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Evaluating the impact of AI-Powered chatbots adoption on customer satisfaction and service management: Perspectives from an emerging market multinational retail corporation

Ephraim Onohuean & Brighton Nyagadza

Abstract

The study evaluates how AI-powered chatbots influence customer satisfaction and service management in a selected multinational retail corporation in Nigeria, to respond to the lack of research on chatbot adoption in the emerging markets, where infrastructure and cultural factors still act as barriers. A quantitative research methodology was applied, with the support of an expanded UTAUT model as the theoretical framework. Data was collected using online survey which was analysed using PLS-SEM. Based on the findings, AI-powered chatbots have a significant impact on response time, information accuracy, and efficiency. The results led to positive effects on customer satisfaction, with trust and perceived service quality mediating adoption. Effectiveness of AI-powered chatbots is limited due to barriers such as unreliable internet, poor digital literacy, and cultural preference of human interaction. The research contributes to the extension of the UTAUT model by combining trust and technological readiness and provides a country-specific model of AI adoption in emerging markets. Findings contributes to AI-powered chatbots chatbot user experience (UX) design strategy development for multinational retail corporations, such as investing in user training, multilingual interface and integration with apps such as WhatsApp to increase adoption in Nigeria. AI-powered chatbots increase service accessibility and involvement and indicate the issue of digital inclusion, which needs to be supported by policies. They are able to cut operational expenses, freeing up personnel to focus on complex tasks and aid in promoting the digital economy. The current research is one of the most initial empirical investigations of AI-powered chatbots adoption by a multinational retail corporation and fills a critical research gap in the literature on customer service innovation in new markets.

JEL Code: O31; M15; L80

Keywords: AI-powered chatbots; multinational retail corporation; Nigeria; user experience (UX) design

Introduction and study background

The deployment of AI-powered chatbots within the customer support sector has experienced significant international growth during the last few years. The global chatbot market reached approximately $8.6 billion in 2024, and according to Business Research (2025), analysts predicted the market to grow to $11.14 billion by 2025, leading to an annual growth rate (CAGR) of 29.5%. The adoption of this technology has been led by multinational companies. By implementing AI chatbots for customer inquiries, Amazon achieves operational excellence, which leads to enhanced consumer satisfaction (Huseynov, 2023; Bashar et al., 2025). Google uses AI chatbots as a unifying element that enables user interaction along with support services throughout its platform ecosystem. The implemented projects help organisations shorten their response times while decreasing costs and increasing their customer satisfaction ratings (Labadze et al., 2023). AI has brought numerous advantages to customer service operations worldwide. AI chatbots deliver continuous customer help with their ability to deal with numerous requests simultaneously while providing customised experiences, which leads to better satisfaction rates. Businesses achieve expense reduction through automation systems and optimise their human workforce effectively (Huseynov, 2023; Mashapure et al., 2025). AI-powered chatbots serve as fundamental global tools or elements which strengthen customer support operations. Amazon and Google represent prominent organisations that have implemented chatbots to optimise their customer support operations while processing many users demand instantly (Uzoka et al., 2024). This technological advancement has positively affected customer satisfaction since customers now receive quick responses from chatbots for their common inquiries. Operational efficiency also relies strongly on chatbots because they help companies reduce human resource costs and redirect their resources efficiently. Customer service depends increasingly on Artificial Intelligence as reflected in global market developments (Kaur, 2023). A significant research gap exists concerning AI-powered chatbots in customer service, including their effects, particularly in emerging markets like in Nigeria, despite their growing acceptance and global success (Misischia et al., 2022). Research about AI chatbots within developed countries exists in abundance, but Nigeria's specific infrastructure and economic environment still require extensive study regarding the implementation of these technologies. The special characteristics of the Nigerian market, including poor digital skills, insufficient internet connectivity, and restricted technological access, could affect how customers receive and benefit from AI-powered solutions for customer support. The selected multinational retail corporation in Nigeria serves as the tested case to study how artificial intelligence-based chatbots influence customer service through this research. Modern industries experience essential changes through the rising use of artificial intelligence (AI) by companies, which enables AI-powered chatbots to supply immediate, tailored consumer engagements (Kumar et al., 2024). It has adopted AI applications according to its global plan, which aims to improve customer relations and cut operational expenses and boost service productivity (Waebuesar et al., 2022). This research aims to explore how AI technologies affect the Nigerian market, specifically where it examines both the strengths and challenges faced by multinational companies operating in the country.

The implementation of AI-powered chatbots by multianational retail coporation in Nigeria, together with their advantages and obstacles, remains poorly researched in extensive studies. The current literature mainly analyses smaller businesses and individual industries within developed economies (Zatsu et al., 2024). Insufficient knowledge exists about how extensively multinational firms modify their AI systems to suit the particular Nigerian market environment, which presents different customer expectations alongside distinct technology readiness and operational limitations compared to developed economies. This research addresses the existing knowledge gap through its examination of customer service improvements and operational efficiency generation resulting from AI-powered chatbots in the selected multianational retail coporation in Nigeria. A study of this multinational company aims to generate important findings about AI adoption effects for Nigerian businesses, including food and beverage firms that use AI for customer interactions and service delivery. The introduction and the adoption of AI-powered chatbots in a country like Nigeria, despite the significant futuristic opportunities it offers, are still at the emerging stage. The rapidly expanding digital economy drives organisations across the world, especially the finance sector and telecommunications industry, and now the food and beverage industry, to use AI solutions (Abdulquadri et al., 2021). The unparalleled adoption of AI technologies remains limited for widespread use in the market because several factors, such as digital literacy issues, unstable and undependable internet connections, and inadequate infrastructures, persist (Ade-Ibijola & Okonkwo, 2023). This study focuses specifically on AI-powered chatbots used for customer service management and satisfaction in a multinational company in Nigeria. The research evaluates the impact of these applications, which are deployed to influence customer service through immediate, tailored consumer engagements. The research investigates this specific type of tool, defining AI Chatbots as software applications that use artificial intelligence (AI) to create automated human-like conversations to identify clients' concerns and offer rapid, customised support. These bots are used by multinational companies in Nigeria to support consumers by answering questions, addressing product-related problems, and offering health content. This research investigates the strategies the selected multianational retail coporation in Nigeria uses to tackle obstacles in its AI implementation of improved customer experience as it operates as a multinational corporation. The internal LLM platform at the selected multianational retail coporation in Nigeria helps both knowledge sharing between employees and increases company-wide productivity.The technology mostly operates in developed nations, yet its achievement impacts the development and improvement of chatbot systems across all global operations. It highlights how large-scale organisations may utilise generative AI to enable customer-facing innovations (HR Grapevine USA, 2024). However, despite these developments, there is insufficient publicly available documentation on the particular deployment metrics or customer adoption levels of AI chatbots inside the selected multianational retail coporation in Nigeria. This highlights the necessity for empirical examination and context-specific insights, which this study intends to provide. The core goal of this research is to evaluate an AI-powered chatbot on customer service management, together with satisfaction rates. The investigation generates knowledge about operational performance results alongside user satisfaction and technical difficulties of AI chatbot deployment within Nigerian consumer markets. The specific objectives are:

1. *To evaluate the effectiveness of AI-driven chatbots in improving customer service performance including response time, information accuracy, and customer satisfaction at the selected multinational retail corporation.*
2. *To examine the adoption challenges and scalability constraints of AI-driven chatbots within the customer support operations of the selected multinational retail corporation.*

The remainder of this article is structured as follows; the first section presents a literature review, hypotheses, and the development of the research conceptual model. A section on methods follows, and then the analysis of results is presented. Discussions, implications, study limitations and future research directions are also presented.

Literature Review

Global and regional context of chatbot adoption

The deployment of AI-powered chatbots in customer support has experienced significant international growth, driven by the increasing need for rapid, personalized service while controlling costs. This technology, which uses Artificial Intelligence (AI) to create automated, human-like discussions, has revolutionized service delivery. Globally, the chatbot market has expanded rapidly, and large multinational organizations like Amazon and Google have implemented them to optimize customer support operations, reduce human resource costs, and boost service productivity (Uzoka et al., 2024). By using Natural Language Processing (NLP) and Machine Learning (ML), chatbots analyze user input to provide relevant, context-matching responses and continually enhance their performance by learning from previous dialogues. In the African market, AI chatbot adoption shows steady growth, with the Nigerian market expected to expand due to technological investments and government initiatives aimed at building a digital economy. AI solutions are being implemented across key sectors, including the finance and telecommunications industries, for process optimization and managing consumer queries. The selected multinational corporation in Nigeria, utilizes AI chatbots across various platforms, including WhatsApp and Facebook Messenger, as part of its global strategy to automate customer service, enhance service quality, and reduce operational costs.

Academic gap

Despite the growing global adoption and the evident advantages of AI-powered chatbots, particularly for customer service, a significant research gap exists regarding their effects and implementation, especially in emerging markets in Nigeria. Most of the existing research concentrates on established economies (such as Europe, the United States, and parts of Asia) where strong digital infrastructure, reliable internet speed, and advanced digital proficiency create near-perfect conditions for chatbot adoption. These enabling environments are often absent in Nigeria, where challenges like unstable and undependable internet connections, inadequate infrastructure, and poor digital literacy persist as barriers. There is insufficient research detailing how the unique socio-technical settings, technological limitations, and diverse social cultures in countries like Nigeria affect the performance and feedback received by AI solutions. While some research addresses chatbot implementation in Nigerian local small and medium-sized enterprises (SMEs) and the banking sector, there is a scarcity of studies focusing on large international corporations like Nigeria. These MNCs face the complexity of synchronizing global technical innovation norms with local customer expectations, cultural differences, and technology readiness levels. Studies of AI customer service technology adoption in the Sub-Saharan African region largely fail to apply comprehensive theoretical frameworks like the Unified Theory of Acceptance and Use of Technology (UTAUT) to explain successful implementation. Limited Focus on User-Centered Barriers: The current literature lacks sufficient measures for factors such as digital trust and psychological preparedness, particularly where users may display a cultural preference for human interaction or distrust non-human service agents processing sensitive requests. This study aims to fill this critical gap by conducting one of the initial empirical investigations of AI chatbot adoption by a multinational corporation in Nigeria, using an expanded UTAUT model (including Trust and Security, and Technology Readiness) to analyze user acceptance patterns within this challenging context. This study is justified by the need to address major gaps in technology adoption research within emerging markets and to generate practical insights for multinational corporations (MNCs) operating in constrained environments.

Importance of examining AI chatbot adoption in emerging markets

The study fills a critical gap in existing literature by examining AI-powered chatbot adoption in customer service within emerging markets, specifically in Nigeria. Most prior research has focused on advanced economies with robust digital infrastructure, overlooking contexts where technological, cultural, and institutional barriers remain significant. By focusing on an emerging market, this research enhances understanding of how AI chatbots function and are adopted in environments marked by infrastructural limitations and cultural resistance to automation.

Nigeria as a distinctive research setting

Nigeria provides a compelling and relevant context due to its status as Africa's largest economy and a growing digital hub, alongside persistent socio-technical challenges. AI adoption is constrained by unreliable internet connectivity, inadequate digital infrastructure, limited broadband access, and frequent power outages. Additionally, low digital literacy, a strong preference for human interaction, and widespread distrust in institutions particularly regarding data privacy further complicate the acceptance of automated customer service solutions.

Theoretical Framework

The research utilizes the Unified Theory of Acceptance and Use of Technology (UTAUT) as its theoretical framework, developed by Venkatesh et al. (2003). UTAUT combines eight pre-existing technology adoption theories into an integrative model to examine user technology adoption and predict individual behavior. The UTAUT model examines user technology adoption and predicts individual behaviour through the identification of essential factors that determine usage frequency after usage intent (Abrahão et al., 2016). The analytical model serves researchers conducting AI chatbot analyses due to its ability to create an integrated framework which explores how organisations and individuals accept technology for customer service applications. The model maintains that the adoption procedure depends heavily on four fundamental characteristics, including Performance Expectancy and Effort Expectancy as well as Social Influence and Facilitating Conditions. The combined operation of these factors shapes how users plan to use technology, along with how they truly utilise it in practice. The four core characteristics serve to describe both customer interactions with AI chatbots at the selected mutinational cooperation in Nigeria and the methods through which the company implements these technological solutions (Anditama and Hidayanto, 2024). Previous research using UTAUT emphasizes four core determinants of adoption: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. These constructs are effective in explaining general technology acceptance, including AI-based customer service tools such as chatbots.

To address UTAUT's contextual limitations, this study proposes an expanded model by incorporating Trust and Security and Technology Readiness, while also introducing Service Quality Perception as a mediating variable. The findings show that Trust and Security significantly influence chatbot adoption, underscoring trust as a critical enabler of technology use in low-trust regulatory environments. However, adoption alone does not guarantee satisfaction; instead, Service Quality Perception mediates the relationship between technology use and customer satisfaction, demonstrating that users must perceive tangible service benefits. The study also reveals context-specific nuances in the traditional UTAUT constructs. Performance Expectancy strongly predicts chatbot adoption but has a weaker direct effect on customer satisfaction, suggesting that Nigerian customers value relational and cultural service elements beyond functional efficiency. In contrast, Technology Readiness does not significantly influence adoption or service quality, challenging assumptions that individual digital competence alone drives technology use in emerging economies. Instead, infrastructural instability and cultural factors appear to play a more decisive role. Overall, the research contributes a localized extension of UTAUT that highlights the importance of trust, service quality, and cultural alignment in AI adoption. It demonstrates that effective technology implementation in emerging markets requires moving beyond technical performance to embrace context-sensitive design, trust-building mechanisms, and user-centered service experiences.

Conceptual model and hypotheses formulation

The conceptual framework expands upon the UTAUT model, focusing on how the four UTAUT elements influence AI-powered chatbot adoption, customer satisfaction, and operational efficiency at the selected multianational retail corporation.

Performance Expectancy

Performance Expectancy shows the extent to which people believe technological tools would enhance their operational output or advance their goal attainment. The measure of performance expectancy in AI-based chatbots addresses how efficiently the program supports customer service activities (Duong et al., 2023). Customers and customer care staff at the selected company in Nigeria will find value in chatbots that deliver rapid response times alongside the capability to deal with high client query numbers and provide superior service quality. On the other hand, The Ease of Human-Technology Interaction is described by Effort Expectancy as how users perceive their interaction's simplicity. User acceptability in AI-powered chatbots depends directly on the ease of use as understood through the construct (Chen et al., 2024). The difficulty of contacting the chatbot or an unfriendly interface will lead to lowered customer engagement willingness toward this technology. Also, The extent to which someone incorporates a specific technology based on what important social figures, including classmates and family members and colleagues, think they should use becomes known as Social Influence. The opinion transformation of customers about interacting with AI chatbots depends heavily on social influence in this scenario. AI technology adoption norms in Nigeria experience influence from cultural factors along with public views about technology and how much support the technology finds inside workplaces (Menon and Shilpa, 2023). And finally, The availability of needed resources and infrastructures forms the basis of facilitating conditions that enable technology usage. The implementation of AI chatbots in Nigeria depends on internet connectivity, together with advanced technology systems and digital training capacity. Empirical findings confirm that Performance Expectancy is a key component of the technology acceptance model and is one of the most powerful and statistically significant predictors of Chatbot Adoption. Despite its strong impact on adoption, its direct effect on Customer Satisfaction in the studied model was not statistically significant, suggesting that efficiency alone might not guarantee full satisfaction. Therefore, it is proposed that:

H1: *The deployment of AI chatbots by the selected multinational retail corporation reduces customer service response times by enabling automated, real-time assistance.*

H2: *AI-powered chatbots at the selected multinational retail corporation provide information with accuracy comparable to or higher than human service agents due to consistent access to centralized knowledge bases.*

Effort Expectancy

In the UTAUT model, the Effort Expectancy measures the belief by users on whether a technology is easy to learn and utilize (Marikyan and Papagiannidis, 2021). In the context of customer service or specifically the AI chatbots, ease of use is critical in order to motivate first-time use and build satisfaction. Users require fast, easy interactions without having to use intricate commands and technical expertise. The positive correlation with Customer Satisfaction corresponds with international results. To illustrate, Alalwan et al. (2018) showed that perceived ease of use of chatbots had a significant positive impact on user satisfaction in banks. In a similar way, Silva, Shojaei and Barbosa (2023) discovered that intuitive chatbot design had played an essential part in determining a positive service experience and fostering reuse intentions. This demonstrates why chatbot interfaces must be basic, conversational, and available to users with a different level of digital literacy. The model indicates that there is no significant effect on Service Quality. Perception of Service Quality is usually built on more than just the ease of usage including accuracy, personalization and empathy (Vu, 2021). Although a chatbot may be convenient to operate, it depreciates service quality when users receive the wrong or the commonly copied answers. Such a weakness translates to the practical issues of natural language processing and the fact that AI systems must be trained and improved constantly (Misischia et al., 2022). Digital literacy is a challenge in the emerging market context in Nigeria. Despite increasing levels of mobile and internet penetration, high percentages of the population still do not have experience managing digital interfaces (Okocha and Dogo, 2024). This digital divide has the potential to influence Effort Expectancy, which seems to be easy to a digitally literate urban customer can become confusing or inaccessible to others. The selected multinational retail cooptation's chatbot design must therefore account for these disparities, possibly through multilingual options, voice input features, or integration with familiar messaging platforms like WhatsApp, which is widely used in Nigeria (Busayo et al., 2023). Therefore, it is proposed that:

H3: *The use of AI chatbots by the selected multinational retail corporation improves first-contact issue resolution by delivering standardized and instant problem-solving responses.*

Trust and Security

Trust and Security is included as an expanded construct in the UTAUT model used in the research. It is defined as customers' assurance in the AI chatbot's capacity to manage their data securely, deliver precise and unbiased responses, and uphold ethical transparency in its operations. The element of trust and security is a critical factor in the implementation of AI-based chatbots at the selected multinational corporation in Nigeria where this study provides convincing empirical justification of its impact (Nyagadza et al., 2025). This empirical finding supports the technology reception literature, which continues to repeat the impact of trust on acceptance in computer-

based systems. Nevertheless, this result is highly relevant in the Nigerian context, where the trust in institutions is historically low, and consumers are highly cautious against the abuse in terms of their data. In this case, trust is not a facilitator but an actionable obstacle that can only be surmounted by the firms to enjoy the returns of technology. Therefore, it is proposed that:
H4: *Higher customer perceptions of trust and data security increase the adoption and continued use of AI-driven chatbots at the selected multinational corporation.*

Technology Readiness
Technology Readiness measures the extent to which customers and workers at the selected multinational retail cooperation in Nigeria are technologically proficient and psychologically primed to adopt and effectively employ AI-powered chatbots. The introduction and adoption of AI-powered chatbots in Nigeria are limited by factors such as poor digital literacy and unstable internet connections. While internet access is expanding, only a fraction of Nigerians manage to acquire essential digital skills needed to navigate advanced AI systems. Technical barriers like unreliable internet and digital literacy challenges play a vital role in Nigerian acceptance, as the system works best with stable connectivity and proper skills. However These results challenge UTAUT's universal assumptions about Facilitating Conditions in emerging markets contexts. While Uren and Edwards (2023) propose that Facilitating Conditions, including technological readiness, uniformly drive adoption, this study suggests that in Nigeria, such readiness may be decoupled from actual usage behaviour due to systemic, cultural, and infrastructural barriers. This analysis suggests that Technology Readiness, though traditionally important, is not a primary driver of AI chatbot adoption at the selected multianational retail coporation in Nigeria. Instead, success depends on combining readiness with trust-building, contextual adaptation, and overcoming systemic barriers an insight critical for both practice and theory in emerging markets. Technology Readiness is not meaningfully related to adoption behaviour in this model. Although Nigerian clients can use digital banking and smartphones, the use of AI chatbots in customer service may require their trust, locally relevant and culturally acclimated situation, which may not be addressed with a simple readiness (Mogaji, 2020). The discrepancy is in line with previous articles warning against the homogenous technological adoption in different contexts (Dwivedi et al., 2019). Equally, emerging markets can have limiting factors such as the lack of infrastructure, unstable internet, costs of data, and language challenges, being particularly restrictive to tech-savvy users (Kumar and Ciddikie, 2023). Thus, the assumption of the selected multianational retail coporation in Nigeria that chatbots are adopted by digitally literate people is not empirically relevant. Therefore, it is proposed that:
H5: *Greater technological readiness among customers and employees enhances the effective adoption of AI-powered chatbots by reducing resistance and improving interaction quality.*

Customer Satisfaction
Customer satisfaction is generally considered the final measure of success in any technology-mediated interaction of service and satisfaction is debatable and strongly localized. Customer It casts doubt as to whether AI chatbots are reaching higher performance levels in the minds of customers in Nigeria. Although it is claimed that perceived usefulness is vital in satisfaction, this result hints at ambivalence. Nigerians are unlikely to trust chatbots to substitute the subtlety of human service, particularly settings where the area of digital dependability is minimal. More crucially, it presents a challenge to techno-optimistic narratives that view automation as a universally desirable upgrade (Busayo et al., 2023). Customer Satisfaction was revealed as the only critical mediator of Service Quality corroborating past studies that highlighted the service provider's behavior in the perceived quality rather than actual quality as the most impactful driver of satisfaction (Parasuraman et al., 1988; Lee et al., 2019). Nevertheless, the research indicates that such concepts as quality may be socially constructed instead of being purely technical because

consumers consider AI chatbots under the prism of cultural expectations, previous experience with services, and peer pressure (Aldulaimi et al., 2024). Therefore, it is proposed that:
H6: *The implementation of AI-powered chatbots positively influences customer satisfaction by improving service efficiency, accuracy, and availability.*

Chatbot Adoption

Chatbot adoption is the primary dependent variable, refering to the extent to which customers and the selected company workers adopt and frequently use AI chatbots for customer support. The purpose of the research is to respond to the lack of research on chatbot adoption in emerging markets, where infrastructural and cultural factors act as barriers. The current research is one of the most initial empirical investigations of AI chatbot adoption by a multinational in Nigeria. The results demonstrated that the conceptual model has high explanatory power, accounting for 62.7% of the variance in Chat Adoption. This highlights that perceived usefulness and trust are robust drivers in the selected multinational retail cooperation in Nigeria setting. Chatbot adoption is also influenced by cultural preferences, as societies that value human interaction tend to resist automation. Perceived usefulness (Performance Expectancy) is the strongest determinant of AI-powered Chatbot adoption among customers and employees at the selected multinational corporation.

Methodology

This research is guided by a positivist approach, viewing reality as objective, visible, and measurable, suitable for finding patterns and testing theories. It employs a deductive approach to study hypotheses based on previous theories using real observations. The study uses quantitative methods, collecting data from AI chatbot users through an online survey. The design involves Partial Least Squares Structural Equation Modelling (PLS-SEM) through SmartPLS 4, which is suitable for modeling complex sets of latent variables with medium-sized samples.

Sampling procedure and characteristics

The analysis targeted the selected multianational retail coporation in Nigeria's customers who had interacted with the selected multination company's AI-driven chatbot via WhatsApp, the website, or social media platforms. Purposive sampling was chosen to ensure participants had direct experience with the subject matter. Eligibility criteria included being at least 18 years old, having internet access, and having chatted with the selected multianational retail coporation in Nigeria's chatbot within the last six months. Individuals without chatbot contact were excluded. A total of 200 questionnaires were distributed, with an expected 120 valid responses required for Partial Least Squares Structural Equation Modelling (PLS-SEM), which is suitable for 100-200 cases. Competent participants were found through online platforms, WhatsApp broadcasts, and social media ads. The sample size requirements is justified knowing that PLS-SEM does not require a large sample size and may be used appropriately with 100–200 cases, according to established research guidelines (Hair et al., 2021). The method is deemed appropriate for beginning research with medium-sized samples. The use of this method (PLS-SEM) allows for the rigorous, theory-driven assessment of how AI-powered chatbots influence customer service management. The online survey was conducted through Google Forms for a period of Three weeks to gather the necessary data. The screening criterion ensures the temporal relevance of the experience, as respondents must have used the chatbot within the prior six months.

Respondents' demographics

The demographic analysis included age distribution, education level, digital literacy, and chatbot usage frequency. The majority of respondents were young, working adults, with 44% aged 25-34 years old and 47.5% aged 35-44. Very few were below 24 or above 45. For education Level, respondents showed high levels of education, with 62.5% holding at least a bachelor's degree and

23% having postgraduate qualifications. Only 2.5% had secondary education as their highest level. For digital Literacy, 71.5% rated their digital literacy as good, and 15.5% as excellent. Very few reported very poor or poor digital literacy. And for chatbot usage frequency, 51.5% had used the chatbot 2–3 times, 34.5% once, and 14% more than 3 times in the past six months. This indicates that most respondents had first-hand experience.

Measurement instrument and questionnaire design

Data was collected using a self-administered questionnaire developed with Google Forms. The instrument was built using principles of the Unified Theory of Acceptance and Use of Technology (UTAUT) framework by Venkatesh et al. (2003). It consisted of five sequential sections: Section A (Screening) with two eligibility questions based on chatbot interaction; Section B (Demographic Profile) collecting age, education level, and digital literacy information; Section C (Chatbot Usage Experience) measuring Performance Expectancy, Effort Expectancy, Trust, and Service Quality using a 5-point Likert scale . Researchers use Likert-type items in technology adoption studies because they can correctly capture people's opinions about technology (Boone and Boone, 2012). Section D (Overall Satisfaction and Adoption) assessing customer satisfaction and adoption behavior; and Section E (Perceived Challenges) featuring two open-ended questions for feedback and recommendations. All items in Sections C and D were created as reflecting indicators. A pilot test with 10 participants led to refinements in wording, structure, and sequencing. Ethical precautions, including consent, confidentiality, anonymity, and voluntary participation, was soughted for and granted by the relevant committee at the institution.

Statistical analysis plan

Data analysis was conducted using SmartPLS 4 software, applying Partial Least Squares Structural Equation Modeling (PLS-SEM) to evaluate both measurement and structural models. This approach is suited for complex relationships among UTAUT constructs.

Reliability analysis

Internal consistency was assessed using Cronbach's Alpha and Composite Reliability (CR), with values exceeding 0.70 indicating internal consistency. Convergent validity was examined using Average Variance Extracted (AVE), with values above 0.50 considered satisfactory. Discriminant validity was assessed using the Fornell-Larcker criterion and the HTMT ratio. All Cronbach's Alpha and CR values for constructs (Chat Adoption, Effort Expectancy, Performance Expectancy, Trust and Security) exceeded 0.70, and all AVE values were above 0.50, confirming satisfactory internal consistency and convergent validity.

Measurement model with standardised factor loadings

The reliability and validity of the indicators were assessed through various tests. Indicator reliability was confirmed with high outer loadings above 0.70. Internal consistency was established with Composite Reliability and Cronbach's Alpha values exceeding 0.70. Convergent validity was verified with Average Variance Extracted values above 0.50. Discriminant validity was confirmed using the Fornell-Larcker criterion and HTMT ratio. Specifically, the indicators showed strong loadings, such as Chat Adoption (0.925 and 0.926), Customer Satisfaction (1.000), Effort Expectancy (0.911 and 0.900), Performance Expectancy (0.819, 0.907, and 0.893), and Trust and Security (0.903 and 0.918), and Service Quality and Tech Rediness at 1.00 demonstrating the reliability and validity of the measurement model. These high loadings indicate that the items are strong indicators of their underlying constructs.

Ethical considerations

The study adhered to high ethical standards, obtaining clearance from an academic supervisor and following university research ethics policy. Participants' rights and information were protected through: Informed consent statements, Anonymity guarantees, Secure data storage compliance with BERA (2018) and Nigerian data protection guidelines. The survey was designed to be non-intrusive, clear, and concise, ensuring participants' dignity, autonomy, and privacy.

Results

The results section provided an analysis of the demographic profile, measurement model assessment, and structural model results, relying on Partial Least Squares Structural Equation Modelling (PLS-SEM). This method is appropriate given the use of multiple latent variables, reflective indicators, and a medium sample size (Hair et al., 2021).

Structural model assessment

Path coefficients was estimated to determine the strength and direction of relationships between constructs. Bootstrapping (5,000 samples) was used to assess the statistical significance (*p*-values) of the hypothesised paths. Effect sizes (f^2) and coefficient of determination (R^2) was used to evaluate the explanatory power of the independent constructs. Where applicable, predictive relevance (Q^2) was also examined to validate the model's robustness. Each hypothesis (H1–H5) derived from the conceptual model was evaluated through structural paths in the SEM model. All analyses was conducted at a 5% significance level ($p < 0.05$). Both statistical significance and practical relevance (via effect sizes) was considered during interpretation. For path coefficients, the model showed positive relationships between Performance Expectancy and Chat Adoption (0.424), and Trust and Security and Chat Adoption (0.284), indicating that usefulness and trust are strong predictors of adoption. Other paths, like Tech Readiness → Chat Adoption (0.008), demonstrated low influences. For Bootstrapping Hypothesis Testing; Performance Expectancy → Chat Adoption (p=0.000) and Trust and Security → Chat Adoption (p=0.000) demonstrated strong, statistically significant connections and predictive value for adoption. The correlation Service Quality → Customer Satisfaction (p=0.000) was also significant. Other paths, such as Tech Readiness, were non-significant. Also, for the R^2 Values; The model showed a high explanatory power, explaining 62.7% of the variance in Chat Adoption. Customer Satisfaction (44.0%) and Service Quality (23.9%) also had significant levels of explained variance. And for Effect Sizes (f^2); Performance Expectancy indicated a medium effect (0.164) on Chat Adoption, and Trust and Security indicated a small-to-medium effect (0.075) . Other paths showed negligible effect sizes. In summary, the structural model outcomes indicated that Performance Expectancy and Trust and Security are both valid predictors of Chat Adoption in the selected multinational retail cooperation in Nigeria setting. The R^2 and f^2 values confirmed good explanatory power, validating the relevance of the hypothesized framework in explaining AI chatbot adoption in emerging markets. H1 (reductions in service support time) and H4 (trust and security favourably affect uptake) were strongly supported. H2 (accuracy matching human agents) and H3 (positive effects on customer satisfaction) received partial support, suggesting their effects were not consistently strong. H5 (increased technological readiness improves adoption) was not supported.

Common method bias (CMB)

To lower the danger of social desirability bias and interviewer influence, particularly relevant in self-administered online surveys, SmartPLS 4 was used after the data was collected to check the measurement model and make sure each latent variable was reliable and valid. Indicator reliability was checked by looking at the outer loadings (outer loadings above 0.70 are considered acceptable). Convergent validity was validated by Average Variance Extracted (AVE), with values > 0.50 regarded as satisfactory. Discriminant validity was proven using the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio, ensuring that constructs were empirically distinct. To further increase validity, the questionnaire was constructed with neutral language, randomised item order, and assured anonymity and confidentiality for all responders.

The standardised root mean square residual (SRMR)
The standardised root mean square residual (SRMR): Values of SRMR less than 0.08 are evidence of good model fit. The Saturated model had an SRMR of 0.048, and the Estimated model had an SRMR of 0.049, indicating that the structural model adequately represents the observed relations among the constructs.

Structural model
In summary, the structural model outcomes indicated that Performance Expectancy and Trust and Security are both valid predictors of Chat Adoption. The R^2 and f^2 values confirmed good explanatory power, validating the relevance of the hypothesized framework in explaining AI chatbot adoption in emerging markets. H1 (reductions in service support time) and H4 (trust and security favourably affect uptake) were strongly supported. H2 (accuracy matching human agents) and H3 (positive effects on customer satisfaction) received partial support, suggesting their effects were not consistently strong. H5 (increased technological readiness improves adoption) was not supported. The main purpose of the research is to test the effect of the determinants of the performance expectancy, effort expectancy, social influence, facilitating conditions, trust and security, and technology readiness on the adoption of chatbots, customer satisfaction, and a perception of service quality within the Nigerian context. This chapter relies on the findings obtained by Partial Least Squares Structural Equation Modelling (PLS-SEM) conducted with the help of SmartPLS, where both the measurement model evaluation and the structural model verification are listed.

Demographic profile of respondents
This section enumerates the demographic nature of individuals who participated in the study as 200 respondents. Analysis of the sample is critical to the meaning of their view towards chatbots with AI powers, the desire to embrace them and the selected multinational retail corporation in Nigeria. This demographic analysis enables us to explain the findings concerning issues that affect individuals, including their age, level of education, digital literacy and how familiar they are with the chatbot service offered.

Measurement Model Assessment
Outer Loadings
Table 1: Outer Loadings

	Outer loadings
AB1 <- Chat Adoption	0.925
AB2 <- Chat Adoption	0.926
CS1 <- Customer Satisfaction	1.000
EE1 <- Effort Expectancy	0.911
EE2 <- Effort Expectancy	0.900
PC <- Tech Readiness	1.000
PE1 <- Perfomance Expectancy	0.819
PE2 <- Perfomance Expectancy	0.907
PE3 <- Perfomance Expectancy	0.893
SQ1 <- Service Quality	1.000
TR1 <- Trust and Security	0.903
TR2 <- Trust and Security	0.918

Source: Field Data (2025)

Every indicator had high standardised outer loadings that surpassed the suggested criterion or threshold of 0.70 (Hair et al., 2021). The coefficients of all the Chat Adoption indicators were loaded at 0.925 and 0.926; Customer Satisfaction was loaded at 1.000; the coefficients of the Effort Expectancy were 0.911 and 0.900, and the Performance Expectancy were loaded at 0.819 and 0.907. Trust and Security items loaded 0.903 and 0.918, and Service Quality and Tech Readiness got perfect loadings of 1.000. High loadings show that the items are strong indicators of the underlying constructs. The Customer Satisfaction, Tech Readiness and Service Quality constructs were single-item variables with fixed patterns, i.e., the measurements were direct and unambiguous.

Internal consistency reliability

Table 6: Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) value.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Chat Adoption	0.833	0.833	0.923	0.857
Effort Expectancy	0.782	0.783	0.901	0.821
Performance Expectancy	0.844	0.853	0.906	0.763
Trust and Security	0.794	0.797	0.906	0.829

Source: Field Data (2025)

Internal consistency was assessed using Cronbach's Alpha and Composite Reliability (CR). The Cronbach's Alpha and CR values of all constructs exceeded the point of 0.70, which indicates internal consistency. All the AVE values were above 0.50, which implies that convergent validity is satisfactory. The given results prove that latent constructs accurately represent the intended conceptual domains, which affirms the sufficiency of the measurement model.

Discriminant validity

Table 7: Discriminant validity

	Chat Adoption	Customer Satisfaction	Effort Expectancy	Performance Expectancy	Service Quality	Tech Readiness	Trust and Security
Chat Adoption	0.926						
Customer Satisfaction	0.572	1.000					
Effort Expectancy	0.662	0.597	0.906				
Performance Expectancy	0.758	0.615	0.768	0.874			
Service Quality	0.469	0.439	0.362	0.431	1.000		
Tech Readiness	-0.068	-0.108	-0.060	-0.076	-0.132	1.000	

Trust and Security	0.730	0.572	0.696	0.794	0.490	-0.067	0.910

Source: Field Data (2025)

The inter-construct correlations are lower than diagonal values (square roots of AVE), hence meeting the Fornell-Larcker criteria for discriminant validity. Although there are some moderate correlations (e.g. Trust and Security with Performance Expectancy = 0.794), there is conceptual distinctiveness between constructs in the model.

Discriminant validity

Table 8: Discriminant validity

	Chat Adoption	Customer Satisfaction	Effort Expectancy	Performance Expectancy	Service Quality	Tech Readiness	Trust and Security
Chat Adoption							
Customer Satisfaction	0.627						
Effort Expectancy	0.821	0.674					
Performance Expectancy	0.900	0.669	0.946				
Service Quality	0.514	0.439	0.409	0.466			
Tech Readiness	0.075	0.108	0.068	0.089	0.132		
Trust and Security	0.896	0.641	0.882	0.969	0.550	0.077	

Source: Field Data (2025)

The Heterotrait-Monotrait Ratio (HTMT) criteria were used to measure discriminant validity. The majority of HTMT ratios measure less than the conservative 0.85 threshold mark. Some of the higher values (e.g., Performance Expectancy and Trust and Security at 0.969) are indicative of conceptual redundancy, yet they are at levels deemed as acceptable in exploratory models. In general, the HTMT statistics confirm discriminant validity and justify the utilisation of the model in performing a hypothesis test. The findings show that the survey questions indicate good reliability in measures of the UTAUT construct (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Trust and Security, Technology Readiness) and the dependent variables (Chatbot Adoption, Customer Satisfaction).

Structural model results

Table 9: Structural model path coefficients

	Path coefficients
Customer Satisfaction -> Chat Adoption	0.106
Effort Expectancy -> Customer Satisfaction	0.270
Effort Expectancy -> Service Quality	-0.010
Performance Expectancy -> Chat Adoption	0.424

Performance Expectancy -> Customer Satisfaction	0.257
Performance Expectancy -> Service Quality	0.113
Service Quality -> Chat Adoption	0.102
Service Quality -> Customer Satisfaction	0.187
Tech Readiness -> Chat Adoption	0.008
Tech Readiness -> Service Quality	-0.097
Trust and Security -> Chat Adoption	0.284
Trust and Security -> Customer Satisfaction	0.088
Trust and Security -> Service Quality	0.400

Source: Field Data (2025)

The model shows positive relationships (i.e. an intermediate relationship) between Performance Expectancy and Chat Adoption (0.424), and Trust and Security and Chat Adoption (0.284). which means that usefulness and trusrt are strong predictors of adoption. The other routes, like Tech Readiness →Chat Adoption (0.008), demonstrate low influence, hence low direct impacts.

Bootstrapping hypothesis testing

Table 10: Bootstrapping results for hypotheses

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Customer Satisfaction -> Chat Adoption	0.106	0.116	0.094	1.117	0.264
Effort Expectancy -> Customer Satisfaction	0.270	0.265	0.138	1.951	0.051
Effort Expectancy -> Service Quality	-0.010	-0.007	0.090	0.111	0.911
Performance Expectancy -> Chat Adoption	0.424	0.415	0.088	4.800	0.000
Performance Expectancy -> Customer Satisfaction	0.257	0.260	0.145	1.775	0.076
Performance Expectancy -> Service Quality	0.113	0.116	0.117	0.971	0.332
Service Quality -> Chat Adoption	0.102	0.101	0.054	1.903	0.057
Service Quality -> Customer Satisfaction	0.187	0.186	0.054	3.493	0.000
Tech Readiness -> Chat Adoption	0.008	0.008	0.055	0.148	0.882
Tech Readiness -> Service Quality	-0.097	-0.097	0.061	1.607	0.108
Trust and Security -> Chat Adoption	0.284	0.282	0.074	3.851	0.000
Trust and Security -> Customer Satisfaction	0.088	0.093	0.094	0.941	0.347

Trust and Security -> Service Quality	0.400	0.397	0.113	3.532	0.000

Source: Field Data (2025)

Confidence interval indicators that yield a p-value of less than 0.05 have statistical significance. Performance Expectancy - Chat Adoption (p= 0.000) and Trust and Security - Chat Adoption (p= 0.000) demonstrate that H1 and H5 have a strong connection, or rather, they have a powerful predictive value, and they tend to significantly predict the adoption. The correlation Service Quality - Customer Satisfaction (p=0.000) proves to be significant as well. All the other paths, like Tech Readiness, were non-significant, which means that they do not have much explanatory power regarding those predictors.

Table 11: R^2 Values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Chat Adoption	0.627	0.635	0.065	9.624	0.000
Customer Satisfaction	0.440	0.465	0.125	3.527	0.000
Service Quality	0.239	0.253	0.054	4.391	0.000

Source: Field Data (2025)

The model has a high explanatory power that explains 62.7% of the variance in Chat Adoption. Customer Satisfaction (44.0%) and Service Quality (23.9) also contain significant, albeit less decisive, levels of variance explained, which is evidence for other impacting factors.

Effect size (f^2)

Table 12: Effect size

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Customer Satisfaction -> Chat Adoption	0.018	0.032	0.038	0.464	0.642
Effort Expectancy -> Customer Satisfaction	0.052	0.071	0.066	0.786	0.432
Effort Expectancy -> Service Quality	0.000	0.004	0.006	0.009	0.993
Performance Expectancy -> Chat Adoption	0.164	0.169	0.077	2.117	0.034
Performance Expectancy -> Customer Satisfaction	0.034	0.057	0.061	0.549	0.583
Performance Expectancy -> Service Quality	0.005	0.010	0.013	0.381	0.704
Service Quality -> Chat Adoption	0.020	0.026	0.023	0.886	0.375
Service Quality -> Customer Satisfaction	0.048	0.056	0.033	1.476	0.140
Tech Readiness -> Chat Adoption	0.000	0.008	0.012	0.015	0.988

Tech Readiness -> Service Quality	0.013	0.018	0.017	0.724	0.469
Trust and Security -> Chat Adoption	0.075	0.082	0.044	1.699	0.089
Trust and Security -> Customer Satisfaction	0.005	0.013	0.018	0.258	0.797
Trust and Security -> Service Quality	0.076	0.083	0.047	1.619	0.105

Source: Field Data (2025)

The Performance Expectancy indicates a medium effect (0.164) on Chat Adoption, and the Trust and Security indicate a small-to-medium effect (0.075). Other paths indicate a negligible effect size, which indicates the minimal contribution to individual variance.

Model Fit Indices

Table 13: Model fit (SRMR)

	Original sample (O)	Sample mean (M)	95%	99%
Saturated model	0.048	0.034	0.045	0.051
Estimated model	0.049	0.036	0.047	0.053

Source: Field Data (2025)

Values of SRMR, which are less than 0.08, are evidence of good model fit, and they indicate that the structural model is adequate in representing the observed relations among the constructs. Generally, structural model outcomes indicate that Performance Expectancy and Trust and Security are both valid predictors of Chat Adoption. The results in R^2 and f^2 prove that the model has good explanatory power, which proves the relevance of the hypothesised framework in explaining the adoption of AI chatbots in emerging markets.

Summary of hypothesis testing results

Table 14: Summary of hypothesis outcomes

Hypothesis	**Hypothesis Statement**	**Decision**
H1	The deployment of AI chatbots by the selected multinational retail corporation reduces customer service response times by enabling automated, real-time assistance..	Supported.
H2	AI-powered chatbots at the selected multinational retail corporation provide information with accuracy comparable to or higher than human service agents due to consistent access to centralized knowledge bases.	Partially supported.
H3	The use of AI chatbots by the selected multinational retail corporation improves first-contact issue resolution by delivering standardized and instant problem-solving responses.	Partially supported.
H4	Higher customer perceptions of trust and data security increase the adoption and continued use of AI-driven chatbots at the selected multinational corporation.	Supported.

H5	Greater technological readiness among customers and employees enhances the effective adoption of AI-powered chatbots by reducing resistance and improving interaction quality.	Not supported.
H6	The implementation of AI-powered chatbots positively influences customer satisfaction by improving service efficiency, accuracy, and availability.	Supported.

Source: Field data (2025).

The analysis shows that H1 and H5 have strong support, with Performance Expectancy and Trust and Security being robust drivers of chatbot adoption. H2 and H3 reveal partial support, which means that the effects on the perceived accuracy and satisfaction are not strong or consistent. H4 and H6 could not be supported, which implies that operational challenges and technology readiness have no or minor direct influence on adoption here. All these findings illustrate the delicateness of technology adoption in emerging markets in Nigeria, where perceived usefulness and trust are core factors, and the absence of infrastructure and user preparedness can have a shortage of greater impact. This empirical practice can guide the practice of implementing AI chatbots in multinational firms working in such an environment and improving their operations. The demographic characteristics showed a sample of the quality of young, educated, and digitally literate participants with first hand experience with chatbots. The construct reliability and validity were confirmed by the results of the measurement model. Analysis set up on a structural above indicated Performance Expectancy (0.424, = 0.000) and Trust and Security (0.284, = 0.000) were deterministically significant in influencing adoption and satisfaction was mediated by Service Quality (0.187, = 0.000). There was no significant influence of Technology Readiness. The model captured 62.7% of adoption variance which indicates the significance of contextual trust and helpfulness in emerging markets.

Discussion

Performance Expectancy (PE) was identified as a strong and statistically significant driver of AI chatbot adoption at the selected multinational retail corporation in Nigeria (path coefficient b = 0.424; t = 4.800; $p < 0.001$), aligning with UTAUT's premise that perceived usefulness is crucial for technology acceptance (Xue, Rashid and Ouyang, 2024). the selected multinational retail corporations' customers and employees perceived that chatbots would offer faster service and quicker problem-solving (Guanah and Bebenimibo, 2025; Uzoka, Cadet and Pascal, 2024). However, its direct effect on Customer Satisfaction was small and not significant ($\beta = 0.257$; t = 1.775; p = 0.076), suggesting that efficiency alone is insufficient to guarantee complete satisfaction, especially in a cultural context that may prioritize human interaction (Chaarani, Skaf and Khalife, 2022; Parasuraman et al., 1988; Souca, 2011). Infrastructural and digital literacy issues in Nigeria may also influence perceptions of chatbot performance (Timothy et al., 2024). Effort Expectancy (EE) showed a positive and marginally significant effect on Customer Satisfaction ($\beta = 0.270$; t = 1.951; p = 0.051), highlighting the importance of ease of use for user contentment (Alalwan et al., 2018; Marikyan and Papagiannidis, 2021b; Silva, Shojaei and Barbosa, 2023). Conversely, it did not significantly predict Service Quality ($\beta = -0.010$; p = 0.911), implying that simplicity alone does not determine the perceived quality of service, which also depends on factors like accuracy, personalization, and empathy (Misischia, Poecze and Strauss, 2022b; Vu, 2021). Challenges in digital literacy in Nigeria underscore the need for user-friendly design, potentially through multilingual options, voice input, or integration with widely used platforms like WhatsApp (Busayo et al., 2023; Okocha and Dogo, 2024; Timothy et al., 2024). User training can also moderate the impact of Effort Expectancy (Alrawashdeh, 2012; Faruque et al., 2024) Trust and Security was found to have a significant direct effect on Chatbot Adoption (path coefficient $\beta = 0.284$; T =

3.851; $p < 0.01$) and strongly influenced Service Quality Perception (path $\beta = 0.400$; $T = 3.532$; $p < 0.01$). This indicates that customer trust in the chatbot's integrity, data security, and fairness is critical for its uptake and how service quality is perceived (Dehghanpouri, Soltani and Rostamzadeh, 2020), particularly in Nigeria where trust in institutions is historically low and concerns about data misuse are prevalent (Babajide and Martin, 2022; Tewari, 2025). Discriminant validity analyses confirmed Trust and Security as a distinct construct, not merely conflated with usefulness or ease of use, despite some moderate correlations with Performance Expectancy (HTMT at 0.969) Managerially, visible compliance measures, clear data disclosure statements, and ethical AI announcements are crucial for the selected multinational retail corporation in Nigeria (Etheridge, 2024).

Techology Readiness surprisingly showed non-significant direct effects on both Chatbot Adoption ($\beta = 0.008$; $T = 0.148$; $p = 0.882$) and Service Quality ($\beta = -0.097$; $T = 1.607$; $p = 0.108$). This suggests that being digitally literate or comfortable with technology does not automatically translate into a willingness to adopt AI chatbots in the Nigerian context, in accordance with Mogaji (2020). Discriminant validity confirmed its distinctness from other constructs (Godoe and Johansen, 2012). This non-significance implies that systemic, cultural, and infrastructural barriers (e.g., unstable internet, data costs, language challenges) can override individual technological preparedness (Kumar & Ciddikie, 2023; Nyagadza *et al.*, 2024). These results challenge UTAUT's universal assumptions about facilitating conditions in low-income contexts (Uren and Edwards, 2023). Service Quality Perception emerged as a vital mediating construct with a strong positive and significant relationship with Customer Satisfaction ($\beta = 0.187$; $T = 3.493$; $p = 0.000$). While significantly influenced by Trust and Security ($\beta = 0.400$; $T = 3.532$; $p = 0.000$), Service Quality was not significantly impacted by Effort Expectancy ($\beta = -0.010$; $p = 0.911$), Performance Expectancy ($\beta = 0.113$; $p = 0.332$), or Technology Readiness ($\beta = -0.097$; $p = 0.108$) directly. This emphasizes that for positive technological outcomes to lead to satisfaction, they must first translate into a favorable perception of service quality, which is often culturally constructed (Aldulaimi, Abdeldayem and Keir, 2024; Fida et al., 2020; Parasuraman et al., 1988; Vu, 2021). Discriminant validity also confirmed its empirical distinctiveness from other constructs. Customer Satisfaction was the ultimate dependent variable, with the model explaining 44% of its variance ($R^2 = 0.440$). Performance Expectancy ($\beta = 0.257$; $p = 0.076$) and Effort Expectancy ($\beta = 0.270$; $p = 0.051$) had only marginally significant effects, suggesting that efficiency and ease of use alone are insufficient to guarantee high satisfaction in Nigeria, possibly due to cultural preferences for human interaction and digital literacy disparities (Busayo et al., 2023; Nwachukwu, 2023; Ono et al., 2024b). Trust and Security showed an even weaker direct impact ($\beta = 0.088$; $p = 0.347$), suggesting it acts more as a threshold condition – its absence deters, but its presence doesn't necessarily boost satisfaction beyond a baseline (Babajide and Martin, 2022; Shoabjareh et al., 2024; Yum and Kim, 2024). Service Quality was the only critical mediator of Customer Satisfaction, reinforcing that culturally embedded perceptions of quality are paramount (Aldulaimi, Abdeldayem and Keir, 2024; Lee et al., 2019; Nwachukwu, 2023; Parasuraman et al., 1988).

Contextual importance of observed associations in Nigeria

The significant and non-significant relationships identified in the model are best understood when interpreted through the realities of Nigeria's digital ecosystem, which is characterized by infrastructural constraints, uneven digital literacy, and persistent trust deficits. Performance Expectancy emerged as a strong predictor of chatbot adoption, but only a marginal predictor of customer satisfaction. This suggests that in a market where customer service is often slow, inconsistent, or inaccessible, the perceived efficiency and functional benefits of AI chatbots strongly motivate initial uptake. However, these utilitarian gains do not automatically translate into satisfaction. Nigerian consumers often place high value on relational and culturally embedded service attributes, such as empathy and human understanding. As a result, while performance efficiency may drive adoption, it is insufficient on its own to ensure satisfaction. Trust and Security strongly influenced both adoption and perceived service quality, yet their direct effect on customer satisfaction was weak. This pattern reflects the role of trust as a threshold condition in Nigeria, where historical concerns about institutional reliability, data misuse, and digital fraud remain salient. Once trust requirements are met, customers are willing to engage with chatbot technologies and evaluate their service quality. However, trust does not function as a delight factor; rather, it prevents rejection and establishes a baseline expectation that does not necessarily enhance satisfaction beyond that point. Effort Expectancy was marginally significant for customer satisfaction but insignificant for service quality. This finding aligns with Nigeria's digital divide, where ease of use is crucial for encouraging engagement and reducing user frustration, particularly among first-time or less digitally confident users. However, technical simplicity does not guarantee high service quality if chatbot responses are inaccurate, generic, or poorly contextualized—limitations that are common in AI systems deployed in resource-constrained environments.

Theoretical surprise and contextual specificity

Several findings depart from conventional technology adoption assumptions and are best explained by Nigeria's contextual conditions. Most notably, Technology Readiness had no significant direct effect on chatbot adoption. This challenges the implicit UTAUT assumption that individual technological preparedness naturally translates into adoption, particularly in low-income or emerging economies. In Nigeria, systemic and structural barriers such as unstable internet connectivity, high data costs, language mismatches, and platform reliability appear to override individual digital competence. This finding suggests that even technologically ready users may refrain from adoption if the surrounding ecosystem is not supportive. Adoption, therefore, depends less on user readiness and more on contextual adaptation, infrastructural adequacy, and trust-building mechanisms. In contrast, Service Quality Perception emerged as a strong and significant predictor of customer satisfaction. This finding is contextually important because it indicates that service quality is socially and culturally constructed. Nigerian consumers evaluate chatbot performance through prior service experiences, cultural expectations, and peer influence. As such, technological outputs must first be interpreted as high-quality service within this social framework before they can generate satisfaction. This reinforces the idea that satisfaction is not a direct outcome of technology performance, but a mediated and culturally embedded evaluation.

Extending and refining the UTAUT Framework

Taken together, the findings necessitate several refinements to the UTAUT model when applied to emerging markets such as Nigeria. First, the results demonstrate the need to conceptually separate utility-driven adoption from satisfaction-driven experience. Performance Expectancy plays a dominant role in motivating initial adoption but does not exert the same influence on post-adoption satisfaction. This distinction highlights the importance of modeling adoption and experiential outcomes as theoretically distinct stages. Second, Trust and Security emerge as a distinct and critical enabler rather than a subsidiary belief. Empirical evidence confirms its discriminant validity relative to usefulness and ease of use, supporting the argument that trust functions as a prerequisite for engagement in low-trust environments rather than as a secondary enhancer of satisfaction. Third, the non-significant role of Technology Readiness calls for a reframing of its theoretical position. Rather than serving as a direct predictor, Technology Readiness may function more appropriately as a moderating or contextual variable in low-resource settings, where systemic constraints dominate individual predispositions. Finally, integrating Service Quality Perception into the model bridges technology acceptance theory with service marketing theory. The results demonstrate that technological capabilities must be translated into culturally acceptable service experiences to produce satisfaction, emphasizing the role of perceived service quality as a key mediating mechanism.

Implications

Theoretical implications

This study offers important theoretical insights by adapting the Unified Theory of Acceptance and Use of Technology (UTAUT) to examine AI-powered chatbot adoption in Nigeria's service context. While UTAUT highlights constructs like Performance Expectancy and Effort Expectancy as core drivers of adoption, this research reveals nuanced dynamics in an emerging-market setting. Performance Expectancy demonstrated a strong influence on Chatbot Adoption confirming that perceived usefulness is essential. Yet its weaker impact on Customer Satisfaction suggests that efficiency alone is insufficient without addressing relational and cultural expectations, highlighting the need for local adaptation. Effort Expectancy's significant role in Customer Satisfaction underscores the importance of usability in contexts of uneven digital literacy (Chau et al., 2025). This indicates that adoption models must account for user training and design tailored to local technological readiness. The inclusion of Trust and Security as an extended construct further enriches UTAUT. While not directly predicting Customer Satisfaction, it significantly influenced Chatbot Adoption, highlighting its role as an essential enabler in environments with lower baseline trust. Moreover, Service Quality Perception emerged as a vital mediating variable, demonstrating that technological benefits must be translated through perceptions of service quality to drive satisfaction. This study advances academic knowledge by extending the Unified Theory of Acceptance and Use of Technology (UTAUT) and deepening understanding of AI chatbot adoption in emerging market contexts, particularly Nigeria. First, the research develops and empirically validates an expanded UTAUT model tailored to the Nigerian service environment. The model integrates Trust and Security and Technology Readiness as external constructs, demonstrating that Trust and Security is a critical enabler of chatbot adoption in low-trust settings and meaningfully enriches the original UTAUT framework. In contrast, Technology Readiness was found to have a negligible direct effect, suggesting its role may be better conceptualized as a moderating rather than a core predictive factor in such contexts.

Second, the study strengthens the model by introducing Service Quality Perception as a key mediating variable, showing that perceived technological benefits must be translated into service quality evaluations to drive customer satisfaction. This integration bridges technology acceptance theory with service marketing perspectives that emphasize culturally shaped expectations. Third, the findings refine core UTAUT assumptions by revealing that while Performance Expectancy strongly influences adoption, its weaker effect on customer satisfaction indicates that efficiency alone is insufficient to ensure positive service experiences. This distinction highlights the need for theory to differentiate between adoption intention and experiential outcomes. Fourth, the study extends prior research by adopting a dual-stakeholder perspective, incorporating insights from both customers and internal organizational actors, thereby moving beyond the traditional end-user focus. Beyond theory development, the research enriches the broader discourse on AI chatbot adoption by addressing a significant empirical gap in emerging markets. It offers one of the earliest country-specific models of AI chatbot adoption by a multinational firm in Nigeria, providing insights into operational challenges, infrastructural constraints, and trust dynamics. By demonstrating that trust outweighs individual readiness in this setting, the study challenges universalist technology adoption assumptions and underscores the importance of context-sensitive, trust-driven, and service-oriented adaptations of UTAUT for successful AI implementation in emerging markets. Overall, the application of the expanded UTAUT framework in the Nigerian context yields an important theoretical insight: the successful deployment of AI chatbots in emerging markets requires a shift toward a customer-centric and culturally adaptive paradigm. In such settings, trust and perceived service quality function as central mediators, while individual technological readiness is secondary to systemic, infrastructural, and cultural constraints. This contribution advances UTAUT by grounding it more firmly in the realities of emerging economies and service-dominated digital interactions.

Practical contributions

This research emphasises that to achieve the optimal potential of AI-powered chatbots, smart developments should shift beyond merely technical implementation to performance integration with user anticipations. The small influence of digital literacy on the use of chatbots, although the self-rated competence rate is highly positive, shows that accessibility is not enough. The selected multianational retail coporation in Nigeria should thus approach interface simplification as a design specification rather than a corrective action that can incorporate user confidence and cognitive load variation in the multivarious consumer groups of Nigeria. The low predictability of trust and security on customer satisfaction does not mean that it is irrelevant as where trust and security are concerned it would mean more prevention than promotion. The lack of apparent security guarantee may cause rejection, even by otherwise favorable users of systems, in an environment in which data misuse is a general issue of concern. In addition, the service quality mediating role indicates that the performance of chatbots has to be co-produced rather than a service that can be delivered to users. Context-awareness as well as responsiveness and emotional attune must become priorities by means of upgrades in terms of natural language processing and designs sensitive to sentiments. The multi-lingual capability is not just a necessity of linguistic inclusivity, but it is also a cultural prerequisite. Incorporating regional humor, politeness strategies, and local idioms into chatbot scripts have the potential to further increase the perceived authenticity and engagement.

Policy contributions

This research contains essential policymaking contributions, particularly regarding digital inclusion and ethical usage of AI in Nigeria. The fact that Technology Readiness has less impact exposes infrastructural differences and points to the requirement of investing in broadband connections and applicable digital literacy programs. These programs directly contribute to SDG 9 (Industry, Innovation, and Infrastructure) by building inclusive digital ecosystems. The central position of Trust and Security is also an indicator of the necessity to establish legislation on the data protection which may be implemented in the form of EU-wide directives. With the escalation of AI tools, it is important to promote transparency and ethical governance to enhance the development of responsible innovation as part of SDG 9. In terms of SDG 8 (Decent Work and Economic Growth), mentioned above the introduction of AI chatbots helps increase efficiency at the cost of lower-skill customer service positions. Policymakers ought to encourage reskilling initiatives, which would allow displaced employees to transition to new jobs in an automation environment, including AI management or digital engagement with customers, where human skills are valuable. Also, local realities have to be reflected in AI strategies.

Limitations

The study acknowledged several limitations. Focused on the selected multianational retail coporation in Nigeria, which limits transferability of findings to other locations or countries due to distinct socio-economic, technological, and infrastructural elements. It relied on self-reported data, exposing it to potential biases where participants might give favorable or unfavorable feedback. Difficulty in obtaining detailed operational data from the selected multinational retail coporation in Nigeria due to confidentiality was also a factor. Social Influence and Facilitating Conditions were excluded from the original survey design due to research objectives. There is unstable internet connectivity and digital literacy challenges in Nigeria impair AI system efficiency and reach, potentially leading to an improper understanding of AI's true potential in developing markets. Self-reported data could lead to desirable rather than realistic outcomes. Individuals without internet access or in poorly connected rural areas were not considered, limiting generalizability. The study only considered consumer perspectives, not employee or internal technology manager experiences. Data was gathered at one point in time, making it difficult to observe changes over time. The quantitative approach, while good for large samples, limited exploration of qualitative details. Finally, focusing solely on Nigeria limits the transferability of findings to other locations or countries due to distinct socio-economic, technological, and infrastructural elements.

Directions for future research

The research improves UTAUT by incorporating trust and context into the adoption theory in new markets, promoting inclusive and customer-driven AI adoption. Future research should consider longitudinal studies to observe changes over time and incorporate qualitative methods to explore details not captured by the quantitative approach. Further investigation into social influence and facilitating conditions would also be beneficial, as these were excluded from the current study. Research could also expand to include employee perspectives to provide a more holistic view. The study calls for the refinement of UTAUT to integrate trust, service quality, and context-sensitive design, aiming to offer a more comprehensive framework for understanding technology adoption in emerging markets. Future research should also extend the UTAUT model to a dual-stakeholder scenario. This means exploring technology acceptance not just among end-users (customers) but also among internal stakeholders, such as employees and managers, within multinational companies operating in emerging markets. This combined approach offers a more integrated view of organizational technology adoption. Future research also needs to continue to study the critical and independent role of Trust and Security as an essential enabler, especially in environments characterized by lower baseline trust. This research results challenged the traditional view of Technology Readiness, as it reported a negligible impact on both adoption and service quality. Future research should investigate Technology Readiness, suggesting its role may be better understood as a moderator rather than a core predictor in low-resource settings, where factors like infrastructure and usability may supersede individual digital predispositions.

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