Impact of artificial intelligence on customer engagement from selected banks in Abuja Metropolis, Nigeria: a mediating role of personalization

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Abstract

Purpose: The objective of this research is to explore how Artificial Intelligence applications drive customer engagement in selected Deposit Money Banks in Abuja Metropolis, through the mediating influence of personalization. The research is grounded in the Technology Acceptance Model, aiming to explore how chatbot and biometric technologies influence customer engagement through the lens of personalization.

Design/methodology/approach: The study employed a cross-sectional survey design, targeting online retail customers of five banks Access Bank, First Bank, GTBank, United Bank for Africa, and Zenith Bank within the Abuja Municipal Area Council. A total sample size of 119 respondents involved in the study. The data were collected via a structured five-point Likert scale questionnaire and analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM).

Findings: The results revealed that Biometric Authentication has a positive and significant effect on customer engagement. Chatbots have a negative but significant effect on customer engagement. Personalization has a negative and non-significant effect on customer engagement. For the mediating relationship, personalization does not mediate the relationship between biometric authentication and customer engagement. Personalization does not serve as a mediator between chat-bots and customer engagement

Limitations and Research implications: The study is limited to online retail customers of five banks within a single geographical area (Abuja), which may affect the generalizability of the findings. Future research could expand the geographic scope and consider longitudinal data to observe trends over time.

Practical Implications: The findings suggest the need for banks to develop a comprehensive AI strategy that cohesively integrates chatbots, biometric systems, and personalized services to enhance customer engagement. Emphasis should be placed on improving the effectiveness and customer perception of biometric technologies.

Originality/value: This study contributes to the growing literature on AI adoption in banking by empirically validating the role of personalization as a mediator in the relationship between AI tools and customer engagement. It also extends the application of the Technology Acceptance Model in the context of AI-driven banking services in Nigeria.

Keywords: Artificial Intelligence, Chatbot, Biometric Authentication, Personalisation, Customer Engagement

Introduction

The process of fostering customer engagement has become increasingly intricate in the banking industry due to shifting consumer preferences and the growing reliance on digital financial services (Chauhan et al., 2022). Conventional banking systems often fall short in addressing these dynamic demands, which can lead to diminished customer loyalty,

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dissatisfaction, and attrition. Given the service-oriented nature of banking, maintaining strong customer relationships is crucial to an institution's sustainability. Customer engagement, encompassing cognitive, emotional, and behavioral dimensions, plays a crucial role in shaping loyalty, satisfaction, and overall performance. Consequently, effectively managing engagement strategies has become a strategic imperative for banks seeking to remain competitive in the digital era (Kumar et al., 2019).

According to a survey conducted by Ernst and Young Global (2023), a UK-based company providing consulting, assurance, tax, and transaction services, China has achieved an 83% Artificial Intelligence (AI) adoption rate in financial institutions to enhance customer engagement and operational efficiency, followed closely by India at 81%. The market for AI in financial services is projected to grow from $3.1 billion in 2020 to $7.8 billion by the end of 2025. Similarly, a report by McKinsey and Company (2023), an American multinational strategy and management consulting firm, found that Australia integrates AI into customer interactions and fraud detection, handling 50,000 customer inquiries daily through AI-powered systems. Another McKinsey and Company (2023) survey revealed that Nigeria has a financial technology adoption rate of 29% for generative AI technologies in content creation and communication, with only 14% utilizing AI for workflow automation. This indicates that Nigeria significantly lags behind its counterparts in AI adoption within the banking industry, highlighting the need for further research in this area.

Artificial Intelligence is revolutionizing numerous sectors, with its global impact on banking being especially notable (Udodiugwu et al., 2024). The deployment of AI technologies in banking enables continuous, automated service delivery for routine inquiries, such as checking balances and accessing loan information. Such advancements are particularly accessible to institutions with robust technological and fiscal capabilities. Through AI-driven solutions, including chatbots and biometric authentication, banks can offer personalized customer experiences, process transactions efficiently, and suggest customized financial products. This strategic use of AI not only enhances customer satisfaction but also enables banks to adapt effectively to the ongoing demands of digital transformation (Oyetunji, 2024).

Despite the benefits of Artificial Intelligence in streamlining processes, Ng and Leung (2020) raise concerns that such technologies might suppress employees' potential by promoting overdependence on automated systems. Similarly, Ninness and Ninness (2020) argue that this reliance could hinder the development of practical skills. Adam et al. (2021) emphasize the crucial need for ongoing system maintenance and updates to ensure AI tools operate optimally in banking environments, as lapses could result in operational inefficiencies. Moreover, digital illiteracy among many Nigerian bank customers, especially those in underserved rural areas, poses a significant barrier to interacting with AI-enabled platforms. These challenges are compounded by limited smartphone usage and inconsistent app performance, which further restricts customer engagement with technological solutions.

The paper examines the mediating effect of personalization on the relationship between AI technologies (chatbots and biometric authentication) and customer engagement in the Nigerian banking sector, a relevant and timely issue given the global shift toward digital banking. While the study focuses on an under-researched region (Abuja Metropolis), the novelty is moderate. The topic is well-trodden in broader literature; however, integrating the mediating role of personalization in this specific geographical and cultural context gives the paper some localized value. It is against this backdrop, this study aims to investigate the key factors influencing the application of artificial intelligence in fostering customer engagement within deposit money banks in the Abuja metropolis.

The banking industry is one of Nigeria's largest employers of labour (Tubaro et al., 2020). It has a direct relationship with all private and public enterprises, as well as non-governmental organisations, because it assists these entities in maintaining their financial assets. The worldwide banking industry has adopted AI to transform customer interactions, but Nigerian banks have yet to fully realise AI's benefits for customer engagement. Nigerian banks face obstacles in harnessing AI to boost customer engagement, typically prioritizing automation and cost-cutting over nurturing meaningful relationships, despite its potential to revolutionize customer experiences. Elegunde and Osagie (2020), Skandali et al. (2023), and Udodiugwu et al. (2024) conducted studies on artificial intelligence and customer engagement in the banking sector using relatively small samples of 33, 98, and 128, respectively. The limited sample sizes may heighten the risk of Type I errors, leading to misleadingly significant findings that occur by chance. To mitigate this methodological gap, the current study adopts a more robust sample size of 397. Previous studies, such as those by Elegunde & Osagie (2020) and Udodiugwu et al. (2024), focused solely on employees, while Garg & Sachdeva (2022) and Menezes et al. (2024) included both employees and customers. However, integrating responses from these two groups presents challenges, as customers' perceptions are often subjective, while employees may provide biased or defensive views on AI implementation. These discrepancies make it challenging to draw definitive conclusions about the impact of AI on customer engagement. To address this contextual gap, this study focuses exclusively on customers as respondents.

Volume: 1, Issue: 2, 2025

Despite the challenges discussed earlier, numerous studies have recognized the connection between artificial intelligence (AI) and customer engagement (CE). However, despite this growing body of evidence, a significant gap remains in assessing mediating effects, and there is a lack of robust statistical validation to substantiate these claims. Additionally, methodological limitations, such as study biases and small sample sizes, are prevalent in previous research. As a result, the precise nature and underlying mechanisms of these relationships remain unclear. Consequently, prior findings are inconclusive, leaving a critical gap. To address this, the present study investigates the mediating role of personalization (P) in the relationship between AI and CE, offering deeper insights into AI's holistic impact on CE.

This study aims to investigate the degree to which chatbots affect customer engagement in the Nigerian banking sector, evaluate the influence of predictive analytics on customer engagement, and analyse how content generation shapes customer interactions. Furthermore, the research aims to determine whether personalization acts as a mediator in the relationship between artificial intelligence (including chatbots, predictive analytics, and content generation) and customer engagement in Nigeria's banking industry.

This study contributes to the ongoing discourse on AI adoption by providing empirical evidence within the context of an emerging economy. It further extends the theoretical understanding of personalization as a mediator in the AI-customer engagement relationship, offering a fresh perspective on AI's role in service personalization. Additionally, it provides valuable empirical insights to regulatory bodies, such as the Central Bank of Nigeria, aiding in the development of AI-driven financial regulations that strike a balance between innovation, data privacy, and customer protection.

Literature Review

Customer Engagement

Customer engagement (CE) is a marketing concept focused on fostering long-term relationships between businesses and their customers. Companies employ various strategies to enhance interactions and build customer loyalty (Chen et al., 2022), ultimately creating an emotional bond between the brand and its consumers. In the digital space, engagement is often measured through actions such as clicks, likes, comments, and shares, with influencers playing a crucial role in strengthening this connection (Elegunde & Osagie, 2020). AI further enhances engagement by analysing customer feedback from emails, social media, and online reviews, allowing businesses to understand sentiment and address concerns more effectively.

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In Nigeria, banks leverage AI-driven solutions to deepen customer relationships. For instance, GTBank and Access Bank utilize AI-powered chatbots, such as Habari and Tamara, to respond to inquiries, facilitate transactions, and provide financial advice, thereby enhancing customer interaction and satisfaction (Trunfio & Rossi, 2021). AI enhances customer engagement in the Nigerian banking industry. This could be achieved by providing personalized services, improving response times, ensuring security, and boosting overall customer satisfaction, ultimately leading to increased loyalty and profitability.

Artificial Intelligence

Artificial intelligence (AI) has changed the interaction between machines and humans in strategic ways, as consumers authorise computers to make decisions with minimum human intervention. AI is a promising marketing tool that collects real-time data and analyzes it to meet customer wants (Suraña-Sánchez & Aramendia-Muneta, 2024). Artificial intelligence, cloud computing, machine learning, big data analytics, and social media have significantly transformed digital business, enhancing processes, improving efficiency, and enabling the meeting of future challenges. AI can predict events, understand meaning and language, and assist humans in interacting with machines (Udodiugwu et al., 2024). It operates autonomously without human intervention and self-learns over time. AI in the banking industry is increasingly being used to solve customers' problems, manage accounts, and provide 24/7 online appraisals, while fraud detection systems help identify suspicious transactions in real-time, enhancing trust and security. Customers feel more confident engaging with banks that prioritize fraud prevention. These technologies simplify decision-making processes, reduce false contracts, and improve resource forecasting. They also contribute to the development of new methods of value creation and competitive strategies in businesses (Skandali et al., 2023).

Chatbots

Hepziba and John (2020) defined a chatbot as a digital tool that mimics human conversation using pre-programmed rules and is available 24/7. According to Ahmed (2021), a chatbot is a software agent that enables robots and people to engage in intelligent interactions. Natural Language Processing (NLP) is utilized by chatbots to simulate human speech during human-machine interactions. This means that chatbots are capable of helping businesses to improve customer experience by providing quick responses, answering frequently asked questions, and streamlining interactions. Since business success depends on customer satisfaction, leveraging chatbots may help keep customers engaged and convert potential buyers into loyal customers, as emphasized by several studies and blogs (Ahmed, 2021).

For the purpose of this study, a chatbot is an artificial intelligence (AI)-powered software application designed to simulate human conversation through text or voice interactions. Chatbots can be integrated into websites, messaging apps, or phone systems to assist users by answering questions, providing recommendations, and automating tasks. Chatbots have become an essential tool in the banking sector, revolutionizing customer interactions and service delivery. It provides all-around assistance, helping customers with inquiries, balance checks, and transaction updates without requiring them to wait for human agents. However, challenges such as data security, ethical concerns, and customer trust remain key considerations (Hepziba & John, 2020).

Biometric Authentication

System authentication is an electronic method of identifying individuals. It relies on three key authentication types: (1) possession-based methods (such as ID/swipe cards or tokens), (2) knowledge-based methods (such as PINs or passwords), and (3) biometric authentication (which utilizes an individual's unique physiological and behavioural traits). Biometric authentication is regarded as the most secure method because these characteristics are inherent to a person and cannot be lost, forgotten, or stolen. On the other hand, objects in possession can be taken, and information-based credentials may be forgotten (Mandari & Koloseni, 2016).

Volume: 1, Issue: 2, 2025

Biometric authentication is defined in this study as a security mechanism that verifies an individual's identity through unique biological and behavioural characteristics such as fingerprints, facial recognition, voice patterns, iris scans, or palm prints. This method provides secure and efficient access to accounts, systems, or physical locations by utilizing inherent human traits that cannot be stolen, lost, or forgotten (Chigada, 2020). In the banking sector, biometric authentication is crucial for strengthening security, enhancing customer experience, and minimizing fraud risks. Banks implement biometric technology for identity verification across various financial transactions, including mobile and online banking, ATM withdrawals, and fraud detection. Notably, some Nigerian banks have embraced biometric authentication. Guaranty Trust Bank (GTBank) and Zenith Bank have adopted fingerprint-based authentication for ATM transactions, allowing customers to withdraw cash securely without relying on traditional cards or PINs (Mandari & Koloseni, 2016).

Personalization

Organizations increasingly rely on personalization as a key strategy to adapt their products to customers' diverse needs. Harnessing customer data and segmentation, along with the use of digital tools, they can create customized marketing messages and deliver unique banking experiences. This approach enhances customer satisfaction while also promoting engagement between customers and financial institutions, thereby fostering lasting relationships (Wang et al., 2017).

Personalization, as conceptualized in this study, refers to the customization of products, services, and customer interactions based on individual preferences, behaviours, and financial needs. By leveraging data, technology, and analytics, businesses can create tailored experiences that improve engagement and customer satisfaction. Within the banking industry, personalization involves utilizing customer data to deliver targeted financial solutions. Banks analyze spending behavior, income trends, and transaction histories to suggest appropriate financial products, such as loans, credit cards, and savings plans. Mobile banking platforms further enhance personalization by offering customized dashboards, financial insights, and personalized advisory services based on user activity (Rysin et al., 2023).

Review of Empirical Studies

The Effect of Chatbot Adoption on Customer Engagement

Balaji et al. (2024) evaluated the unleashing of the power of smart chatbots: Transforming banking with artificial intelligence, using a sample size of 285 chatbot customers. Structural equation modelling and the AMOS programme were used to test the hypothesis. The study's findings indicate that smart chatbots have a significant positive impact on customer satisfaction. Their findings highlight the importance of personalized and timely assistance provided by intelligent conversational agents in enhancing the overall customer experience. This supports the proposition that when chatbots are designed with user-centric features, they can substantially influence engagement outcomes. In contrast, Bhalerao and Joseph (2023) explored success factors for chatbots from the perspective of an Indian customer with data collected from 87 respondents in India. Multiple regression analyses were employed for the

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study. The study revealed that efficiency and effectiveness were determined to be strong indicators of chatbot performance for Indian customers, whereas satisfaction (as described by its attributes was not deemed important for Indians due to a lack of support. This divergence may suggest that cultural expectations and service infrastructure play a role in shaping what users value in chatbot interactions.

Sarbabidya and Saha (2020) investigated the role of chatbots in customer service, a study from the perspective of the banking industry in Bangladesh, with a sample size of 125 respondents, including users and employees of digital banking service providers. Their findings reveal that chatbots are valued not only for functional tasks, such as website navigation and real-time support, but also for relational functions, including building emotional bonds and trust through personalized communication and natural language processing (NLP). These findings imply that chatbots can influence both transactional efficiency and affective engagement, depending on how they are integrated and perceived by users. These studies demonstrate a shared recognition of chatbot benefits, particularly in terms of operational support, personalization, and customer experience. However, variation exists in terms of the perceived importance of satisfaction and emotional bonding, which appear to be shaped by regional and cultural contexts, as well as differing implementation strategies.

The Effect of Biometric Authentication on Customer Engagement

Noori and Jailani (2022) conducted a study on the acceptance of biometric authentication technology in mobile banking in Iraq, using a sample size of 391 Iraqi bank customers in Baghdad. The study employed structural equation models and a multiple linear regression model to test the hypotheses. Their findings revealed that performance expectancy (PE), effort expectancy (EE), and perceived security (PS) were significant predictors of behavioural intention (BI) to adopt biometric authentication. Moreover, facilitating conditions (FC) and BI significantly influenced actual usage behaviour (UB). The study also incorporated demographic moderators, finding that age and gender fully moderated the effects of PE and EE on BI, while experience and occupation had partial moderating effects. This study offers a comprehensive perspective by integrating the Unified Theory of Acceptance and Use of Technology (UTAUT) framework with biometric authentication. However, its focus on mobile banking limits its generalizability to broader banking applications, such as ATMs or in-branch services.

Similarly, Mandari and Koloseni (2016) investigated biometric authentication in financial institutions, specifically the intention of banks to adopt biometric-powered ATMs. Advances in Computer Science in Tanzania's financial sector, with a total sample size of 102 customers from 47 banks. The study used multiple regression analysis to analyse the data. Their findings highlight that external pressure and perceived benefit significantly enhance adoption intentions, whereas perceived risk negatively impacts adoption. Interestingly, organizational readiness did not significantly affect adoption, suggesting that internal preparedness may be less influential than external motivators or perceived value. This contrasts with Noori and Jailani (2022), where internal factors such as FC were significant. The Tanzanian study thus contributes an institutional perspective, focusing on organizational decision-making in biometric deployment, in contrast to the individual user-level analysis of the Iraqi study.

Chigada (2020) conducted a qualitative analysis of the feasibility of deploying biometric authentication systems to augment the security protocols of bank card transactions, using 30 sample elements from commercial banks. The study established that banking technology and telecommunications infrastructure were capable of supporting biometric payment systems. It further found that biometric systems can reduce card fraud, supporting the security-enhancing role highlighted by Noori and Jailani (2022). However, Chigada (2020) also identified operational drawbacks, such as congestion and transaction delays during peak periods due to zero-floor limits and increased network traffic, which are issues less emphasized in the other two studies. This introduces a technological constraint dimension, showing that the feasibility of biometric deployment is contingent not just on user acceptance or organizational readiness, but also on infrastructural capacity. It was observed that the multifaceted nature of biometric authentication adoption in banking is such that user perceptions, institutional factors, and infrastructure readiness all interact. While security and usefulness are consistent themes across the studies, each one has a different focus. Noori and Jailani (2022) concentrate on user acceptance and the role of demographic factors. In contrast, Mandari and Koloseni (2016) investigate the drivers of external and organizational adoption. Meanwhile, Chigada (2020) assesses the technical feasibility and associated risks of implementing this approach.

International Journal of Business Sustainability

Volume: 1, Issue: 2, 2025

Mediating Effects of Personalisation

Wang et al. (2017) investigated how personalization and compatibility with past experience affect customers' use of e-banking in southern China, drawing data from 181 bank customers across 30 branches. Their study found that personalization significantly enhanced performance expectancy and reduced effort expectancy, both of which positively influenced customers' intention to continue using e-banking services. Additionally, the effect of personalization was found to be strengthened when users' prior experiences with e-banking were compatible, suggesting that personalization is most effective when it aligns with users' historical interaction patterns. In contrast, Lephale (2021) explored personalization in the telecommunications industry in South Africa, with a sample of 237 customers. The study revealed that personalization directly influenced both attitudinal loyalty (emotional attachment and positive perception) and behavioural loyalty (repeated patronage). Notably, the research introduced the concept of privacy importance as a moderating variable, demonstrating that when customers value privacy, the effect of personalization on attitudinal loyalty becomes stronger. Furthermore, attitudinal loyalty was shown to directly influence behavioural loyalty, suggesting a sequential pathway from personalized services to emotional connection and repeat behaviour. Both Wang et al. (2017) and Lephale (2021) affirm the positive effect of personalization on customer outcomes. However, Wang et al. (2017) emphasize cognitive factors, such as performance and effort expectancy, in banking, while Lephale (2021) focuses on emotional loyalty in telecommunications, with privacy concerns serving as a moderator. The inclusion of prior experience in Wang's study and its absence in Lephale's highlights contextual and conceptual differences that limit cross-sector comparability.

Research Framework and Hypotheses

Grounded in the Technology Acceptance Model (TAM) developed by Davis (1989), this study leverages core constructs such as perceived usefulness (PU) and perceived ease of use (PEOU) to explain how customers interact with AI technologies, specifically chatbots and biometric authentication, in the banking sector. Although TAM is traditionally used to explain users' intention to adopt technology, this study extends its application by examining how the perceived usefulness and ease of use of AI-driven systems foster personalization, which in turn enhances customer engagement (Davis, 1989). In this context, AI technologies serve as tools that enable customers to experience more personalized services, tailored responses, seamless authentication, and 24/7 support, all of which contribute to higher satisfaction and a stronger emotional connection with the banking platform. When customers perceive these technologies as useful in improving their financial tasks and easy to use without significant effort, their cognitive and emotional responses are activated, leading to stronger behavioral

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engagement. Therefore, TAM is adapted in this study to conceptualize the psychological mechanisms through which AI technologies influence personalization (as an internal, perceived experience) and ultimately result in customer engagement (as the behavioral outcome). Despite notable critiques such as its reliance on self-reported data and limited consideration of contextual or cultural variables, TAM remains a relevant and flexible framework for understanding how technological perceptions translate into service personalization and engagement behaviours within digital banking environments.

The conceptual framework presented in Figure 1 shows the interconnections between the independent, dependent, and mediating variables. AI has a direct impact on both customer engagement (CE) and personalization (P), with personalization also influencing CE, thereby highlighting its mediating function. Artificial Intelligence (AI) represents chat-bots and biometric authentication, as the independent variable, while customer engagement is the dependent variable, and personalization acts as the mediator.

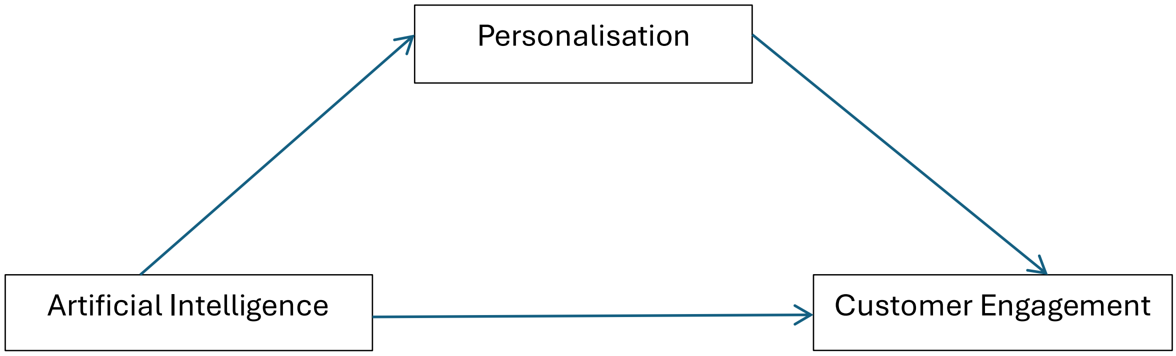

Figure 1
Conceptual Framework
Source: Self-made by the author

Guided by the existing scholarly evidence, the subsequent hypotheses are clearly articulated for empirical testing.

H_1: Biometric authentication positively affects customer engagement.

H_2: Biometric authentication positively affects personalization.

H_3: Chatbot usage positively affects customer engagement.

H_4: Chatbot usage positively affects personalization.

H_5: Personalisation positively affects customer engagement.

H_6: Personalization mediates the effect of chatbot adoption on customer engagement.

H_7: Personalization mediates the effect of biometric authentication on customer engagement.

Methodology

The study employed a descriptive survey research method with a cross-sectional design, which is suitable for gathering data on the variables under investigation. This approach is suitable as data is collected only once, making it a time- and cost-effective alternative to longitudinal studies that require repeated data collection. The study's target population comprises online retail customers of five Deposit Money Banks (DMBs) in the Abuja Municipal

Area Council (AMAC). The banks include Access Bank, First Bank, GTBank, United Bank of Africa, and Zenith Bank. The study's choice of online retail customers is due to their first-hand experience with AI-powered banking services, making them well-suited to provide feedback. The study employed simple random sampling, a probability sampling technique. The rationale for using the approach was that each individual in the population has an identical probability of being chosen, which eliminates bias in the selection process. This increases the fairness and scientific rigor of the study. The study employed G-Power to determine the minimum sample size, using a 95% statistical power and 5% margin of error with 119 respondents. The rationale for adopting G-Power is that it provides a systematic procedure for calculating the number of observations needed to detect an effect of a specified magnitude with a chosen level of confidence. To address the possibility of non-response bias and improve statistical power, the study increased the sample size by 30%, resulting in a total of 155 respondents. These participants were selected across the five banks. Data were collected using a validated, self-administered questionnaire consisting of closed-ended questions measured on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), specifically developed for this study. Descriptive statistics, specifically simple percentages, were used to analyze demographic data, while structural equation modeling (SEM) using SmartPLS 4 was used to test the proposed hypotheses.

Volume: 1, Issue: 2, 2025

Results

Rate of Response

As shown in Table 1, the study distributed 155 questionnaires, with 134 returned, representing an overall response rate of 86%. Following the exclusion of 15 incomplete responses, 119 valid questionnaires were retained, corresponding to a usable response rate of 77%, considered acceptable in organizational research (Dillman et al., 2014; Saunders et al., 2019).

Table 1
Response Rate

	Frequency / Rate
No. of distributed questionnaires	155
Returned questionnaires	134
Usable questionnaires	119
Excluded questionnaires	21
Questionnaires not returned	15
Overall Response Rate	86%
Valid (Usable) Response Rate	77%

Demographic Profile of Respondents

The study involved a total of 119 respondents (see Table 2). The gender distribution shows that 57.1% of the respondents were male, while 42.9% were female, indicating a relatively balanced sample with a slight majority of male respondents. This suggests that both genders were well represented, enhancing the credibility and inclusiveness of the findings. The age data reveal that participants were mainly in the 26–35 bracket, suggesting that responses came from individuals with meaningful workforce experience, thereby supporting the credibility of the survey feedback. The respondents demonstrated strong academic backgrounds, with a majority holding degrees, suggesting that their input was informed and credible for analyzing organizational systems and processes. Being a long-time customer of the banks suggests they

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possess deep knowledge of sector challenges and performance dynamics, enhancing the value of their contributions.

Table 2
Demographic Profile of Respondents

Demography	Frequency	Percentage
Gender		
Male	68	57.1
Female	51	42.9
Age		
15-25	14	11.8
26-35	60	50.4
36-45	24	20.2
46-60	21	17.6
Academic Qualification		
PhD/DBA/Mphil	4	3.4
M.Sc./MBA	11	9.2
B.Sc./HND	65	54.6
Diploma/NCE	27	22.7
SSCE	12	10.1
Years of Operation		
1-5	6	5.0
6-12	23	19.3
13-25	59	49.6
26-35	31	26.1
Total	**119**	**100**

Measurement Model Assessment

In PLS-SEM, the measurement model assessment for reflective constructs involves several key steps: evaluating item reliability (outer loadings between 0.4 and 0.7), internal consistency (Cronbach's Alpha and composite reliability between 0.7 and 0.9), convergent validity (AVE ≥ 0.50), and discriminant validity using the Fornell-Larcker criterion, which requires the square root of AVE to exceed inter-construct correlations (thresholds 0.85–0.90) (Hair et al., 2010; 2014; 2018; Henseler et al., 2009). The estimated PLS-SEM output results are depicted in Figure 2.

The study employed 32 questionnaire items, with 8 items measuring the independent variables (Biometric authentication and chatbot), the dependent variable (customer engagement), and the mediating variable of personalization. Out of the 32 items, the study removed five because the loadings were below 0.40. The excluded items were PSNL1, PSNL4, PSNL6, and PSNL7and PSNL8 only for the mediating variable. According to Hair et al. (2014), indicators with outer loadings between 0.40 and 0.70 should only be removed when their exclusion enhances composite reliability (rho-A and rho-C ≥ 0.70) and AVE (≥ 0.50). As shown in Figure 2 and Table 3, the indicators demonstrate acceptable reliability, with the structure accounting for far more than 50% of their variance.

International Journal of Business Sustainability

Volume: 1, Issue: 2, 2025

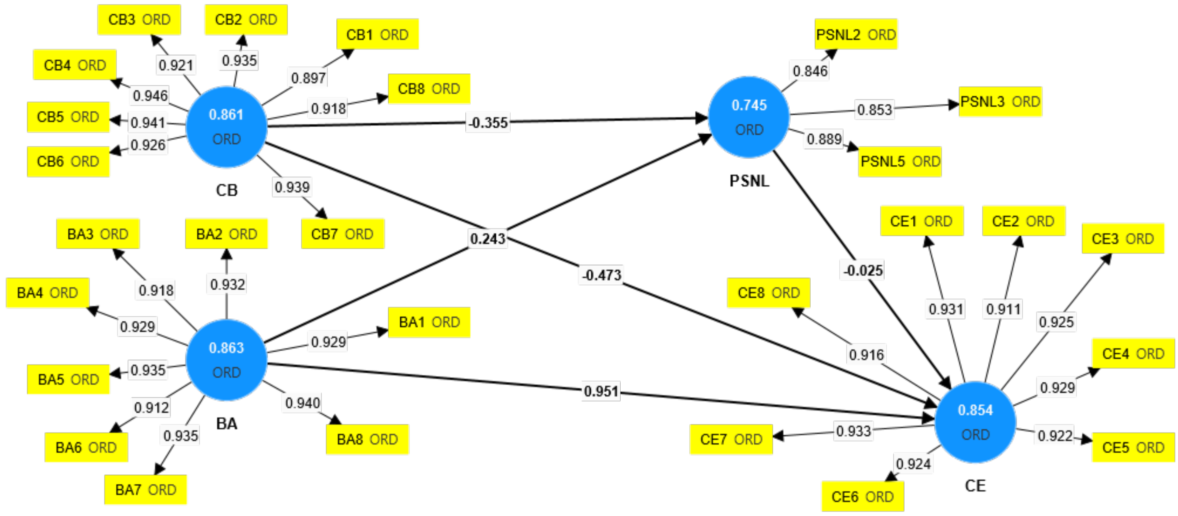

Figure 2
PLS-Path Model

Table 3
Convergent validity and internal consistency reliability

Construct	Item	Outer loadings	AVE	Cronbach's alpha	Rho_a	Rho_c
BA	BA1	0.929	0.863	0.977	0.978	0.98
	BA2	0.932				
	BA3	0.918				
	BA4	0.929				
	BA5	0.935				
	BA6	0.912				
	BA7	0.935				
	BA8	0.940				
CB	CB1	0.897	0.861	0.977	0.99	0.98
	CB2	0.935				
	CB3	0.921				
	CB4	0.946				
	CB5	0.941				
	CB6	0.926				
	CB7	0.939				
	CB8	0.918				
CE	CE1	0.931	0.854	0.976	0.976	0.979
	CE2	0.911				
	CE3	0.925				
	CE4	0.929				
	CE5	0.922				
	CE6	0.924				
	CE7	0.933				
	CE8	0.916				
PSNL	PSNL2	0.846	0.745	0.828	0.828	0.897
	PSNL3	0.853				
	PSNL5	0.889				

Source: Author's Computation using SmartPLS 4

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Convergent validity ensures that indicators of a construct are highly correlated and measure the same concept (Hair et al., 2022; Fornell & Larcker, 1981). This is evaluated using the Average Variance Extracted (AVE), which is calculated from the squared loadings of the items. According to Hair et al. (2014), AVE values must exceed 0.50 to be acceptable. Table 3 indicates that all AVE values fall between 0.745 and 0.863, confirming that each construct explains over 80% of its indicator variance, and thereby meeting the standard for convergent validity. The study evaluated measurement reliability using Cronbach's alpha and composite reliability to determine if the items effectively measure their respective constructs. Cronbach's alpha assumes equal outer loadings among indicators, whereas composite reliability accounts for variability (Hair et al., 2014). Since these methods approach reliability differently, both were used to ensure robust assessment. Reliability is considered acceptable when Cronbach's alpha exceeds 0.70, and composite reliability surpasses 0.708. Table 3 shows that all constructs meet these benchmarks, with alpha values from 0.828 to 0.977 and CR (rho-a and rho-c) values from 0.828 to 0.98, confirming strong internal consistency.

Discriminant validity reflects the degree to which a construct differs from other constructs within the model based on empirical data. It ensures that each construct captures a unique aspect of the phenomena being studied and does not overlap with others. This study employs two widely accepted methods to assess discriminant validity: the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT), as recommended by Hair et al. (2014). Discriminant validity is confirmed when each indicator loads highest on its associated latent construct compared to its loadings on other constructs (Hair et al., 2022; Henseler et al., 2015). These are valuable techniques for identifying potential redundancy among constructs. In contrast, the Fornell-Larcker criterion tests whether the square root of each construct's AVE exceeds its correlations with other latent variables. The results of the Fornell-Larcker and Heterotrait-Monotrait ratio analysis are presented in Table 4 and 5.

Table 4
Discriminant Validity: Fornell-Lacker Criterion

	BA	CB	CE	PSNL
BA	0.929			
CB	0.648	0.928		
CE	0.645	0.148	0.924	
PSNL	0.013	-0.197	0.081	0.863

Source: Author's Computation using Smart PLS 4.0

Table 5
Discriminant Validity: Heterotrait- Monotrait Ratio (HTMT)

	BA	**CB**	**CE**	**PSNL**
BA				
CB	0.662			
CE	0.658	0.149		
PSNL	0.049	0.212	0.09	

Source: Author's Computation using Smart PLS 4.

The results in Table 4 show that for every construct, the square root of the AVE is greater than its correlations with the remaining constructs, demonstrating satisfactory discriminant validity. For instance, BA has a square root of AVE of 0.929, which is higher than its correlations with CB (0.648), CE (0.645), and PSNL (0.013), respectively. The same applies to CB (0.928), CE (0.924), and PSNL (0.863), all of which exceed their corresponding inter-construct correlations. This indicates that each construct captures a unique aspect of the research model. The HTMT approach offers a robust assessment of discriminant validity in PLS-SEM, identifying issues that traditional methods may overlook. Constructs are considered distinct and valid when HTMT values are less than 0.85, supporting credible and accurate structural model estimates. The results in Table 5 indicate that all values are very low, confirming that personalization is empirically distinct from the other constructs in the model. This supports its role as a separate construct, potentially acting as a mediator between AI dimensions and Customer Engagement. The HTMT analysis confirms that the constructs measure unique theoretical concepts, providing confidence that the model is structurally sound for hypothesis testing in SmartPLS 4 (Chin,1998; Fornell & Larcker, 1981; Hair et al., 2022; Henseler et al., 2015).

Structural (Inner) Model Assessment

Following the confirmation of the measurement model's reliability and validity, the study proceeded to assess the structural model by examining relationships between customer engagement and the exogenous variables personalisation and Artificial Intelligence (biometric authentication and chatbots). The study employed a 5,000-sample bootstrapping approach with 119 respondents; the analysis followed guidelines by Hair et al. (2011, 2012, 2014, 2017) and Henseler et al. (2012) to evaluate β-values, T-statistics, p-values, R^2, Q^2, and f^2 for model significance and predictive strength.

The structural model assessment evaluated the direct and indirect relationships among biometric authentication (BA), chatbot usage (CB), personalization (PSNL), and customer engagement (CE). As shown in Table 6, BA exerts a strong and significant positive effect on CE (β = 0.951, t = 13.105), supporting H1. BA also significantly influences PSNL (β = 0.243, t = 2.128), thereby supporting H2. In contrast, the effect of CB on CE is negative and significant (β = –0.473, t = 4.689), leading to the rejection of H3. CB also shows a significant negative effect on PSNL (β = –0.355, t = 3.082), resulting in the rejection of H4. Meanwhile, PSNL does not significantly affect CE (β = –0.025, t = 0.373), so H5 is rejected.

Table 6
Path Coefficients for Direct Effects in the Inner Model

Hypotheses	Path	Std. Beta	Std. Error	t-values	p-values	Decision
H1	BA -> CE	0.951	0.073	13.105	0.000	Accepted
H2	BA -> PSNL	0.243	0.114	2.128	0.033	Accepted
H3	CB -> CE	-0.473	0.101	4.689	0.000	Rejected
H4	CB -> PSNL	-0.355	0.115	3.082	0.002	Rejected
H5	PSNL -> CE	-0.025	0.068	0.373	0.709	Rejected

Source: Author's Computation using Smart PLS 4.

Table 7 presents the results of the mediation analysis. The indirect effect of BA on CE through PSNL is not significant (β = –0.006, t = 0.330), indicating that H6 is rejected. Similarly, PSNL does not mediate the relationship between CB and CE (β = 0.009, t = 0.344), leading to the rejection of H7. Overall, the findings indicate that only the direct paths from BA to CE and BA

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to PSNL are supported, whereas all relationships involving CB and PSNL as predictors or mediators are not supported.

Table 7
Path coefficient for indirect effects of the structural model

Hypotheses	Path	Std. Beta	Std. Error	t-values	p-values	Decision
H6	BA -> PSNL -> CE	-0.006	0.019	0.33	0.741	Rejected
H7	CB -> PSNL -> CE	0.009	0.026	0.344	0.731	Rejected

Source: Author's Computation using Smart PLS 4.

The coefficient of determination, denoted as R^2, is a statistical metric used to evaluate how well the independent variable(s) explain the variation in the dependent variable within a regression model. It represents the proportion (percentage) of the variance in the dependent variable that is accounted for by the independent variable(s). According to Hair et al. (2014, 2017), R^2 values of 0.75, 0.50, and 0.25 can be interpreted as substantial, moderate, and weak, respectively, in the context of social science research. The independent variables in the model (Biometric Authentication and Chat-bots, with Personalization included) explain 54.1% of the variance in Customer Engagement. In line with the guidelines of Hair et al. (2022), this level of R^2 is considered moderately high, suggesting that the model provides a credible prediction of customer engagement. While personalisation indicates that the AI dimensions explain only 7.3% of the variance, which is considered weak predictive accuracy, it suggests that Biometric Authentication and Chat-bots have limited ability to predict in this model.

The f-square (f^2), also known as the effect size, is a statistical metric used in PLS-SEM to assess the impact strength of each exogenous (independent) variable on an endogenous (dependent) variable in the model. It shows how much a specific independent variable contributes to the R^2 value of a dependent variable when that predictor is included in the model. Cohen (1988) and Hair et al. (2022) indicated that 0.02 demonstrates a small effect, 0.15 a medium effect, and 0.35 a large effect. Table 8 shows that BA has a substantial effect on CE, with f^2 = 1.104, making it the strongest predictor in the model. Its impact on Personalization (PSNL) is small with f^2 = 0.037. CB shows a medium effect on CE, with f^2 = 0.262, while its effect on PSNL is small, at f^2 = 0.079. Finally, Personalization has almost no influence on CE, demonstrated by a negligible f^2 = 0.001, indicating that biometric security and chatbot interactions drive engagement more than personalization features.

Table 8
f-square effect size

Path	f-square	Interpretation
BA -> CE	1.104	large effect size
BA -> PSNL	0.037	Small effect size
CB -> CE	0.262	Medium effect size
CB -> PSNL	0.079	Small effect size
PSNL -> CE	0.001	Negligible effect

Source: Author's Computation using SmartPLS 4

Discussion

The aim of this research was to investigate the mediating role of personalization in the relationship between artificial intelligence and customer engagement among selected banks in Abuja, Nigeria. Artificial intelligence was measured by biometric authentication and a chatbot. Based on the hypothesis test results and mediation theory by Hair et al. (2014), the study examined indirect (mediated) effects of Artificial Intelligence (AI), proxied by Biometric Authentication (BA) and Chatbot (CB), on Customer Engagement (CE) through the mediating construct of Personalization (PSNL).

International Journal of Business Sustainability

Volume: 1, Issue: 2, 2025

The positive relationship found between Biometric authentication and customer engagement aligns with earlier works (Mandari & Koloseni, 2016; Noori & Jailani, 2022) who emphasized that Biometric authentication has a significant effect on customer engagement. This finding suggests that customers value biometric authentication, such as fingerprint, facial recognition, or voice authentication, as a modern, secure, and convenient method of accessing banking services. The findings support technology acceptance frameworks, indicating that perceived security and ease of access have a strong influence on customer engagement.

The negative but significant effect of chatbots on customer engagement implies that current chatbot systems are not delivering the level of service customers expect in these banks. These findings align with a study by Bhalerao and Joseph (2023), who revealed that chatbot performance was not satisfactory for Indian banking customers. In a context like Nigeria, people often appreciate human support that is empathetic and personalized. When a chatbot cannot provide this or gives scripted answers that do not resolve concerns, customers may become frustrated, leading to lower engagement. Even though chatbots are widely recognized for their speed and constant availability, they can still have a negative impact in service environments where personal interaction remains important.

Personalization was found to have a negative, yet non-significant, effect on customer engagement. This result suggests that improvements in personalization did not lead to meaningful increases in customer engagement, and in fact, engagement decreased slightly as personalization decreased. However, because the effect is not statistically significant, the relationship is weak and cannot be used to draw firm conclusions with confidence. The current study does not align with previous findings. This finding highlights the need for improvement in personalization strategies and may guide banks in redesigning their digital engagement approaches. This means that customer engagement in Nigerian banking is influenced more strongly by other factors, enabling researchers and managers to prioritize more effective strategies.

Similarly, the analysis shows that personalization does not mediate the relationship between biometric authentication and customer engagement. Essentially, biometric authentication alone does not rely on personalization to impact customer engagement, and current personalization practices are not strong enough to act as a meaningful bridge between biometric technology and user engagement. The current study does not corroborate previous findings. In the context of banking in Nigeria, customers may appreciate biometric authentication for convenience and security, but the way personalization is implemented, perhaps through automated or generic messages, does not enhance this effect. Customers may focus more on the reliability, speed, or security of biometric systems rather than personalized interventions. This finding may also suggest that the level of personalization in these banks is insufficient or not aligned with customers' expectations, which could influence their engagement in a meaningful way.

The analysis indicates that personalization does not mediate the relationship between chatbots and customer engagement. Despite the small positive beta coefficient, the extremely

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low t-value shows that the effect is statistically non-significant. This means that, as currently implemented, personalization does not enhance or strengthen the effect of chatbots on customer engagement. In other words, whether chatbots are used or not, personalization does not significantly influence how these automated systems impact customer engagement. While chatbots offer speed and availability, they may lack the nuanced understanding necessary to deliver meaningful, personalized experiences. Automated or scripted personalization efforts may not sufficiently address customer concerns, which could explain why personalization fails to mediate the relationship.

Conclusion

Based on the findings of this study, it is concluded that Biometric Authentication has a positive and significant effect on Customer Engagement. Chatbots have a negative but significant effect on customer engagement, while personalization has a negative and non-significant effect on Customer Engagement. The study also concludes that personalization does not mediate the relationship between biometric authentication, chatbots, and customer engagement. The negative finding implies that chatbot services, in their current implementation, may not effectively enhance personalization. This could be due to generic or scripted responses rather than individualized interaction. Additionally, the positive findings imply that integrating biometric features (such as facial or fingerprint recognition) enhances personalized user experiences. The following recommendations are put forward for consideration.

1. Given the positive impact of chatbots on the banking sector, Nigerian banks should invest in advanced, natural language processing-based chatbots that can simulate human-like conversations. Regular updates and continuous training of chatbot models will further improve the user experience and foster deeper engagement.
2. Considering the importance of biometric authentication in contributing to security, its impact on customer engagement is limited. Banks should, therefore, consider repositioning biometric tools as enablers of trust and incorporate them with other value-adding services to indirectly improve customer experience.
3. There is a need for the banks to prioritize the integration of personalized services within their AI platforms, particularly chatbots. Given that personalization mediates the relationship between AI technologies and customer engagement, enhancing tailored interactions can significantly improve customer satisfaction, trust, and loyalty.
4. For Artificial Intelligence tools to be effective, banks must ensure reliable digital infrastructure and secure backend systems. Ensuring robust cybersecurity measures, seamless app functionality, and consistent availability of AI services will enhance user trust and sustained engagement.

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