a key area for improvement. All variables are normally distributed, with skewness values between -0.423 and 0.254 and kurtosis values between -0.908 and -0.173, confirming the suitability of the data for analysis. The standard deviations are moderate, ranging from 0.876 to 1.087, reflecting consistent perceptions among respondents. Therefore, banks should focus on enhancing the degree of personalisation and digital features, as well as improving response accuracy to achieve higher customer satisfaction.

Table 8. Descriptive analysis and normality test

	Mean	Standard deviation	Excess kurtosis	Skewness	Number of observations used
Account automation	2.863	0.995	-0.284	0.202	321.000
Account digitalisation	3.324	0.876	-0.812	-0.011	321.000
Fast response	2.863	0.995	-0.284	0.202	321.000
Financial insights	3.209	0.891	-0.173	-0.423	321.000
Personalised offers	3.340	0.973	-0.908	0.254	321.000
Response accuracy	2.769	1.087	-0.765	0.102	321.000

Source: calculated by the authors based on SmartPLS output

Objective and hypothesis two restatement. Objective two: To determine the effect of smart banking solutions on digital support responsiveness. H_{02} : Smart banking solutions have no significant effect on digital support responsiveness (Fig. 2). Figure 2 illustrates the path model, showing the correlations among the components of smart banking – automated account management, personalised financial insights, and digital support responsiveness. It reveals a strong positive relationship originating from

automated account management, which facilitates responsiveness, and a slightly negative influence from personalised financial insights. This indicates that automation plays a more significant role in enhancing support responsiveness than do banking strategies focused primarily on personalisation. Table 9 presents the reliability and validity measures, confirming that all constructs exhibit high internal consistency, composite reliability, and convergent validity.

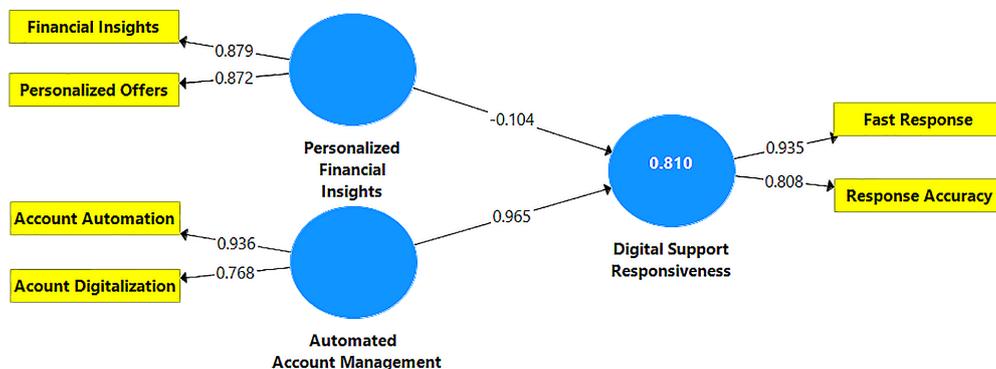


Figure 2. A path model of smart banking solutions and digital support responsiveness

Source: calculated by the authors based on SmartPLS output

Table 9. Construct reliability and validity

	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
Automated account management	0.761	0.845	0.733
Digital support responsiveness	0.707	0.865	0.764
Personalised financial insights	0.795	0.868	0.766

Source: calculated by the authors based on SmartPLS output

Table 9 shows that all constructs demonstrate strong reliability, as the Cronbach's alpha values exceed the recommended threshold of 0.7 (automated account management: 0.761, digital support responsiveness: 0.707, personalised financial insights: 0.795), confirming internal consistency of the measurement items. Further evidence of reliability is provided by the composite reliability values (0.845-0.868). The average variance extracted (AVE) values exceed 0.5 across all constructs (0.733-0.766), demonstrating a high

level of convergent validity, whereby the indicators accurately reflect their respective constructs. These sound psychometric properties confirm that the measurement model is both reliable and valid, providing banks with assurance that the specified dimensions are useful for enhancing the responsiveness of digital support and improving customer satisfaction. Table 10 presents the AVE square roots and inter-construct correlations, demonstrating strong discriminant validity among the studied constructs.

Table 10. Discriminant validity

	Automated account management	Digital support responsiveness	Personalised financial insights
Automated account management	0.856		
Digital support responsiveness	0.796	0.874	
Personalised financial insights	0.654	0.527	0.875

Source: calculated by the authors based on SmartPLS output

Table 10 indicates that the square roots of the AVE values (bold diagonal: automated account management – 0.856, digital support responsiveness – 0.874, personalised financial insights – 0.875) are higher than the inter-construct correlations, thereby confirming strong discriminant validity. The correlation between automated account management and digital support responsiveness (0.796) is notably high, indicating a strong association, whereas the correlation between personalised financial insights and digital

support responsiveness (0.527) is moderately high, suggesting a weaker connection. This confirms that all constructs capture distinct yet theoretically related concepts, implying that banking institutions should prioritise automation elements, which have a stronger link to support responsiveness, over personalisation initiatives. The VIF values indicate that the components of smart banking solutions are free from multicollinearity and can therefore be evaluated as independent predictors of digital support responsiveness (Table 11).

Table 11. Inner variance inflation factor values

	Automated account management	Digital support responsiveness	Personalised financial insights
Automated account management		1.747	
Digital support responsiveness			
Personalised financial insights		1.747	

Source: calculated by the authors based on SmartPLS output

In Table 11, the VIF values for automated account management and personalised financial insights are both 1.747, which is well below the critical threshold of 5.0. This confirms that the independent variables do not exhibit problematic multicollinearity and, therefore, the independent variables (components of smart banking solutions) can be regarded as distinct yet independent predictors of

digital support responsiveness. The absence of problematic correlations allows for a more accurate assessment of each variable's contribution. Accordingly, banks can better identify which functions of smart banking solutions most strongly enhance support responsiveness and design more targeted improvement measures to increase customer satisfaction. The bootstrapping results indicate that

automated account management has a strong and statistically significant effect on digital support responsiveness, while personalised financial insights show a negative and non-significant effect (Table 12).

Table 12. Bootstrapping results showing path coefficients for the structural model

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
Automated account management -> Digital support responsiveness	0.965	0.965	0.023	41.759	0.000
Personalised financial insights -> Digital support responsiveness	-0.104	-0.103	0.086	1.209	0.084

Source: calculated by the authors based on SmartPLS output

The bootstrapping outcomes in Table 12 reveal that automated account management exerts a strong and significant influence on digital support responsiveness ($p < 0.001$, $\beta = 0.965$, $t = 41.759$), whereas personalised financial insights exhibit a negative and non-significant effect ($p = 0.084$, $\beta = 0.104$, $t = 1.209$). These results indicate that customers primarily associate the effectiveness and speed of digital support with automated account functions rather than with personalised financial advice. The marked difference in the strength and significance of

coefficients underscores that the primary objective for banking organisations implementing AI should be to invest in automated account management services, thereby improving responsiveness levels and customer satisfaction within the identified banking context. Table 13 shows that automated account management and personalised financial insights together explain a substantial proportion of the variance in digital support responsiveness, highlighting the crucial role of smart banking solution features.

Table 13. Coefficient of determination score

	R-square	R-square adjusted
Digital support responsiveness	0.810	0.809

Source: calculated by the authors based on SmartPLS output

Table 13 shows an R-square value of 0.810, indicating that 81.0% of the variance in digital support responsiveness is explained by automated account management and personalised financial insights. The adjusted R-square of 0.809 suggests that the result is not inflated by multiple predictors. This represents a remarkably high level of explanatory power, indicating that smart banking solution features are key determinants of responsiveness in digital banking support. The minimal difference between the two R-square

values also demonstrates that the model is highly parsimonious, implying that banks can confidently focus on these specific aspects of smart banking solutions to enhance support responsiveness and, consequently, customer satisfaction, without unnecessary resource expenditure. Table 14 presents the effect sizes (f^2), showing that automated account management has a very strong practical impact on digital support responsiveness, while personalised financial insights play only a minor role.

Table 14. Assessment of the effect size (f^2)

	Automated account management	Digital support responsiveness	Personalised financial insights
Automated account management		2.802	
Digital support responsiveness			
Personalised financial insights		0.033	

Source: calculated by the authors based on SmartPLS output

The effect size (f^2) of automated account management on digital support responsiveness in Table 14 is very large (2.802), indicating strong practical significance, whereas the value for personalised financial insights is very small (0.033). Based on the criteria developed by Cohen, the effects of account automation are substantial, while the personalisation features play a negligible role in determining

digital support responsiveness. This pronounced difference in effect sizes highlights the importance of allocating resources to the development of advanced account automation systems rather than heavily investing in enhanced customisation options when the main aim is to improve digital customer support responsiveness and increase customer satisfaction levels.

Based on the main findings of this study, the following recommendations are proposed: over the next six months, banks should enhance fund transfer encryption and implement multi-factor authentication to further increase customer satisfaction following security upgrades. They should also display real-time payment alerts (including transaction details) and electronic receipts to reduce customer contact requests. In the particular cases of Zenith Bank, Access Bank, First Bank, GTBank, and UBA, quarterly audits of digital services are recommended to evaluate the efficiency of security and confirmation against industry standards, ensuring competitiveness in Nigeria's rapidly developing digital banking market.

Furthermore, to improve account responsiveness and enhance customer satisfaction, banks should implement end-to-end account automation, including AI-driven chatbots and predictive services. The relevance of personalised financial insights should be redefined to complement rather than compete with automated systems through timely and relevant information sharing during service interactions – a strategy capable of strengthening customer engagement. Zenith Bank, Access Bank, First Bank, GTBank, and UBA should also conduct quarterly reviews of the digital customer experience, measuring automation performance in terms of resolution speed, accuracy, and customer effort to maintain a competitive advantage.

The results indicate a significant effect of digital payment systems on service reliability, with secure fund transfers having a stronger and statistically significant impact ($\beta = 0.379$, $t = 6.962$, $p < 0.001$) compared to instant payment confirmations, which show no significant effect ($\beta = 0.367$, $t = 1.942$, $p = 0.057$). Together, these two factors account for 47.2% of the variance in service reliability ($R^2 = 0.472$), with moderately large effect sizes for secure fund transfers ($f^2 = 0.139$) and instant payment confirmations ($f^2 = 0.130$). These findings support those of J. Dutta *et al.* (2024) and L. AlHchemi (2024), who concluded that transaction security strengthens trust in digital banking, and align with T. Khiaonarong *et al.* (2021), who emphasised the crucial role of payment confirmations in perceived trustworthiness. The customer benefits of secure and reliable digital payments – such as higher satisfaction and loyalty – led S. Srajan *et al.* (2024) to prioritise this as a strategic element of digital banking.

Similarly, the responsiveness of digital support has a substantial impact on smart banking solutions, which differ in their components. Automated account management shows a very strong and significant effect ($\beta = 0.965$, $t = 41.759$, $p < 0.001$), while personalised financial insights exhibit a weak and non-significant negative effect ($\beta = -0.104$, $t = 1.209$, $p = 0.084$). Together, they explain 81.0 per cent of the variance in digital support responsiveness ($R^2 = 0.810$); automated account management demonstrates a large impact ($f^2 = 2.802$), whereas personalised financial insights have a small impact ($f^2 = 0.033$). Those findings are consistent with V. Nagubathula (2025),

who highlighted the potential of automation to increase digital responsiveness and satisfaction. Nonetheless, the insignificance of the personalisation effect differs from that reported by D. Epstein & K. Quinn (2020), suggesting that it is likely to be a matter of implementation. A. Uzoka *et al.* (2024) also noted that an appropriate level of personalisation is required to maintain optimal AI-driven outcomes in banking.

In summary, the results suggest that the reliability and efficiency of digital banking services are largely determined by the quality of secure fund transfers and the functionality of automated account management, whereas payment confirmations and personalised financial insights play a secondary role. These findings emphasise the need for banks to prioritise investment in technologies that ensure security and automation, as these are the key drivers of customer trust, improved digital support responsiveness, and overall satisfaction and loyalty.

CONCLUSIONS

The research supports the conclusion that digital payment systems have a significant influence on the reliability of services in the Nigerian banking sector. The correlation for secure fund transfers was shown to be the strongest statistically significant predictor, whereas instant payment confirmation was not found to be significant. Together, these variables accounted for nearly 50% of the variance in service reliability. These findings highlight the importance of strengthening both security infrastructure and confirmation mechanisms, since customers are concerned about their transactions being secure and timely. The likelihood of similar effects points to the need for banks to adopt a comprehensive, systemwide approach to enhancing digital payment mechanisms rather than a selective or fragmented strategy.

Similarly, the study demonstrates that smart banking solutions exert a strong influence on the responsiveness of digital support. Automated account management emerged as the most influential predictor, showing both high statistical and practical significance, whereas personalised financial insights had a weak and statistically insignificant impact overall. To enhance their ability to meet digital needs effectively, banks should invest in a high degree of automation, not only through workflow optimisation and self-service solutions but also by reviewing personalisation features to ensure they do not hinder the speed of digital engagement. The varied influence of these factors implies that resource allocation must be strategically managed to achieve optimal customer satisfaction. Future studies could explore AI's impact on other banking metrics, such as customer retention or loyalty, or conduct cross-industry comparisons to better understand AI's broader implications. Longitudinal research could also assess the long-term effects of AI innovations, enriching the understanding of AI's role in shaping dynamic customer satisfaction trends.

ACKNOWLEDGEMENTS

Sincere appreciation is extended to Opeyemi Emmanuel Babawale for valuable feedback and contributions throughout the study. Gratitude is also expressed to Zenith Bank, Access Bank, First Bank, GTBank, and UBA Bank, Ilorin Branch, for providing the necessary facilities and environment for this research. Appreciation is likewise extended to all participants and contributors whose cooperation was vital to the project's success.

FUNDING

The authors declare no competing interests and no relevant financial or non-financial interests to disclose, either directly or indirectly related to this publication.

CONFLICT OF INTEREST

There is no conflict of interest relevant to the content of this manuscript.

REFERENCES

- [1] Agarwal, S., Agarwal, B., & Gupta, R. (2022). Chatbots and virtual assistants: A bibliometric analysis. *Library Hi Tech*, 40(4), 1013-1030. doi: [10.1108/lht-09-2021-0330](https://doi.org/10.1108/lht-09-2021-0330).
- [2] Agustawan, D.A. (2024). Digital banking transformation AI enhances efficiency and customer experience seminar perspective industry. *WACANA Jurnal Ilmiah Ilmu Komunikasi*, 23(1), 191-200. doi: [10.32509/wacana.v23i1.4130](https://doi.org/10.32509/wacana.v23i1.4130).
- [3] Akinepalli, S. (2024). Societal impact of test automation: Reducing human error in critical systems. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 10(6), 527-535. doi: [10.32628/cseit24106184](https://doi.org/10.32628/cseit24106184).
- [4] Al-Hchemi, L.H. (2024). Evaluating generative AI in enhancing banking services efficiency. *Economic Forum*, 14(4), 47-54. doi: [10.62763/ef/4.2024.47](https://doi.org/10.62763/ef/4.2024.47).
- [5] Al-kfairy, M., Mustafa, D., Kshetri, N., Insiew, M., & Alfandi, O. (2024). Ethical challenges and solutions of generative AI: An interdisciplinary perspective. *Informatics*, 11(3), article number 58. doi: [10.3390/informatics11030058](https://doi.org/10.3390/informatics11030058).
- [6] Alnaser, F.M., Rahi, S., Alghizzawi, M., & Ngah, A.H. (2023). Does artificial intelligence (AI) boost digital banking user satisfaction? Integration of expectation confirmation model and antecedents of artificial intelligence enabled digital banking. *Heliyon*, 9(8), article number e18930. doi: [10.1016/j.heliyon.2023.e18930](https://doi.org/10.1016/j.heliyon.2023.e18930).
- [7] American Sociological Association's Code of Ethics. (2018, June). Retrieved from <https://surl.lj/tjcklz>.
- [8] Aziz, A.A. (2025). The mediating role of customer satisfaction on the effect of service quality on post-purchase intention. *Journal of Management and Business Insight*, 2(2), 135-143. doi: [10.12928/jombi.v2i2.1190](https://doi.org/10.12928/jombi.v2i2.1190).
- [9] Blümel, J.H., Zaki, M., & Bohné, T. (2024). Personal touch in digital customer service: A conceptual framework of relational personalization for conversational AI. *Journal of Service Theory and Practice*, 34(1), 33-65. doi: [10.1108/jstp-03-2023-0098](https://doi.org/10.1108/jstp-03-2023-0098).
- [10] Chikaipa, Y., Jailosi, L.D., & Tyagi, A.D. (2025). engagement and retention enhancement using machine learning in customer service & support. *International Journal of Advanced Research in Science, Communication and Technology*, 5(4), 233-243. doi: [10.48175/ijarsct-25131](https://doi.org/10.48175/ijarsct-25131).
- [11] Dhiman, N., Jamwal, M., & Kumar, A. (2023). Enhancing value in customer journey by considering the (ad)option of artificial intelligence tools. *Journal of Business Research*, 167, article number 114142. doi: [10.1016/j.jbusres.2023.114142](https://doi.org/10.1016/j.jbusres.2023.114142).
- [12] Dutta, J., Barman, S., Sen, S., Routh, A., Chattopadhyay, M., & Chattopadhyay, S. (2024). Easypay: A user-friendly blockchain-powered payment gateway. *Cluster Computing*, 27, 10633-10652. doi: [10.1007/s10586-024-04506-3](https://doi.org/10.1007/s10586-024-04506-3).
- [13] Enholm, I.M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. *Information Systems Frontiers*, 24, 1709-1734. doi: [10.1007/s10796-021-10186-w](https://doi.org/10.1007/s10796-021-10186-w).
- [14] Epstein, D., & Quinn, K. (2020). Markers of online privacy marginalization: Empirical examination of socioeconomic disparities in social media privacy attitudes, literacy, and behavior. *Social Media + Society*, 6(2), 1-13. doi: [10.1177/2056305120916853](https://doi.org/10.1177/2056305120916853).
- [15] Fjelland, R. (2020). Why general artificial intelligence will not be realized. *Humanities and Social Sciences Communications*, 7, article number 10. doi: [10.1057/s41599-020-0494-4](https://doi.org/10.1057/s41599-020-0494-4).
- [16] Gabriel-Okwuchi, C.J. (2025). Analysis of emerging technologies and banking industry service delivery in Nigeria. *Asian Journal of Economics, Business and Accounting*, 25(2), 77-90. doi: [10.9734/ajeba/2025/v25i21665](https://doi.org/10.9734/ajeba/2025/v25i21665).
- [17] Huang, C., Zhang, Z., Mao, B., & Yao, X. (2022). An overview of artificial intelligence ethics. *IEEE Transactions on Artificial Intelligence*, 4(4), 799-819. doi: [10.1109/taai.2022.3194503](https://doi.org/10.1109/taai.2022.3194503).
- [18] Jan, Z., Ahamed, F., Mayer, W., Patel, N., Grossmann, G., Stumptner, M., & Kuusk, A. (2023). Artificial intelligence for industry 4.0: Systematic review of applications, challenges, and opportunities. *Expert Systems with Applications*, 216, article number 119456. doi: [10.1016/j.eswa.2022.119456](https://doi.org/10.1016/j.eswa.2022.119456).
- [19] Katragadda, M.K.C. (2025). Transforming financial services through predictive analytics and banking systems integration. *World Journal of Advanced Research and Reviews*, 26(1), 1264-1272. doi: [10.30574/wjarr.2025.26.1.1167](https://doi.org/10.30574/wjarr.2025.26.1.1167).
- [20] Khiaonrong, T., Leinonen, H., & Rizaldy, R. (2021). Operational resilience in digital payments: Experiences and issues. *IMF Working Papers*, 288, 3-36. doi: [10.5089/9781616355913.001](https://doi.org/10.5089/9781616355913.001).

- [21] Koldovskiy, A. (2024). Strategic infrastructure transformation: Revolutionizing financial sector management for enhanced success. *Acta Academiae Beregsasiensis. Economics*, 5, 323-332. doi: [10.58423/2786-6742/2024-5-323-332](https://doi.org/10.58423/2786-6742/2024-5-323-332).
- [22] Lee, J.-C., & Chen, X. (2022). Exploring users' adoption intentions in the evolution of artificial intelligence mobile banking applications: The intelligent and anthropomorphic perspectives. *International Journal of Bank Marketing*, 40(4), 631-658. doi: [10.1108/ijbm-08-2021-0394](https://doi.org/10.1108/ijbm-08-2021-0394).
- [23] Lestari, D., Octavianti, S., & Suhartono, A. (2025). The impact of product quality and service quality on customer satisfaction. *International Journal Multidisciplinary Science*, 4(1), 34-44. doi: [10.56127/ijml.v4i1.1924](https://doi.org/10.56127/ijml.v4i1.1924).
- [24] Lillengren, P., Johansson, R., Lindqvist, K., Mechler, J., & Andersson, G. (2016). Efficacy of experiential dynamic therapy for psychiatric conditions: A meta-analysis of randomized controlled trials. *Psychotherapy*, 53(1), 90-104. doi: [10.1037/pst0000024](https://doi.org/10.1037/pst0000024).
- [25] Nagubathula, V. (2025). AI and human-AI collaboration in enterprise integration and document automation. *International Journal on Science and Technology*, 16(1), 1-38. doi: [10.71097/ijst.v16.i1.2317](https://doi.org/10.71097/ijst.v16.i1.2317).
- [26] Odio, P.E., Okon, R., Adeyanju, M.O., Ewim, C.P.-M., & Onwuzulike, O.K. (2025). Blockchain and cybersecurity: A dual approach to securing financial transactions in Fintech. *Gulf Journal of Advance Business Research*, 3(2), 380-409. doi: [10.51594/gjabr.v3i2.89](https://doi.org/10.51594/gjabr.v3i2.89).
- [27] Oliver, R.L. (1977). Effect of expectation and disconfirmation on postexposure product evaluations: An alternative interpretation. *Journal of Applied Psychology*, 62(4), 480-486. doi: [10.1037/0021-9010.62.4.480](https://doi.org/10.1037/0021-9010.62.4.480).
- [28] Otto, A.S., Szymanski, D.M., & Varadarajan, R. (2020). Customer satisfaction and firm performance: Insights from over a quarter century of empirical research. *Journal of the Academy of Marketing Science*, 48, 543-564. doi: [10.1007/s11747-019-00657-7](https://doi.org/10.1007/s11747-019-00657-7).
- [29] Prentice, C., Weaven, S., & Wong, I.A. (2020). Linking AI quality performance and customer engagement: The moderating effect of AI preference. *International Journal of Hospitality Management*, 90(1), article number 102629. doi: [10.1016/j.ijhm.2020.102629](https://doi.org/10.1016/j.ijhm.2020.102629).
- [30] Rane, N.L., Achari, A., & Choudhary, S.P. (2023). Enhancing customer loyalty through quality of service: Effective strategies to improve customer satisfaction, experience, relationship, and engagement. *International Research Journal of Modernization in Engineering Technology and Science*, 5(5), 427-452. doi: [10.56726/irjmets38104](https://doi.org/10.56726/irjmets38104).
- [31] Sravan, S.S., Mandal, S., Alphonse, P.J.A., & Ramesh, P.L. (2024). A partial offline payment system for connecting the unconnected using internet of things: A survey. *ACM Computing Surveys*, 57(2), article number 31. doi: [10.1145/3687132](https://doi.org/10.1145/3687132).
- [32] Ukpe, E. (2025). Empowering Nigeria's e-society: A comprehensive exploration of cutting-edge digital services. *East African Journal of Information Technology*, 8(1), 80-91. doi: [10.37284/eajit.8.1.2995](https://doi.org/10.37284/eajit.8.1.2995).
- [33] Uzoka, A., Cadet, E., & Ojukwu, P.U. (2024). Leveraging AI-powered chatbots to enhance customer service efficiency and future opportunities in automated support. *Computer Science & IT Research Journal*, 5(10), 2485-2510. doi: [10.51594/csitrj.v5i10.1676](https://doi.org/10.51594/csitrj.v5i10.1676).
- [34] Yamane, T. (1967). *Statistics: An introductory analysis (2nd ed.)*. New York: Harper and Row.

Штучний інтелект та задоволеність клієнтів у банківському секторі Нігерії

Олувайомі Омотайо Олота

Кандидат наук з бізнес-адміністрування
Університет Ілоріна
240003, вул. Університетська, 1, м. Ілорін, Нігерія
<https://orcid.org/0009-0008-6633-9919>

Олатунде Натаніель Акінкунмі

Магістр з бізнес-адміністрування
Університет Ілоріна
240003, вул. Університетська, 1, м. Ілорін, Нігерія
<https://orcid.org/0009-0005-3414-1236>

Ебенезер Олувадамиларе Балогун

Магістр з бізнес-адміністрування
Університет Ілоріна
240003, вул. Університетська, 1, м. Ілорін, Нігерія
<https://orcid.org/0000-0003-0419-188X>

Анотація. Інтеграція штучного інтелекту (ШІ) у банківський сектор трансформувала рівень задоволеності клієнтів, зокрема завдяки таким інноваціям, як цифрові платіжні сервіси та «розумні» банківські рішення. Тому це дослідження було спрямоване на вивчення впливу штучного інтелекту на задоволеність клієнтів у банківському секторі. Конкретними завданнями було визначено: дослідити вплив цифрової платіжної системи на надійність послуг у банківському секторі; а також вплив «розумних» банківських рішень на оперативність цифрової підтримки, яку надає банківський сектор. Для проведення дослідження було використано описовий дизайн опитування. Застосовано метод простої випадкової вибірки. Розмір вибірки було визначено за формулою визначення вибірки Т. Ямана. Дані, отримані за допомогою анкетування, були проаналізовані із застосуванням PLS-SEM у програмі SmartPLS. Результати показали, що цифрові платежі позитивно та суттєво впливають на надійність послуг у банківському секторі; безпечний переказ коштів ($\beta = 0,379$, $T = 6,962$, $p = 0,000$); миттєве підтвердження платежу ($\beta = 0,367$, $T = 1,942$, $p = 0,057$). Також встановлено, що «розумні» банківські рішення позитивно та частково суттєво впливають на оперативність цифрової підтримки, яку надає банківський сектор (автоматизоване управління рахунками ($\beta = 0,965$, $T = 41,759$, $p = 0,000$); персоналізовані фінансові поради ($\beta = -0,104$, $T = 1,209$, $p = 0,084$). Зроблено висновок, що штучний інтелект позитивно впливає на задоволеність клієнтів у вибраних банках Нігерії. Результати дослідження мають практичну цінність для банківського сектору Нігерії, оскільки висвітлюють, як технології штучного інтелекту можуть бути ефективно застосовані для підвищення задоволеності та лояльності клієнтів. Керівники банків, розробники цифрових стратегій та менеджери з обслуговування клієнтів можуть використати ці висновки для ухвалення рішень щодо інвестицій у персоналізовані ШІ-рішення, системи миттєвої підтримки та інтелектуальну автоматизацію сервісів, що сприятиме зміцненню довгострокових відносин із клієнтами

Ключові слова: цифрова платіжна система; розумне банківське рішення; оперативність цифрової підтримки; надійність послуг; лояльність клієнтів