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Effect of AI-Driven Marketing Communication on Consumer Trust: A Study of Selected Fintech Companies in Lagos State, Nigeria

[1]Aka Deborah O.,
[2]Shorun Joel D.,
[3]Adegbuyi Kofoworola V., & [4]Ademilua Victor A.
[1,2,3&4]*Department of Business Management,*
College of Management and Social Sciences, Covenant University, Ota, Ogun State

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Corresponding Author:
Aka Deborah O.

Abstract

The rapid proliferation of artificial intelligence (AI) in Nigeria's fintech sector has fundamentally transformed how financial service providers communicate with consumers, yet the trust implications of this shift remain empirically underexplored. This study examined the effect of AI-driven marketing communication on consumer trust in selected fintech companies in Lagos State, Nigeria. AI-driven communication was operationalised across four dimensions: automated responsiveness, personalised AI communication, message accuracy, and data security while consumer trust was measured through customer reliability, credibility, confidence, and perceived service quality. Anchored in the Technology Acceptance Model (TAM/UTAUT) and the Mayer, Davis, and Schoorman Trust Theory, the study adopted a positivist, cross-sectional quantitative design. A total of 480 copies of a structured questionnaire were distributed electronically and in hard copy across seven NUC-accredited universities in Lagos State, selected via stratified proportionate random sampling from a population of 110,236. Of these, 466 were correctly completed and returned, yielding a valid response rate of 97.07%. Data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) with 5,000 bootstrap subsamples via SmartPLS 4. The null hypothesis was rejected at the 0.001 significance level. Findings revealed a hierarchical, security-anchored trust architecture in which data security exerted the strongest effect on all trust components, the study concludes that data security constitutes the foundational condition for consumer trust formation in the Lagos fintech context, and that investment in responsiveness and personalisation without a strong security and accuracy base yields suboptimal trust outcomes. Practically, the findings call for fintech operators to priorities transparent encryption communication, real-time accuracy mechanisms, and trust-layered personalisation strategies.

Background to the Study

In recent years, artificial intelligence has significantly reshaped how firms communicate with customers. Using chatbots, automated emails, predictive messaging, personalised notifications, and virtual assistants, companies now engage consumers with minimal human intervention. AI-powered communication systems improve service speed, reduce operational costs, and enhance content personalisation in modern marketing environments (Etuk, Akpan, & Awah, 2025). Communication is central to all marketing efforts and to the building of relationships between firms and consumers. In financial services especially, where perceived risk is high and products are largely intangible, consumer trust is critical for adoption, retention, and brand loyalty. Recent marketing studies show that trust directly influences digital purchase intention, repeat usage, and brand advocacy in technology-based services (Babatunde, Odejide, Edunjobi, & Ogundipe, 2024; Dudu, Alao, & Alonge, 2024).

In the fintech sector, AI-driven communication has become a core competitive marketing tool (Abinabo, Shagari, & Mashi, 2025). Fintech companies rely almost entirely on digital platforms to acquire users, resolve complaints, process transactions, and deliver personalised financial services. Unlike traditional banks that still operate physical branches, fintech firms operate as fully digital brands. As a result, the quality, responsiveness, accuracy, and security of their communications strongly shape consumer perception and trust (Graham, Nisar, Prabhakar, Meriton, & Malik, 2025). In Nigeria, the fintech industry has grown rapidly over the past decade, with Lagos emerging as the dominant innovation hub. Fintech firms such as Paystack, Flutterwave, OPay, Moniepoint, PalmPay, Carbon, and Kuda currently dominate digital payments, lending, savings, and remittance services (Oladeji & Ogunleye, 2023). The success of these firms depends largely on consumer confidence in digital systems, data privacy, transparency, and consistent communication.

A central dimension through which AI-driven communication shapes consumer trust is automated responsiveness, which refers to the capacity of AI systems to deliver immediate, consistent, and accurate replies to consumer enquiries without human intervention. In fintech environments where transactions are time-sensitive and service failures carry direct financial consequences, the speed and consistency with which automated systems respond significantly influences consumer reliability, that is, the degree to which consumers feel they can dependably count on a fintech firm to fulfil its service promises (Oyekunle, Matthew, Preston, & Boohene, 2024). When AI-powered chatbots and virtual assistants respond promptly and consistently across multiple touchpoints, they reinforce consumer confidence in the firm's operational integrity. Conversely, delayed responses, system errors, or contradictory automated messages erode reliability perceptions, increasing the likelihood of customer attrition (Okeke, 2025). In the Nigerian fintech context, where a significant proportion of users are first-time digital financial service adopters, the experience of automated responsiveness serves as a primary signal of institutional reliability (Oriji, Shonibare, Daraojimba, Abitoye, & Daraojimba, 2023).

Beyond responsiveness, the personalisation of AI-driven communication represents a critical determinant of consumer credibility, defined as the extent to which consumers perceive the information and recommendations provided by a fintech platform as honest, accurate, and relevant to their individual circumstances. Personalised AI communication involves the use of machine learning algorithms, behavioural data, and predictive analytics to tailor financial messages, product recommendations, and service interactions to individual users (Etuk, Akpan, & Awah, 2025). When consumers receive communications that reflect their financial behaviour, preferences, and history, they are more likely to perceive the firm as knowledgeable, trustworthy, and genuinely customer-centric (Bansal, Kumar, Dogra, Alohbi, & Saini, 2024). However, poorly executed personalisation, including irrelevant recommendations, erroneous profiling, or excessive data utilisation, can undermine credibility by raising concerns about the accuracy of AI judgements and the ethical use of consumer data (Eshiett, 2024; Lee, 2024). In the Nigerian fintech ecosystem, where consumer scepticism about digital institutions remains elevated, the credibility of AI-generated communications plays a decisive role in shaping sustained engagement (Benjamin, Amajuoyi, & Adeusi, 2024).

The accuracy of messages delivered through AI-driven communication channels constitutes another significant driver of consumer trust, specifically through its effect on consumer confidence, defined here as the degree of certainty consumers hold regarding the correctness of information, transaction records, and service outcomes communicated by fintech platforms. Message accuracy encompasses the precision of transaction notifications, account summaries, loan disclosures, and promotional offers generated by automated systems (Abinabo, Shagari, & Mashi, 2025). Inaccurate automated messages, whether resulting from system errors, algorithmic miscalculations, or poorly designed natural language generation, can produce direct financial harm and significantly damage consumer confidence in the integrity of a fintech firm. In competitive markets such as Lagos, where switching costs are low and alternative platforms are readily accessible, a single instance of material inaccuracy in automated communication can trigger irreversible trust breakdown (Oyeniyi, Ugochukwu, & Mhlongo, 2024). The relationship between message accuracy and consumer confidence is therefore particularly acute in fintech, where communication errors carry consequences that extend beyond reputational damage into tangible financial risk for the consumer (Alhajjaj & Ahmad, 2022).

Data security, encompassing the technical and procedural safeguards that protect consumer financial information from unauthorised access, misuse, or breach, plays a foundational role in shaping consumers'perceived service quality in AI-driven fintech environments. Perceived service quality, in this context, refers to consumers'overall assessment of the superiority of a fintech firm's service offering relative to their expectations, a judgement increasingly mediated by concerns about how AI systems handle sensitive personal and financial data (Graham, Nisar, Prabhakar, Meriton, & Malik, 2025). AI-driven communication systems necessarily collect, process, and transmit substantial volumes of consumer data to enable personalisation, fraud detection, and real-time service delivery. Where consumers perceive these systems as secure, transparent in their data practices, and compliant with regulatory expectations, their overall assessment of service quality is enhanced (Frank, Jacobsen, Søndergaard, & Otterbring, 2023). Conversely, data breaches, opaque privacy policies, and incidents of unauthorised data use substantially degrade perceived service quality and, by extension, overall consumer trust. In Nigeria's evolving regulatory environment, concerns about data security in fintech have become increasingly prominent among both consumers and policymakers, making this dimension especially relevant to understanding trust dynamics in the sector (Oyekunle, Matthew, Preston, & Boohene, 2024).

Despite the growing deployment of AI in fintech operations, empirical studies that simultaneously examine automated responsiveness, personalised communication, message accuracy, and data security as distinct pathways through which AI-driven communication affects consumer trust, across reliability, credibility, confidence, and perceived service quality respectively, remain limited, particularly within the Nigerian context (Benjamin, Amajuoyi, & Adeusi, 2024). This study therefore seeks to bridge this gap by empirically examining the effect of AI-driven communication on consumer trust among selected fintech companies in Lagos, Nigeria, with a view to informing managerial practice, policy formulation, and future research in this domain (Sharma & Adeniyi, 2025).

Objective of the Study

This study examined the influence of automated responsiveness on Consumer Trust (Customer Reliability, Customer Credibility, Consumer Confidence, and Customer perceived service-quality) among selected fintech companies in Lagos, Nigeria,

Research Question

How does automated responsiveness influence Consumer Trust (Customer Reliability, Customer Credibility, Consumer Confidence, and Customer perceived service-quality) among selected fintech companies in Lagos, Nigeria,

Research Hypothesis

Automated responsiveness has no significant effect on Consumer Trust (Customer Reliability, Customer Credibility, Consumer Confidence, and Customer perceived service-quality) among selected fintech companies in Lagos, Nigeria,

Literature Review

This section presents the conceptual, empirical, and theoretical review of the study's dependent and independent variables and their related constructs.

Artificial Intelligence: Definition and Evolution

Artificial intelligence (AI) refers to the simulation of human cognitive processes including learning, reasoning, problem-solving, perception, and natural language understanding by computer systems (Oxfordson, 2026). The concept of AI emerged formally in the mid-twentieth century and has since undergone several phases of evolution: from rule-based expert systems in the 1970s and 1980s, to machine learning paradigms in the 1990s, and more recently to deep learning, natural language processing (NLP), and generative AI systems in the 2010s and 2020s (Daudu, Osimen, & Abubakar, 2025). Early AI systems were largely symbolic and deterministic, operating on pre-programmed rules. The advent of statistical machine learning shifted AI toward data-driven approaches, enabling systems to improve performance through experience without being explicitly programmed. Deep learning, a subset of machine learning built on multi-layered neural networks, has particularly transformed AI capabilities, enabling high-accuracy performance in tasks such as image recognition, speech processing, and text generation (Uzoaru et al., 2025). In the context of financial services, AI has evolved from backend fraud detection and algorithmic trading tools to front-end customer-facing systems including chatbots, virtual assistants, personalisation engines, and automated advisory platforms. This trajectory reflects the broader maturation of AI from a research curiosity to a commercially deployed infrastructure reshaping industry globally, and particularly within African fintech ecosystems (Ogundele et al., 2025).

AI in Financial Services

The application of AI in financial services has accelerated rapidly over the past decade, driven by increasing data availability, declining computational costs, and intensifying competitive pressures. AI technologies in financial services can be categorised into four broad functional domains: risk management and fraud detection, credit scoring and lending, customer service automation, and regulatory compliance (Onoja, Abba, Edeh, Akpadaka, & Dang, 2026). In each domain, AI reduces operational costs, improves decision accuracy, and enhances customer experience. In fraud detection, machine learning algorithms analyse transactional patterns in real time to identify anomalies indicative of fraudulent activity. In credit scoring, AI leverages alternative data sources including mobile phone usage histories, social network data, and mobile money transactions to assess the creditworthiness of individuals who lack formal banking records, thereby supporting financial inclusion objectives (Ogundele et al., 2025).

Customer service automation represents one of the most visible applications of AI in financial services. Chatbots, virtual assistants, and interactive voice response systems powered by NLP allow financial institutions to handle large volumes of customer inquiries simultaneously, at any time, and at significantly lower cost than human agents (Abdulquadri, Mogaji, Kieu, & Nguyen, 2021). This transformation of customer communication has profound implications for consumer trust and experience, particularly in emerging economies where access to physical banking infrastructure may be limited. The role of AI in advancing sustainable banking and improving service efficiency has been empirically documented in Nigeria. Ogundele et al. (2025) found that AI adoption in selected Nigerian quoted banks was significantly associated with improvements in service delivery speed, error reduction, and customer satisfaction, though challenges relating to infrastructure quality and regulatory gaps persisted. Such evidence underscores the importance of understanding how AI-driven communication specifically shapes consumer trust in the Nigerian fintech context.

Fintech: Evolution and Conceptual Boundaries

The term "fintech" a portmanteau of financial technology broadly describes the application of technology to deliver or improve financial services. While the convergence of finance and technology predates the internet era, the current generation of fintech is characterized by digital-native business models that bypass traditional financial intermediaries, leveraging mobile platforms, cloud computing, big data analytics, blockchain, and AI to deliver services ranging from payments and lending to insurance and wealth management (Daudu et al., 2025). The evolution of fintech can be traced through three distinct waves. The first wave (pre-2008) was characterised by the digitisation of back-end infrastructure and the emergence of electronic payment systems. The second wave (2008–2015), catalysed by the global financial crisis and the proliferation of smartphones, saw the rise of peer-to-peer lending, mobile banking, and digital wallets. The third wave (2015–present) is defined by AI integration, open banking, and the emergence of platform-based ecosystems that co-create value with consumers and third-party developers (Daudu et al., 2025).

In Nigeria, the fintech sector has grown explosively, fueled by a young, technology-literate population, widespread mobile phone penetration, and substantial gaps in traditional banking access. Lagos, as the economic capital and largest city, serves as the primary hub for fintech innovation in sub-Saharan Africa (Abdulquadri et al., 2021). The Central Bank of Nigeria (CBN) has progressively liberalised the regulatory environment through payment system frameworks, licensing regimes, and regulatory sandbox programmes, encouraging the proliferation of fintech startups and the digital expansion of incumbent banks (Aidonojie, Majekodunmi, & Adeyemi-Balogun, 2023). However, the rapid growth of fintech in Lagos has also introduced new consumer protection challenges, particularly around data privacy, algorithmic transparency, and the risks of over-reliance on automated systems. These challenges intersect directly with questions of consumer trust, making the Lagos fintech ecosystem a particularly salient context for studying how AI-driven communication dimensions shape trust perceptions.

AI-Driven Communication and Applications

AI-driven communication refers to the deployment of AI technologies to mediate, automate, personalise, and optimize interactions between organisations and their customers. In the fintech sector, AI-driven communication manifests across multiple touchpoints: automated chatbots and virtual assistants that handle queries; recommendation engines that surface personalised product offers; notification systems that deliver real-time transaction alerts; and AI-assisted compliance tools that communicate regulatory information to customers (Etuk, Akpan, & Awah, 2025). The theoretical grounding of AI-driven communication draws on multiple disciplines, including human-computer interaction (HCI), information systems, marketing communications, and behavioural science. Central to this literature is the recognition that effective digital communication must be responsive, relevant, accurate, and secure to engender positive consumer outcomes including trust, satisfaction, and continued usage intention (Jafri, Amin, Abdul-Rahman, & Nor, 2024). Four dimensions of AI-driven communication are particularly relevant to this study: automated responsiveness, personalised communication, message accuracy, and data security. Each dimension captures a distinct aspect of how AI mediates communication in ways that can either build or erode consumer trust. The following subsections define and explore each dimension in turn, followed by the corresponding consumer trust components.

Automated Responsiveness

Automated responsiveness refers to the capacity of AI-powered communication systems to generate timely, contextually appropriate, and consistent replies to customer inquiries, without the delay inherent in human-staffed service channels. In fintech environments, automated responsiveness is primarily delivered through chatbots, interactive voice response (IVR) systems, automated email and SMS notifications, and AI-assisted helpdesks (Uzoaru et al., 2025).

The literature identifies two primary dimensions of automated responsiveness: speed of response and contextual adequacy. Speed refers to the latency between a customer inquiry and the system-generated reply, which in AI-powered systems can be near-instantaneous. Contextual adequacy, on the other hand, concerns the degree to which the automated response correctly understands and addresses the customer's underlying intent a dimension far more challenging to achieve, particularly for complex, open-ended, or emotionally charged queries (Hennighausen, Navarro-Schar, & Eller, 2025).

Research on chatbot adoption in Nigerian financial services reveals a clear gap between speed and contextual quality. Abdulquadri et al. (2021) found that while Nigerian bank customers appreciated the immediacy of chatbot responses, satisfaction levels dropped sharply when chatbots failed to understand dialect, local expressions, or context-specific financial queries. Similarly, Uzoaru et al. (2025) highlighted the significant challenges of developing locally adaptive conversational agents in Nigeria, particularly for users whose primary language is Hausa or other indigenous languages rather than formal English. The relationship between automated responsiveness and customer trust is theoretically complex. High responsiveness can signal organisational reliability and commitment to customer service, thereby reinforcing trust. However, when responsiveness is achieved through rigid, script-bound automation that fails to handle exceptions gracefully, it can paradoxically erode trust by communicating institutional indifference to the individual customer's circumstances (Okeke, 2025). This duality underlies Hypothesis H_{01} of this study, which examines whether automated responsiveness has a significant effect on customer reliability in Lagos fintech companies.

Personalised AI-Driven Communication

Personalisation in AI-driven communication refers to the tailoring of content, tone, timing, channel, and product or service recommendations to the individual characteristics, preferences, behaviours, and context of each customer. In fintech, personalisation is enabled by the analysis of large datasets transaction histories, app usage patterns, browsing behaviour, and demographic profiles through machine learning algorithms that identify patterns and predict individual needs (Abdulquadri, 2025). The importance of personalisation in financial services communication is well established. Customers who receive communications that are relevant to their specific situation such as timely savings prompts, customised loan offers calibrated to their repayment capacity, or proactive fraud alerts based on their typical transaction patterns report higher levels of satisfaction, stronger brand loyalty, and greater willingness to share data with their service provider (Ezenwafor, Ayodele, & Esiti, 2022). These outcomes collectively enhance consumer credibility perceptions, as personalisation signals that the organisation understands and cares about the individual customer.

However, the deployment of personalisation in the Lagos fintech context faces distinctive challenges. Digital literacy disparities mean that a significant segment of the population may not recognise personalised communication as genuinely tailored, or may alternatively interpret it with suspicion as evidence of surveillance (Farinloye, Omotoye, Oginni, Moharrak, & Mogaji, 2024). Furthermore, the lack of multilingual AI systems capable of personalising communication in Yoruba, Igbo, Hausa, and other major Nigerian languages significantly constrains the inclusivity and effectiveness of personalisation strategies. Abdulquadri (2025) argues that effective personalisation in self-service technologies must preserve user autonomy, ensuring that customers retain the ability to override recommendations and adjust preferences, rather than experiencing personalisation as coercive or intrusive. This autonomy-preserving dimension of personalisation is particularly important in contexts where algorithmic authority may be perceived with scepticism, as in emerging markets with limited regulatory oversight of AI systems. Hypothesis H_{02} of this study investigates whether personalised AI-driven communication has a significant effect on customer credibility in Lagos fintech services.

Message Accuracy

Message accuracy in the context of AI-driven communication refers to the correctness, completeness, clarity, and transparency of information delivered to customers through automated and algorithmically mediated channels. In financial services, where errors in information can have direct monetary consequences, message accuracy is a critical determinant of consumer trust and confidence (Dantsoho, Ringim, Hasnan, & Kura, 2021).

Message accuracy encompasses several distinct but interrelated attributes. Factual correctness ensures that the information provided such as account balances, interest rates, transaction statuses, and loan eligibility criteria is accurate and up to date. Completeness ensures that all material information relevant to the customer's decision is disclosed, without omission of important conditions or risks. Clarity ensures that information is communicated in language appropriate to the customer's level of financial literacy. Transparency ensures that AI-driven systems disclose their automated nature and the basis of any recommendations they make (Onoja, Abba, Edeh, Akpadaka, & Dang, 2026).

The role of bank reputation as a moderating factor in the relationship between AI communication accuracy and consumer outcomes has been empirically demonstrated.

Dantsoho et al. (2021) found that among Nigerian e-banking customers, the positive effect of AI quality including message accuracy on continuous usage intention was significantly stronger for banks with higher reputations, suggesting that institutional trust amplifies the impact of accurate communication. This moderating effect has important implications for fintech startups, which typically operate with lower brand equity than established banks. Inaccurate or misleading AI communication can rapidly and severely damage consumer confidence. In sensitive financial contexts such as loan approvals, investment returns, or fraud alerts, a single significant error in automated messaging can trigger loss of trust that is difficult to rebuild (Onoja, Abba, Edeh, Akpadaka, & Dang, 2026). This vulnerability underscores the importance of robust quality assurance mechanisms, human oversight protocols, and transparent error-correction procedures in fintech AI communication systems. Hypothesis H_{03} of this study examines whether message accuracy has a significant effect on consumer confidence in fintech companies.

Data Security in AI-Driven Communication

Data security in the context of AI-driven fintech communication refers to the robustness of technical, organisational, and procedural measures that protect consumer data including personal identification information, transaction records, biometric data, and behavioural profiles from unauthorised access, breach, misuse, or loss. In AI-powered systems, the scale and sensitivity of data collected and processed create distinctive security challenges that go beyond those of traditional IT systems (Onatuyeh et al., 2025).

AI systems in fintech collect and process data across an extensive surface area: mobile applications, web interfaces, biometric authentication systems, third-party API integrations, and cloud storage environments. Each interface represents a potential vulnerability, and the aggregation of diverse data streams creates high-value targets for cybercriminal exploitation. The Nigerian financial sector has experienced a significant increase in cyber threats including phishing, identity theft, SIM swap fraud, and account takeover attacks, which directly undermine consumer confidence in digital financial services (Esoimeme, 2024).

Onatuyeh et al. (2025) empirically examined the relationship between cybersecurity practices and customer trust in Nigerian businesses, finding that perceived data security was one of the strongest predictors of consumer trust across both banking and fintech sectors. Critically, however, their findings also revealed that current data security implementations were rated as inadequate by a substantial proportion of Nigerian consumers, reflecting a perception gap between the security measures deployed by fintech firms and customers' expectations. This gap is further exacerbated by weak and inconsistently enforced data protection regulations, as highlighted by Aidonojie et al. (2023), who documented the limitations of Nigeria's legal framework for fintech data privacy prior to the passage of the Nigeria Data Protection Act 2023. The role of data security extends beyond technical protection to encompass transparency in data practices clearly communicating to customers how their data is collected, stored, processed, shared, and used by AI systems. Onoja et al. (2026) found that AI disclosure practices in Nigerian deposit money banks had a significant positive effect on financial performance, suggesting that transparency about AI and data use functions as a trust-building signal. Hypothesis H_{04} of this study investigates whether data security of AI-driven communication has a significant effect on customer-perceived service quality in fintech firms.

AI-Driven Communication and Consumer Trust

Consumer trust in the context of digital financial services refers to the willingness of a customer to be vulnerable to the actions of a service provider based on positive expectations about that provider's ability, benevolence, and integrity (Mayer, Davis, & Schoorman, 1995). Trust in AI-driven fintech environments is a multidimensional construct that encompasses cognitive, affective, and behavioural dimensions: cognitive trust involves belief in the competence and reliability of the system; affective trust involves positive feelings of security and comfort; and behavioural trust is evidenced by the willingness to engage in transactions and share personal data with the service provider (Bello & Karupiah, 2022).

Consumer trust is considered a critical antecedent of digital service adoption and sustained usage. In fintech specifically, where consumers transact with entities that may lack the physical presence, regulatory visibility, and brand heritage of traditional banks, trust is a particularly scarce and valuable resource. Onatuyeh et al. (2025) established that among Nigerian businesses including fintech firms, perceived security and facilitating conditions were significant antecedents of trust, which in turn positively influenced intention to use digital banking services. This study operationalises consumer trust across four components customer reliability, customer credibility, consumer confidence, and perceived service quality each of which captures a distinct dimension of the trust construct in the fintech context. These are examined in the following subsections.

The Technology Acceptance Model (TAM) and Its Extensions

The Technology Acceptance Model (TAM), proposed by Davis (1989), provides the foundational theoretical framework for this study. Rooted in the Theory of Reasoned Action (TRA) and the Theory of Planned Behaviour (TPB), TAM posits that the adoption of a technology is primarily determined by two cognitive beliefs: Perceived Usefulness (PU) the degree to which a user believes the technology will enhance their performance and Perceived Ease of Use (PEOU) the degree to which using the technology is free of effort. These beliefs jointly shape users' attitudes toward the technology, their behavioural intentions to use it, and ultimately their actual usage behaviour (Davis, 1989).

TAM has been widely applied to understand consumer adoption of digital financial services, including internet banking, mobile banking, and fintech platforms. Its core constructs map naturally onto the AI-driven communication context: consumers' perceptions of how useful automated communication systems are (PU) and how easy they are to interact with (PEOU) are expected to influence their attitudes toward the fintech service provider and their trust in the service (Ayanwale et al., 2025). When AI-driven communication is perceived as useful providing timely, accurate, and personalised information and easy to engage with requiring minimal cognitive effort to understand and navigate it is expected to generate positive attitudes and stronger trust.

TAM2, proposed by Venkatesh and Davis (2000), extended the original model by incorporating additional determinants of PU, including subjective norms (social influence), image, job relevance, output quality, and result demonstrability. These extensions are particularly relevant in the Lagos fintech context, where social influence and peer recommendation play significant roles in fintech adoption decisions, particularly among younger, urban consumers who rely heavily on social networks for financial product information.

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh, Morris, Davis, and Davis (2003), further synthesised TAM with multiple competing models, proposing four core determinants of usage intention and behaviour: performance expectancy, effort expectancy, social influence, and facilitating conditions. UTAUT's broader scope accommodates the influence of infrastructure quality a critical facilitating condition in Nigeria on the effectiveness of AI-driven communication systems in building consumer trust (Farinloye et al., 2024).

In applying TAM and its extensions to the present study, it is argued that each of the four AI-driven communication dimensions (automated responsiveness, personalisation, message accuracy, and data security) functions as a determinant of perceived usefulness and perceived ease of use. Highly responsive, personalised, accurate, and secure AI communication enhances PU by demonstrating that the fintech service can effectively meet the consumer's informational and transactional needs, and enhances PEOU by reducing cognitive load and uncertainty. These perceptions, in turn, positively influence the consumer trust components (customer reliability, credibility, confidence, and perceived service quality) that constitute the dependent variable of this study. Despite its strengths, TAM has important limitations in this context. The model focuses primarily on initial adoption decisions and individual rational cognition, paying insufficient attention to the emotional, relational, and institutional dimensions of trust that are particularly salient in fintech environments. TAM also does not account for how trust evolves over time through repeated interactions, nor does it adequately capture the role of social and cultural contexts in shaping technology perceptions (Olubiyi, 2025). These limitations are addressed by integrating TAM with the Mayer et al. Trust Theory.

Methodology

The study adopted a positivist research philosophy, which emphasized the use of natural-resource methods to investigate social phenomena, particularly the relationship between AI-driven marketing communication and consumer trust. The study adopted a cross-sectional quantitative design. The sample size for this study was determined using the Yamane (1967) formula, which remains widely used in business and marketing research involving finite populations (Okechukwu, Odo, & Nnabuko, 2024; Oyetade, Bello, &

Akinlalu, 2024). A total of 480 copies of a structured questionnaire were distributed electronically and in hard copy across seven National Universities Commission-accredited universities in Lagos State, selected via stratified proportionate random sampling from a population of 110,236. Of these, 466 were correctly completed and returned, yielding a valid response rate of 97.07%. Data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) with 5,000 bootstrap subsamples via SmartPLS 4. The null hypothesis was rejected at the 0.001 significance level. The Cronbach's alpha coefficients were interpreted according to the following criteria: Excellent = a ≥ 0.9 – (Stake's testing is high) Good = 0.7 ≤ a < 0.9 – (Stake's testing is low) Acceptable = 0.6 ≤ a < 0.7 Unacceptable = 0.5 ≤ a < 0.6 Poor = a < 0.5

Test of Hypothesis

The hypothesis is tested using PLS-SEM implemented in SmartPLS 4 (Ringle, Wende, & Becker, 2024), with 5,000 bootstrap subsamples (Hair et al., 2022). For each hypothesis, the measurement model is evaluated first through composite reliability (CR ≥ 0.80), average variance extracted (AVE ≥ 0.50), Cronbach's alpha ($\alpha \geq 0.70$), and outer factor loadings (≥ 0.50). The inner structural model is assessed through R^2, f^2 (Cohen, 1988), path coefficients (β), T-statistics, and Q^2predict. A hypothesis is rejected when $p < 0.05$ ($T > 1.96$).

Hypothesis: Automated Responsiveness and Consumer Trust

H_0: Automated responsiveness has no significant effect on Consumer Trust (Customer Reliability, Customer Credibility, Consumer Confidence, and Customer Perceived Service Quality) in fintech companies in Lagos.

Table 1: Factor Loadings for Automated Responsiveness on Consumer Trust

Construct / Indicator	Outer Loading	VIF	CR	AVE	Cronbach's α	Items
Automated Responsiveness			0.875	0.636	0.809	4
AR1	0.818	1.765				
AR2	0.789	1.658				
AR3	0.787	1.660				
AR4	0.794	1.565				
Customer Reliability			0.852	0.590	0.769	4
CR1	0.795	1.597				
CR2	0.761	1.567				
CR3	0.780	1.502				
CR4	0.735	1.390				
Customer Credibility			0.844	0.577	0.762	4
CC1	0.845	1.587				
CC2	0.796	1.573				
CC3	0.671	1.411				
CC4	0.716	1.406				
Consumer Confidence			0.853	0.593	0.776	4
CON1	0.780	1.433				
CON2	0.672	1.443				
CON3	0.822	1.709				
CON4	0.798	1.531				
Customer Perceived Service Quality			0.881	0.649	0.820	4
PSQ1	0.826	1.768				
PSQ2	0.806	1.657				
PSQ3	0.808	1.566				
PSQ4	0.783	1.590				

Source: Smart PLS 4 Algorithm Output (Researchers' Survey, 2026)

Table above confirms that all constructs satisfy minimum psychometric thresholds. The Automated Responsiveness construct achieves CR = 0.875, AVE = 0.636, and Cronbach's alpha = 0.809, with factor loadings ranging from 0.787 (AR3) to 0.818 (AR1), all above 0.70. VIF values of 1.565–1.765 are well below the 5.0 threshold for multicollinearity. AR1 (chatbot promptness) is the strongest indicator, consistent with the frequency distribution, which found that this item had the highest agreement rate (77.2%). The four Consumer Trust constructs all achieve CR values above 0.844, AVE values of 0.577–0.649, and Cronbach's alphas above 0.762. Customer Perceived Service Quality achieves the strongest measurement properties (CR = 0.881, AVE = 0.649). CC3 records the lowest loading overall (0.671), indicating that advisory credibility shares somewhat less variance with the credibility construct than the other three items, consistent with the interpretation that AI financial advice credibility is a partially distinct sub-dimension. All VIF values across all constructs remain below 2.0, confirming the absence of multicollinearity. The measurement model for H_{01} satisfies all validity and reliability criteria (Hair et al., 2022).

Evaluation of Inner Structural Model for H_0

Automated Responsiveness explains 22.5% of variance in Customer Reliability ($R^2 = 0.225$; $R^2adj = 0.223$), 24.8% in Customer Credibility ($R^2 = 0.248$; $R^2adj = 0.247$), 21.3% in Consumer Confidence ($R^2 = 0.213$; $R^2adj = 0.211$), and 24.2% in Customer Perceived Service Quality ($R^2 = 0.242$; $R^2adj = 0.240$). Effect sizes (f^2) range from 0.270 (Consumer Confidence) to 0.330 (Customer Credibility), classified as medium-to-large per Cohen's (1988) benchmarks. Q^2predict values confirm satisfactory out-of-sample predictive relevance across all four endogenous constructs (Reliability = 0.215; Credibility = 0.238; Confidence = 0.203; PSQ = positive), establishing that the model possesses both explanatory power and predictive accuracy.

Figure 1: Predictive R-Path Coefficients of Automated Responsiveness and Consumer Trust.

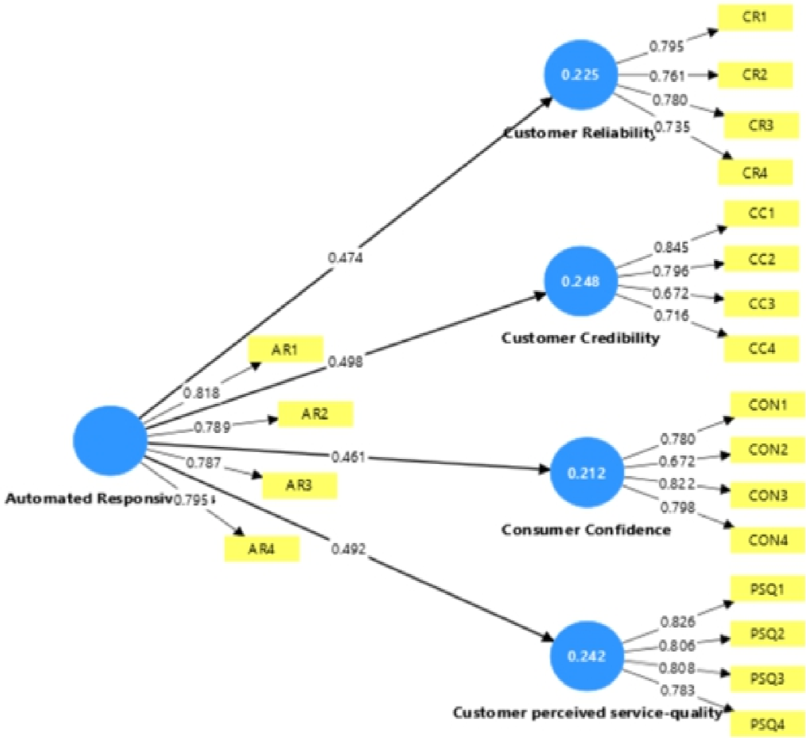

Figure 1 above displays the SmartPLS 4 path model for H_0. The two thickest structural arrows connecting to Customer Credibility ($\beta = 0.498$) and Customer Perceived Service Quality ($\beta = 0.492$) visually confirm that automated responsiveness most powerfully influences cognitive-evaluative and service-assessment trust dimensions. The arrows to Customer Reliability ($\beta = 0.474$) and Consumer Confidence ($\beta = 0.461$) are slightly thinner but remain substantially weighted, confirming a universally positive but differentiated effect profile. The R^2 values within each trust component circle (0.225 for Reliability, 0.248 for Credibility, 0.213 for Confidence, 0.242 for PSQ) communicate the proportion of variance explained by automated responsiveness alone, with Credibility emerging as the dimension most responsive to this communication feature.

Figure 2: Bootstrapping and p-values for Automated Responsiveness and Consumer Trust.

Figure 2 confirms, through T-statistics (all above 10.0) and 95% confidence intervals entirely above zero, that the positive direction and significance of all effects are statistically secure across 5,000 bootstrap subsamples. The P-values of < 0.001 for all four paths confirm that the probability of observing effects this large under the null hypothesis is less than 1 in 1,000, definitively supporting the rejection of H_{01}.

Table 2: Path Coefficients for Automated Responsiveness and Consumer Trust

Path Relationship	β (O)	STDEV	T-Statistic	P-Value	Decision
AR → Customer Reliability	0.474	0.041	11.540	<0.001	Significant H_{01} Rejected
AR → Customer Credibility	0.498	0.040	12.487	<0.001	Significant H_{01} Rejected
AR → Consumer Confidence	0.461	0.043	10.627	<0.001	Significant H_{01} Rejected
AR → Customer Perceived Service Quality	0.492	0.043	11.332	<0.001	Significant H_{01} Rejected

Source: SmartPLS 4 Algorithm Output (Researcher's Survey, 2026)

Table 3: R^2, R^2 Adjusted, and f^2 Effect Sizes for the H_0

Endogenous Construct	R^2	R^2 Adj.	f^2	Effect Size Classification
Customer Reliability	0.225	0.223	0.290	Medium–Large
Customer Credibility	0.248	0.247	0.330	Medium–Large
Consumer Confidence	0.213	0.211	0.270	Medium
Customer Perceived Service Quality	0.242	0.240	0.319	Medium–Large

Source: SmartPLS 4 Bootstrapping Output (Researcher's Survey, 2026)

Table 3 confirms all four paths are significant at $p < 0.001$, with T-statistics substantially exceeding the 1.96 critical value. The path to Customer Credibility is strongest (β = 0.498, T = 12.487), indicating that a one-standard-deviation increase in perceived automated responsiveness is associated with approximately a half-standard-deviation increase in credibility perceptions. The very low bootstrapped standard deviation (0.040) confirms exceptional estimation stability. The path to Consumer Confidence is weakest (β = 0.461), reflecting that emotional resolution of vulnerability requires more than demonstrated operational competence. The path to Customer Perceived Service Quality (β = 0.492, T = 11.332) confirms responsiveness as a primary service quality marker. The null hypothesis H_0 is rejected: automated responsiveness has a significant positive effect on all four components of consumer trust in Lagos fintech companies.

Discussion of Findings

The empirical findings stress-test the study's two theoretical frameworks TAM/UTAUT and Mayer et al.'s (1995) Trust Theory against the specific social, institutional, and technological realities of the Lagos fintech context. This section evaluates what the findings confirm and what they complicate within each framework, articulates the specific theoretical contributions generated by their integration, and presents the study's overarching theoretical claim: a three-tier security-anchored consumer trust architecture distinctive to institutionally constrained fintech markets. The Technology Acceptance Model (Davis, 1989) predicts that perceived usefulness (PU) and perceived ease of use (PEOU) of technology features generate positive user evaluations and continued engagement. In this study's framework, the four AI communication dimensions map onto TAM antecedents: automated responsiveness enhances PEOU by reducing the cognitive effort of service interaction; personalisation enhances PU by increasing the relevance of information received; message accuracy enhances PU by making AI-generated information instrumentally valuable for financial decisions; and data security enhances PEOU by reducing perceived risk-related cognitive burden. The consistently significant positive paths from all four dimensions to all four Consumer Trust components are broadly consistent with TAM's core prediction.

TAM predicts roughly equivalent trust returns from all features that enhance PU or PEOU, without distinguishing the hierarchy of effects generated by different communication dimensions. The data refute this: the f^2 differential between Data Security (average: 0.711) and Personalisation (average: 0.206) is more than threefold, a gap TAM cannot theories, predict, or explain. TAM is necessary but insufficient for understanding AI-driven consumer trust in fintech: it specifies the general cognitive mechanism but cannot account for the hierarchy of effects. UTAUT's (Venkatesh et al., 2003) facilitating conditions construct provides additional leverage: the infrastructure-constraining environment of Lagos network variability, NLU limitations, regulatory uncertainty moderates responsiveness's ability to generate sustained confidence effects, consistent with Farinloye et al.'s (2024) finding of non-significant responsiveness effects ($\beta = 0.08$, $p = 0.31$) for low-digital-literacy subgroups where facilitating conditions are weakest.

TAM2's output quality construct (Venkatesh & Davis, 2000) provides a direct theoretical bridge to the accuracy-credibility finding: high message accuracy is the clearest instantiation of output quality in AI communication. The very large f^2 of 0.646 for accuracy-credibility confirms that output quality is not merely a usefulness antecedent but a credibility antecedent of the first order a relationship TAM2 implies but does not explicitly theories in trust terms. This study therefore extends TAM2's output quality construct by demonstrating its direct, very large effect on the credibility dimension of consumer trust specifically, providing a more granular and actionable theoretical specification than TAM2 itself offers. UTAUT's social influence construct also partially explains the reliability-personalisation finding: in a social context where fintech platforms are shared through peer recommendations, personalised communication that confirms one's transaction patterns signals reliable, consistent, personalised tracking, which is particularly valued

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Automated Responsiveness and Consumer Trust

The rejection of the H_0 confirms that Automated Responsiveness significantly and positively influences all four Consumer Trust dimensions (β range: 0.461–0.498; T-statistics: 10.627–12.487; $p < 0.001$; f^2 range: 0.270–0.330). This finding is consistent with the empirical literature: Abdulquadri et al. (2021) found responsiveness significantly predicted satisfaction and usage intention ($\beta = 0.61$, $p < 0.001$) among Nigerian bank chatbot users; Oyekunle et al. (2024) reported that automated responsiveness significantly influenced trust ratings among Nigerian digital financial service users; and Paramaiah et al. (2026) found responsiveness to be the strongest predictor of perceived service quality ($\beta = 0.67$, $p < 0.001$) in an Asian e-commerce context. So far, consistent with the prior literature. But the argument must go further.

The contribution here is threefold. First, where prior studies measured responsiveness's effect on a single trust proxy, this study simultaneously estimates its effect across four trust components and reveals a differential structure: the effect is weakest on Consumer Confidence ($\beta = 0.461$, $f^2 = 0.270$) and strongest on Customer Credibility ($\beta = 0.498$, $f^2 = 0.330$). This differential reveal that automated responsiveness functions primarily as a competence signal, not a safety signal. When an AI system responds promptly and consistently, it communicates to the consumer that the fintech organisation has the operational capability to monitor transactions and generate contextually adequate replies precisely the ability dimension of Mayer et al.'s (1995) trustworthiness framework, which most directly shapes credibility perceptions. Confidence, by contrast, involves emotional security and reduced vulnerability, a state that requires more than demonstrated operational competence. Responsiveness without security assurance or accuracy guarantees cannot resolve the emotional vulnerability that defines confidence, particularly in a market where consumers who experienced prior accuracy or service failures retained persistent low confidence for extended periods.

Second, the f^2 values of 0.270–0.330 in this study are lower than the β of 0.67 found by Paramaiah et al. (2026). This gap matters: this study's sample consists of daily and weekly AI users (77.3% combined) for whom responsiveness is a baseline expectation, not a premium differentiator. When responsiveness is taken for granted, its marginal trust contribution diminishes. This is a habit-formation dynamic that cross-sectional studies capturing initial user impressions like Oyekunle et al.'s (2024) survey-based assessment cannot detect. The implication is that responsiveness yields diminishing trust returns as users become habituated, suggesting that fintech platforms should not treat continued investment in response speed as a reliable long-term trust-building strategy without simultaneously investing in accuracy and security features that generate compounding trust returns.

Third, this study directly addresses the gap identified in the literature: no prior study had simultaneously estimated the disaggregated effect of automated responsiveness on all four trust components using PLS-SEM within the Lagos fintech context. The evidence bases previously available characterized by Uzoaru et al.'s (2025) finding that NLU limitations reduced trust scores by 22–35%, and Farinloye et al.'s (2024) finding that responsiveness had a non-significant effect ($\beta = 0.08$, $p = 0.31$) for low-literacy subgroups, could not resolve which trust dimension was most and least responsive to responsiveness improvements. This study resolves it: credibility and service quality are most responsive; confidence is least. This resolution has direct design implications: platforms seeking to build consumer credibility should prioritise AI response consistency and availability; platforms seeking to build consumer confidence must target data protection and information accuracy.

Conclusion

The study concludes that consumer trust in Lagos fintech follows a hierarchical, security-anchored architecture in which adequate perceived data protection is the foundational condition for reliability and credibility formation. Message accuracy provides ongoing communicative confirmation of institutional integrity, and automated responsiveness and personalisation function as trust-deepening enhancements within a pre-established trust environment. Fintech platforms that invest in responsiveness and personalisation without first establishing strong security and accuracy foundations risk building consumer trust on an inadequate base.

Recommendations

From the findings of this study, the researchers made the following recommendations to the relevant stakeholders:

- **i.** Data security was found to be the dominant predictor of all four consumer trust dimensions, generating very large effect sizes across all components. Fintech companies should therefore treat data security infrastructure as their foremost consumer trust investment, not merely a compliance obligation. This includes investment in end-to-end encryption, AI-powered fraud detection, real-time intrusion prevention, and proactive security communication.
- **ii.** The finding that DS2 (encryption confidence) recorded the highest factor loading confirms that encryption features are the most legible and consequential security signals to consumers. Fintech managers should therefore make encryption capabilities explicitly visible across all AI-driven consumer touchpoints.

iii. It is recommended that fintech companies implement rigorous quality assurance protocols for all AI-generated communications, including automated validation of transaction alerts against real-time ledger data, error-rate monitoring with immediate human escalation, and transparent error-correction procedures. AI systems should also be designed to disclose their automated nature and the basis of financial advice, reinforcing the integrity dimension of credibility that technical accuracy alone cannot fully address.

References

Abdulquadri, A. O. (2025). Personalization and user autonomy in self-service experiences, In *Practical applications of self-service technologies across industries* (pp. 443–474). IGI Global. doi:10.4018/979-8-3373-4667-0.ch016

Abdulquadri, A., Mogaji, E., Kieu, T. A., & Nguyen, N. P. (2021). Digital transformation in financial services provision: A Nigerian perspective to the adoption of chatbot, *Journal of Enterprising Communities: People and Places in the Global Economy*, *15*(2), 258–281. doi:10.1108/JEC-06-2020-0126

Abinabo, P., Nuhu Shagari, J., & Mashi, M. S. (2025). Impact of artificial intelligence on customer engagement from selected banks in Abuja metropolis, Nigeria: A mediating role of personalization, *International Journal of Business Sustainability*, *1*(2). doi:10.25299/ijbs.2025.22584

Aidonojie, P. A., Majekodunmi, T. A., & Adeyemi-Balogun, O. J. (2023). The legal issues concerning the operation of Fin-Tech in Nigeria, *Jurnal Media Hukum*, *30*(2), 78–97. doi:10.18196/jmh.v30i2.18337.

Alhajjaj, H., & Ahmad, A. (2022). Drivers of the consumers adoption of fintech services, *Interdisciplinary Journal of Information, Knowledge, and Management*, *17*, 259–281. doi:10.28945/4971

Ayanwale, M. A., Adelana, O. P., Bamiro, N. B., Olatunbosun, S. O., Idowu, K. O., & Adewale, K. A. (2025). Large language models and GenAI in education: Insights from Nigerian in-service teachers through a hybrid ANN-PLS-SEM approach, *F1000Research*, *14*. doi:10.12688/f1000research.161637.1

Babatunde, S. O., Odejide, O. A., Edunjobi, T. E., & Ogundipe, D. O. (2024). The role of AI in marketing personalization: A theoretical exploration of consumer engagement strategies, *International Journal of Management & Entrepreneurship Research*, *6*(3), 936–960.

Bansal, C., Kumar, A., Dogra, N., AlZohbi, G., & Saini, C. P. (2024). AI chatbots in fintech sector: A study towards technological convergence, *Recent Advances in Computer Science and Communications*, *18*(5). doi:10.2174/0126662558325422240926103718

Bello, A. B., & Karupiah, P. (2022). Dispositional dimension of trust on customer interaction with the banking sector: A SmartPLS approach, *International Journal of Business and Society*, *23*(2), 877–894. doi:10.33736/IJBS.4843.2022

Benjamin, L. B., Amajuoyi, P., & Adeusi, K. B. (2024). Marketing, communication, banking, and fintech: Personalization in fintech marketing, enhancing customer communication for financial inclusion, *International Journal of Management & Entrepreneurship Research*, *6*(5), 1687–1701. doi:10.51594/ijmer.v6i5.1142

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.), Lawrence Erlbaum Associates.

Dantsoho, M. A., Ringim, K. J., Hasnan, N., & Kura, K. M. (2021). Moderating role of bank reputation on the relationship between artificial intelligence (AI) quality, satisfaction and continuous usage intention of e-banking services, *Central Asia and the Caucasus*, *22*(5), 311–329. doi:10.37178/ca-c.21.5.029

Daudu, B. O., Osimen, G. U., & Abubakar, A. T. (2025). Artificial intelligence, fintech, and financial inclusion in African digital space. In *FinTech and Financial Inclusion: Leveraging Digital Finance for Economic Empowerment and Sustainable Growth* (pp. 268–282). Routledge. doi:10.4324/9781003514114-19

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology, *MIS Quarterly*, *13*(3), 319–340. doi:10.2307/249008

Dudu, O. F., Alao, O. B., & Alonge, E. O. (2024). Advancing financial inclusion through digital payment platforms in emerging markets, *Finance & Accounting Research Journal*, *6*(11), 2028–2052. doi:10.51594/farj.v6i11.1696

Esoimeme, E. E. (2024). Barriers to implementing new technologies for AML/CFT functions: The case of Nigeria, In *Global anti-money laundering regulation: Developing countries compliance challenges* (pp. 113–135). Routledge. doi:10.4324/9781003253808-9

Eshiett, I. O. (2024). FinTech privacy security and customer engagement in Nigerian financial sector, *Open Access Research Journal of Science and Technology*, *12*(2), 155–168. doi:10.53022/oarjst.2024.12.2.0146

Etuk, A., Okon Akpan, A., & Awah, A. E. (2025). Analysis of the influence of AI-driven services on customer perception in the Nigerian e-commerce sector, *International Journal of Interdisciplinary Research in Marketing and Management*, *12*(1), 1–15.

Ezenwafor, E. C., Ayodele, A. A., & Esiti, B. G. (2022). E-service quality dimensions and customer satisfaction among users of automated saving platforms in a typical developing economy, *World Review of Entrepreneurship, Management and Sustainable Development*, *18*(5–6), 566–580. doi:10.1504/WREMSD.2022.125641

Farinloye, T., Omotoye, O., Oginni, A., Moharrak, M., & Mogaji, E. (2024). Bridging the digital divide: Consumer engagement with transportation payment apps in emerging economies, *Journal of Consumer Behaviour*, *23*(6), 3011–3029. doi:10.1002/cb.2388

Frank, D., Jacobsen, L., Søndergaard, H. A., & Otterbring, T. (2023). In companies we trust: Consumer adoption of artificial intelligence services and the role of trust in companies and AI autonomy. *Information Technology and People*, *36*(8), 155–180. doi:10.1108/itp-09-2022-0721

Graham, G., Nisar, T. M., Prabhakar, G., Meriton, R., & Malik, S. (2025). Chatbots in customer service within banking and finance: Do chatbots herald the start of an AI revolution in the corporate world? *Computers in Human Behavior*, *165*, 108570. doi:10.1016/j.chb.2025.108570

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.

Hennighausen, C., Navarro-Schar, V. G. Y., & Eller, E. (2025). AI-mediated communication in e-commerce: Implications for customer trust, *International Journal of Consumer Studies*, *49*(5). doi:10.1111/ijcs.70111

Jafri, J. A., Amin, S. I. M., Abdul-Rahman, A., & Nor, S. M. (2024). A systematic literature review of the role of trust and security on fintech adoption in banking. *Heliyon*, *10*(1). doi:10.1016/j.heliyon.2023.e22980

Lee, L. (2024). Enhancing financial inclusion and regulatory challenges: A critical analysis of digital banks and alternative lenders through digital platforms, machine learning, and large language models integration, *SSRN Electronic Journal*. doi:10.2139/ssrn.4799209

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust, *Academy of Management Review*, *20*(3), 709–734. doi:10.5465/amr.1995.9508080335

Ogundele, A. T., Ibitoye, O. A., Akinterinwa, O. O., Abraham, A., Felix, I. O., & Gift, A. T. (2025). The role of artificial intelligence in advancing sustainable banking and service efficiency in Nigerian financial institutions: An assessment of selected quoted banks, *Journal of Sustainable Development Law and Policy*, *16*(1), 282–307. doi:10.4314/JSDLP.V16I1.15

Okechukwu, E. M., Odo, J., & Nnabuko, J. O. (2024). Service marketing strategies and customer satisfaction: Evidence from commercial banks in Southeast, Nigeria. *International Journal of Interdisciplinary Research in Marketing and Management*, *11*(2), 1–15.

Okeke, T. C., Ezeh, G. A., & Nnedum, O. A. U. (2025). Service quality dimensions and customer satisfaction with online services of Nigerian banks, *Journal of Internet Banking and Commerce*, *20*(3).

Oladeji, M. A., & Ogunleye, T. T. (2023). Digital disruption and the transformation of Nigerian banking: The fintech challenge, *African Journal of Business and Economic Research*, *18*(2), 135–151.

Olubiyi, T. O. (2025). Service quality in the age of artificial intelligence: Evidence from listed telecommunication businesses in sub-Saharan Africa, In *Human-centric AI in digital transformation and entrepreneurship* (pp. 339–358). IGI Global. doi:10.4018/979-8-3693-8009-3.ch016

Onatuyeh, E. A., Oghorodi, D., Okpako, E. A., Ojei, E., Osakwe, G., Chinedu, N. B., Nwankwo, W. (2025). Cybersecurity and business survival in Nigeria: Building customer's trust, *African Journal of Applied Research*, *11*(1), 786–813. doi:10.26437/ajar.v11i1.882

Onoja, W. D., Abba, M. I., Edeh, O. P., Akpadaka, O. S., & Dang, D. Y. (2026). Artificial intelligence disclosure and bank performance: Evidence from deposit money banks in an emerging market, *African Journal of Economic and Management Studies*. doi:10.1108/AJEMS-07-2025-0539

Oriji, O., Shonibare, M. A., Daraojimba, R. E., Abitoye, O., & Daraojimba, C. (2023). Financial technology evolution in Africa: A comprehensive review of legal frameworks and implications for AI-driven financial services, *International Journal of Management & Entrepreneurship Research*, *5*(12), 929–950. doi:10.51594/ijmer.v5i12.627

Oxfordson, O. D. (2026). Artificial intelligence in digital marketing: Readiness and adoption among Nigerian enterprises, *International Journal of Artificial Intelligence and Machine Learning*, *6*(1), 132–149. doi:10.51483/IJAIML.6.1.2026.132-149

Oyetade, B. J., Bello, A. O., & Akinlalu, O. S. (2024). Inventory management practices and SMEs' performance in Lagos State, *International Journal of Research and Innovation in Social Science*, *8*(5), 958–979. doi:10.47772/IJRISS.2024.805068

Oyekunle, D., Matthew, U. O., Preston, D., & Boohene, D. (2024). Trust beyond technology algorithms: A theoretical exploration of consumer trust and behavior in technological consumption and AI projects, *Journal of Computer and Communications*, *12*(6), 72–89. doi:10.4236/jcc.2024.126006

Oyeniyi, L. D., Ugochukwu, C. E., & Mhlongo, N. Z. (2024). Implementing AI in banking customer service: A review of current trends and future applications, *International Journal of Science and Research Archive*, *11*(2), 1492–1505. doi:10.30574/ijsra.2024.11.2.0639

Paramaiah, C., Nalluri, V., Chang, J.-R., Babu, D. S., Kumar, A., & Kumar, S. (2026). AI-driven service quality in e-commerce: Expectation–perception gaps using interval-valued Pythagorean fuzzy analysis, *Asian Journal of Interdisciplinary Research*, *9*(1), 186–203. doi:10.54392/ajir26112

Ringle, C. M., Wende, S., & Becker, J.-M. (2024). *SmartPLS 4. SmartPLS GmbH,* Retrieved from https://www.smartpls.com

Sharma, V., & Adeniyi, A. E. (2025). Bridging the gap: AI-powered FinTech and its impact on financial inclusion and financial well-being, *Discover Artificial Intelligence*, *5*(1). doi:10.1007/s44163-025-00465-9

Uzoaru, G. C., Ayogu, I. I., Odii, J. N., Onyeka, A. C., Nwanga, M. E., Nwokoma, F. O., Otuonye, A. I. (2025). A systematic review of natural language understanding-related challenges in conversational agent development, *International Journal of Engineering Trends and Technology*, *73*(6), 520–549. doi:10.14445/22315381/IJETT-V73I6P143

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies, *Management Science*, *46*(2), 186–204. doi:10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view, *MIS Quarterly*, *27*(3), 425–478. doi:10.2307/30036540

Yamane, T. (1967). *Statistics: An introductory analysis* (2nd ed.), Harper and Row.