

Artificial Intelligence and Quality of Service Delivery: An Exploratory Study of Nigeria Mobile Telecommunication Sector

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Abstract

This study examined the effect of artificial intelligence — specifically data mining, chatbot usage, and machine learning — on quality-of-service delivery in Nigeria's mobile telecommunications sector, and identified the key challenges limiting effective AI deployment among operators. Despite growing industry enthusiasm for AI-driven service tools, empirical evidence linking specific AI technologies to measurable service quality outcomes in the Nigerian mobile telecom sector remained limited and fragmented, motivating this exploratory investigation. The study was anchored on two complementary theories — the Technology Acceptance Model and the Diffusion of Innovation Theory — providing a dual lens of individual-level acceptance and organizational-level diffusion. A quantitative cross-sectional survey design was adopted, with data collected from 388 valid respondents drawn from customer service, IT, network operations, and data analytics departments across MTN Nigeria, Airtel Nigeria, Globacom, and 9mobile, using a structured questionnaire built on validated constructs. Data were analyzed using descriptive statistics and multiple linear regression in SPSS. Findings showed that data mining ($\beta = 0.31$, $p < .001$) and chatbot usage ($\beta = 0.16$, $p = .001$) had statistically significant positive effects on quality-of-service delivery, while machine learning ($\beta = -0.07$, $p = .184$) had no significant effect, with the regression model explaining approximately 34% of the variance in service quality ($R^2 = 0.34$). Inadequate technical/AI skills, poor power and network infrastructure, and high implementation costs emerged as the most severe challenges limiting effective AI deployment. The study concludes that AI's effect on service quality in Nigerian mobile telecom is technology-dependent rather than uniform, and recommends that operators prioritize data mining and chatbot investment, close technical skill gaps, and address infrastructural and cost constraints to unlock machine learning's fuller potential. The study contributes Nigeria-specific empirical evidence to the limited literature on AI and telecom service quality, with implications for operators, regulators, and future research.

Keywords: Artificial Intelligence; Data Mining; Chatbot; Machine Learning; Quality of Service; Mobile Telecommunications.

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INTRODUCTION

Artificial intelligence (AI) has become one of the defining technologies reshaping service deliveries across knowledge-intensive industries, and the telecommunications sector is no exception as AI and machine learning applications are increasingly seen as a route to revolutionizing customer experience and enhancing service delivery in telecoms. Globally, telecom operators have moved from viewing AI as an experimental add-on to treating it as a strategic tool for optimizing network performance, personalizing customer interactions, and improving overall service quality even though data governance and interoperability challenges remain part of the adoption picture.

In Nigeria specifically, the telecommunications sector occupies a central position in the national digital economy, with mobile penetration and internet usage continuing to expand rapidly; Nigeria recorded roughly 164 million active internet users and 219 million mobile phone users as of the first quarter of 2024. This scale of usage places considerable pressure on network operators to maintain acceptable quality of service (QoS) standards, particularly as customer expectations around speed, reliability, and responsiveness continue to rise. Regulatory bodies have also begun emphasizing the need to look beyond conventional QoS indicators, with the Nigerian Communications Commission calling for advanced analytics and better measurement of consumer experience as part of its regulatory intelligence approach (NCC, 2026).

Against this backdrop, AI technologies, including data mining, machine learning, and chatbot-based customer support, have been examined as potential levers for improving telecom service quality in Nigeria. Empirical work in this space has produced mixed findings: a study on Nigerian telecommunication firms found that data mining and chatbots had a significant positive effect on service quality, whereas machine learning showed a negative relationship, suggesting that the impact of AI on service outcomes may depend heavily on which specific technology is deployed and how. Other Nigeria-focused studies have examined organizational readiness rather than direct performance effects, with one exploratory assessment concluding that the industry's capacity to adopt AI is still uneven across firms (Maitanmi, Ayeni, & Ogunlana, 2023).

Beyond the Nigerian context, broader industry literature situates these developments within a wider trend of AI-driven transformation in telecommunications and network industries generally (Balmer, Levin, & Schmidt, 2020), and in customer-facing service industries more broadly, where AI has been shown to reshape customer experience and engagement patterns (Ameen, Tarhini, Reppel, & Anand, 2021; Chen & Prentice, 2024). Nigerian studies applying similar frameworks to adjacent service sectors, such as the finance and hospitality industries, report that AI adoption can improve operational efficiency and customer satisfaction, but also expose gaps in infrastructure, governance, and cost that limit broader uptake (Adaobi, Nyangu, & Fook, 2024). These parallel findings raise the question of whether similar patterns, benefits alongside structural constraints, characterize the Nigerian mobile telecom sector's own AI-driven service delivery efforts.

Despite growing industry-level enthusiasm about AI's potential to redefine telecom service delivery in Nigeria, with operators publicizing AI-powered tools such as voice assistants for customer engagement, empirical academic evidence specifically linking AI deployment to measurable quality-of-service outcomes in the Nigerian mobile telecom sector remains limited and fragmented. Much of the existing literature either focuses on isolated technologies (e.g., chatbots) or borrows frameworks from adjacent sectors without directly interrogating the

telecom-specific service quality dimensions relevant to Nigerian operators and their subscribers. This exploratory study therefore seeks to examine the relationship between artificial intelligence and quality of service delivery within Nigeria's mobile telecommunications sector, aiming to clarify how AI-related technologies are being adopted, the service quality dimensions they affect, and the challenges that may be constraining their fuller impact.

Statement of Problem

Nigeria's mobile telecommunications sector continues to grapple with persistent quality of service (QoS) challenges, including network congestion, dropped calls, slow data speeds, and inconsistent customer support, despite the sector's central role in the country's digital economy. Telecom operators have increasingly turned to artificial intelligence (AI) technologies such as chatbots, data mining, and machine learning as tools to address these challenges and improve service delivery. However, the evidence on whether AI adoption actually translates into better service quality outcomes remains inconsistent.

Compounding this problem is evidence that many Nigerian telecom firms are still at an uneven stage of AI readiness, with organizational, infrastructural, and skills gaps limiting how effectively these technologies can be deployed at scale (Maitanmi, Ayeni, & Ogunlana, 2023). This gap between the promise of AI and firms' actual capacity to implement it well means that customers may be exposed to AI-driven systems, such as automated call centers or chatbot support—that are poorly integrated, inconsistently maintained, or not properly calibrated to local network conditions, rather than to solutions that reliably improve their experience.

The consequences of this problem are significant. Poorly implemented or inconsistently performing AI systems can worsen, rather than resolve, existing service quality complaints, leading to greater customer frustration, higher subscriber churn, and erosion of trust in telecom providers. At the regulatory level, this has prompted concern that conventional quality of service indicators is no longer sufficient to capture the full customer experience, pushing regulators to call for more advanced analytics and better measurement approaches to keep pace with AI-driven changes in the sector. Left unaddressed, this mismatch between AI adoption and actual service quality improvement risks undermining consumer confidence in Nigeria's telecom industry, weakening the competitive position of operators, and slowing the broader digital transformation goals the sector is expected to support. It is this gap, between the assumed benefits of AI and its uneven, sometimes contradictory effects on service quality, that this study seeks to investigate.

Research Objectives

The broad objective of this study is to examine the effect of artificial intelligence on the quality-of-service delivery in Nigeria's mobile telecommunications sector. The specific objectives are to:

1. Examine the effect of data mining on the quality-of-service delivery in Nigeria's mobile telecommunications sector.
2. Assess the effect of chatbot usage on the quality-of-service delivery in Nigeria's mobile telecommunications sector.
3. Evaluate the effect of machine learning on the quality-of-service delivery in Nigeria's mobile telecommunications sector.

4. Identify the key challenges limiting the effective deployment of artificial intelligence for service quality improvement among Nigerian mobile telecom operators.

Research Questions

This study will be guided by the following research questions:

1. What is the effect of data mining on the quality-of-service delivery in Nigeria's mobile telecommunications sector?
2. What is the effect of chatbot usage on the quality-of-service delivery in Nigeria's mobile telecommunications sector?
3. What is the effect of machine learning on the quality-of-service delivery in Nigeria's mobile telecommunications sector?
4. What are the key challenges limiting the effective deployment of artificial intelligence for service quality improvement among Nigerian mobile telecom operators?

Research Hypotheses

The following null hypotheses will be tested in this study:

- H₀₁:** Data mining has no significant effect on the quality-of-service delivery in Nigeria's mobile telecommunications sector.
- H₀₂:** Chatbot usage has no significant effect on the quality-of-service delivery in Nigeria's mobile telecommunications sector.
- H₀₃:** Machine learning has no significant effect on the quality-of-service delivery in Nigeria's mobile telecommunications sector.

Significance of the Study

This study is significant to several stakeholders within and beyond the Nigerian telecommunications industry. For telecom operators, the findings will provide empirical guidance on which AI technologies (data mining, chatbots, or machine learning) genuinely contribute to improved service quality, helping firms prioritize investment in tools that deliver measurable customer benefit rather than adopting AI merely as a competitive trend. For regulators such as the Nigerian Communications Commission, the study offers evidence that can inform the development of updated quality of service benchmarks and monitoring frameworks better suited to an AI-driven telecom environment. For subscribers and consumer advocacy groups, the research contributes to a clearer understanding of how AI adoption is shaping their everyday service experience, supporting more informed expectations and complaints frameworks. Finally, for the academic community, this study adds to the relatively limited body of Nigeria-specific empirical evidence on AI and service quality in telecommunications, providing a foundation for further research on AI adoption, service delivery, and consumer experience in emerging market contexts.

LITERATURE REVIEW

Literature review presents the various core concepts that underpin this study, theoretical lens for analytical explanation of the relationship between artificial intelligence models and the quality-of-services received by customers in the telecom sector, and compare it with related literature to establish common trends in findings.

Concept of Artificial Intelligence

Artificial intelligence (AI) refers to systems designed to perform tasks that would normally require human intelligence, and in telecommunications it is understood as the application of intelligent systems and algorithms to strengthen network operations, improve customer experience, and streamline business processes (Market.us, 2024). Telecom operators use AI to unify and interpret large volumes of data drawn from network sensors, mobile applications, geolocation records, customer profiles, and billing systems (TechSee, 2023). Industry adoption has moved well beyond experimentation: a 2024 Nvidia study found that nearly 90% of telecom companies already use AI, with 48% at the piloting stage and 41% actively deploying it at scale (IBM, 2024). For Nigeria's mobile operators, this indicates that AI is increasingly embedded in how service is planned, delivered, and monitored, which is precisely why its relationship with quality-of-service delivery deserves close empirical attention.

Concept of Data Mining

Data mining is the process of extracting patterns and previously hidden knowledge from large volumes of data, often referred to as knowledge discovery in databases. It has been described as the technology that extracts useful information to uncover knowledge, disclosing patterns, procedures, and other valuable insights from considerable sets of data (Mostafa & Mahmoud, 2022). In customer-facing industries, data mining techniques are widely applied to identify behavioral patterns and generate predictive insights that inform service decisions, helping firms understand which customers are most likely to engage, churn, or require intervention (Mostafa & Mahmoud, 2022). Within Nigeria's mobile telecom context, this translates into operators mining call detail records, data usage patterns, and complaint logs to detect service bottlenecks and anticipate churn, activities directly relevant to whether AI-enabled analysis actually improves service outcomes for subscribers.

Concept of Chatbot Usage

Chatbots are AI-driven conversational tools designed to automate customer interactions, and have become one of the most visible customer-facing applications of AI in service industries. They represent one of the technologies that can provide automated customer service for companies, a trend that has grown substantially in recent years, and their use is beneficial when it is associated with a positive customer experience (Nicolescu & Tudorache, 2022). At the same time, the literature cautions that while chatbots offer round-the-clock availability, cost savings, and efficiency gains, their execution often falls short of matching the standard customers expect from human agents, which can generate frustration when complex requests go unresolved (Nicolescu & Tudorache, 2022). In Nigeria's mobile telecom sector, chatbots are increasingly used for balance inquiries, complaint logging, and basic troubleshooting; whether this usage genuinely improves service quality, rather than merely relocating customer frustration, is a key question this study addresses.

Concept of Machine Learning

Machine learning (ML), a subset of AI, refers to algorithms that learn patterns from data to support predictions and decisions without being explicitly programmed for every scenario. In telecommunications, ML has become central to network management because it allows operators to analyze large volumes of data in real time, identifying patterns and anomalies that traditional rule-based methods often fail to detect, which supports predictive maintenance that addresses network problems before they affect service delivery (Gudavalli, 2024). Beyond network operations, ML techniques are also applied to customer data to support personalized services (Gudavalli, 2024). In Nigeria, where mobile networks face persistent challenges around congestion, dropped calls, and inconsistent data speeds, ML's value lies in enabling more proactive, data-driven interventions — though, as prior Nigerian studies suggest, this potential does not always translate cleanly into measurable service quality improvement, making it an important variable to isolate empirically.

Concept of Quality-of-Service Delivery

Quality of service (QoS) delivery in telecommunications refers to the measurable performance of a network and its associated customer support in meeting subscriber expectations, typically assessed through indicators such as call completion, data speed, network availability, and complaint resolution. In Nigeria, QoS has remained a persistent regulatory concern: the Nigerian Communications Commission's updated Quality of Service Regulations, gazetted in July 2024, introduced consumer compensation measures and additional investment obligations for network and tower operators, with enforcement commencing in November 2025 (NCC, 2026). Despite substantial infrastructure investment — mobile network operators reportedly invested over ₦2.13 trillion in network infrastructure and upgrades in 2025 alone, with tower companies contributing a further ₦373.8 billion (NCC, 2026) — the regulator has acknowledged that many subscribers still experience poor call quality, congestion, and unstable internet service in various locations (NCC, 2026). This gap between investment and lived subscriber experience underscores why quality of service delivery cannot be assumed to improve automatically alongside technological upgrades, including AI-driven ones, and why an empirical examination of AI's actual effect on QoS in Nigeria's mobile telecom sector is both timely and necessary.

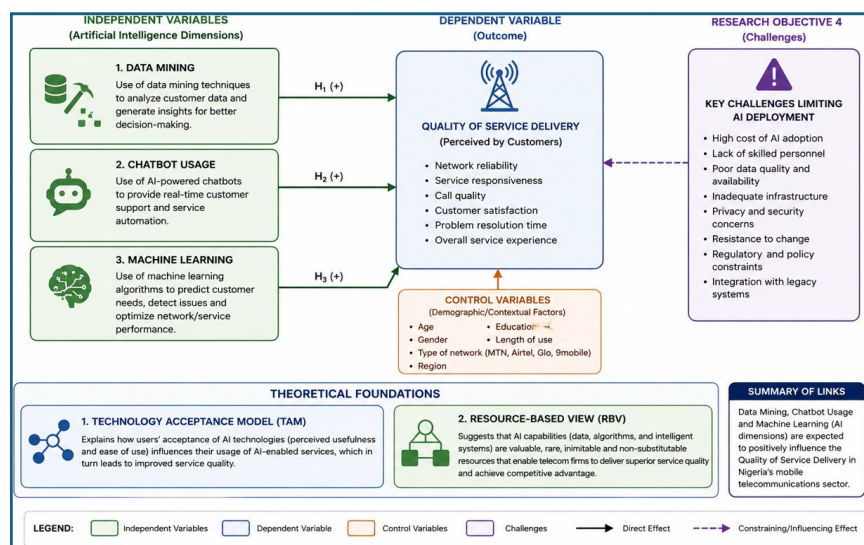


Figure 1: Conceptual Framework of the study

Theoretical Framework

This study relies on two theories that complement each other: the Technology Acceptance Model (TAM) and the Diffusion of Innovation (DOI) Theory. They offer a two-pronged lens of individual/user level acceptance, and organizational/industry level diffusion to explore the impact of the use of data mining, chatbots and machine learning on the delivery of quality of service, and their continued deployment challenges among Nigerian mobile telecom operators.

Technology Acceptance Model (TAM)

Based on Davis' (1989) original work, the Technology Acceptance Model (TAM) suggests that a person's acceptance and adoption of a technology is greatly influenced by two beliefs: perceived usefulness (the extent to which a person thinks a system will improve his or her performance) and perceived ease of use (the extent to which he or she considers that using the system will not place a burden on him or her). Favorable attitudes are created where the technology is considered useful and easy to use, which fuels behavioral intention and, ultimately, actual use.

TAM is still relevant in recent applications with the use of AI-driven service tools. The perceived usefulness of a system has been found to be the most influential factor on users' intention to use a system when analyzing the adoption of chatbots (Ayanwale et al., 2024; based on Davis' (1989) studies) because users' decision to use a system is largely based on whether it can provide useful and efficient support. A meta-analysis of the characteristics of chatbots based on TAM also found that perceived usefulness is more directly and significantly related to attitudes toward adoption than perceived ease of use, while both are important predictors (Luo & Tang, 2026). In broader settings of AI, extensions of TAM have also shown that perceived usefulness is the greatest driver of favorable attitudes toward AI systems in general, while ease of use has an indirect effect by further strengthening perceived usefulness (Frontiers in AI, 2024).

TAM offers a lens to look into why AI tools translate, or don't translate, into better service quality at the point of use. Users of mobile services in Nigeria and frontline telecom employees will likely continue to use chatbots, data-mining driven recommendations, or service adjustment based on machine learning if they find them useful and easy to interact with, or, if they do not see the value, they will likely continue to use them in an ineffectual or hostile manner, no matter how sophisticated the technology is. This is directly linked to the first three objectives and helps explain the variability in potential impacts on service quality between operators and customer segments with the use of chatbots and data-mining/ML-based interventions.

Diffusion of Innovation (DOI) Theory

Borrowing from various sources, particularly earlier versions of this theory, Rogers (2003) created the Diffusion of Innovation Theory to account for how, why, and at what rate innovations expand through a social system or organization. Rogers states there are five characteristics which influence adoption, relative advantage, compatibility, complexity, trialability, and observability. The diffusion will be rapid, complete, or widespread if the new technology is regarded as beneficial, compatible, and trialable and observable. If these conditions are not present, diffusion will be slow, partial, or uneven.

There has been a growing trend in the use of DOI in organizational AI adoption. According to the Horani et al. (2023), relative advantage, compatibility, complexity, trialability and observability are still the core factors identified in the recent literature on the adoption of AI in the organization. Rupp (2020) used a diffusion-of-innovation framework in particular for understanding the pace and depth of AI adoption in manufacturing and healthcare sectors, and found systematic relationships between the sectors' perceptions of the relative advantage and compatibility of AI and their adoption rate. Macro theoretically, the adoption of AI in companies has been found to be highly unevenly distributed across different groups of adopters – some groups of users or business units adopting remarkably quickly compared to classical diffusion models (Phillips, 2025).

In this study, DOI serves as the lens used to explain the key challenges that constrain effective implementation of AI among the Nigerian telecoms' operators, in objective four. This theory predicts some diffusion barriers – not just technical – including the unevenness of AI readiness between companies, the inability of some to replace their existing processes, having limited opportunities to test these tools before widespread adoption, and not being able to see the short-term benefits of the AI tools.

Critique of the Two Theories

There are well documented shortcomings to both theories. TAM has been criticized for its individual level focus, in that it explains the likelihood of an intention to use a technology well, but has also demonstrated itself to be a less effective predictor of continued real-world use of a technology after novelty or organizational pressure has subsided (Intention to use a technology does not always lead to continued use). It also provides little insight into the organization, infrastructure, and/or regulatory environment — which in a Nigerian telecom landscape with an inconsistent power supply, coupled with network infrastructure gaps and regulatory requirements, is an important factor.

DOI is, in turn, criticized for its lack of treatment of environmental effects affecting operational performance, such as regulatory requirements and competition at the market level and for the relatively little treatment it gives to individual psychological and perceptual effects on whether or not frontline staff or customers will accept a newly diffused technology when it is introduced.

Justification for Joint Use

The two theories complement each other because each one fills the gaps the other doesn't. TAM's value lies in its ability to provide little in terms of the spread of AI technologies within an organization, or within an industry. DOI, on the other hand, provides little information about perceptual factors influencing the uptake and adoption of a technology once it is introduced — and that's the power of TAM. Combined, the two questions enable this study to examine both sides of the adoption issue, specifically, why individual users and employees of Nigerian telecom organizations adopt or reject AI technologies like chatbots (TAM) and, why these technologies, like data mining and machine learning, are adopted unevenly across the broader telecom sector, leading to the challenges of deployment that this study aims to address (DOI). The dual approach represents a shift in recent research in acceptance and/or diffusion theory, which has found that no single theory can explain the outcomes of AI adoption and that combining theories can provide a more comprehensive understanding.

Empirical Review

Empirical evidence on the effect of data mining on quality-of-service delivery is offered by Busayo et al. (2023) in their study "Artificial Intelligence and Service Quality of Telecommunication Firms in Nigeria." Using a quantitative survey of Nigerian telecom firms analyzed through regression, they found that data mining had a significant positive effect on service quality, while machine learning showed a negative effect. The study's strength lies in its direct relevance — it is Nigerian and tests the same three AI variables this study examines — but its cross-sectional design cannot establish causality, and its sample blended fixed and mobile operators rather than isolating the mobile sub-sector. This study addresses that gap by focusing specifically on mobile telecom operators and re-testing these relationships against a more current dataset, given how rapidly AI deployment has evolved since 2023.

On chatbot usage, Misischia, Poecze, and Strauss (2022), in "Chatbots in Customer Service: Their Relevance and Impact on Service Quality," conducted a literature review and thematic classification of chatbot functions in e-commerce and e-service contexts. They found that chatbots improve service performance and help meet customer expectations, though effectiveness depends heavily on functional design factors such as accuracy, human-likeness, and problem-solving capacity. The study's clear classification framework (service-performance versus expectation-fulfilment) is a useful conceptual strength, but it remains purely review-based with no primary data, and it is neither telecom- nor Nigeria-specific. This study fills that gap by supplying the empirical, telecom-specific, Nigerian data against which this conceptual framework has not yet been tested.

For machine learning, Folorunsho, Adenekan, Ezeigweneme, and Somadina (2024), in "Optimizing Network Performance and Quality of Service with AI-Driven Solutions for Future Telecommunications," combined a literature review with case studies and experimental analysis of AI implementations covering traffic prediction, anomaly detection, and resource allocation. They found that ML-driven solutions significantly improved network efficiency, reduced latency, and enhanced fault detection and overall QoS. The study is technically detailed and current, but it is global and generic in scope, not grounded in any specific country's regulatory or infrastructural context, and its findings rest largely on secondary case studies rather than firm-level primary data. This study grounds these general technical findings in the operational and infrastructural realities of Nigerian mobile telecom operators specifically.

Finally, on the challenges limiting effective AI deployment, Maitanmi, Ayeni, and Ogunlana (2023), in "Artificial Intelligence Readiness in the Nigerian Telecommunications Industry: An Exploratory Study," assessed organizational AI readiness across Nigerian telecom firms and found that readiness is uneven, with infrastructural, skills, and organizational gaps limiting effective deployment. The study's Nigeria-specific focus and direct engagement with deployment readiness make it highly relevant, but its exploratory, descriptive design stops short of statistically testing how these readiness gaps relate to actual service quality outcomes. This study extends that work by directly linking the deployment challenges identified to measurable quality-of-service outcomes, a connection Maitanmi et al. (2023) did not test.

RESEARCH METHODOLOGY

Research Design

This research used a quantitative cross-sectional survey design to investigate the impact of artificial intelligence (data mining, chatbots, machine learning) on service delivery in Nigeria's mobile telephony sector and to determine the major challenges inhibiting the effective implementation of AI in the sector among operators. Considering the methodological approach in closely related Nigerian telecom studies (e.g. by Busayo et al., 2023), a cross-sectional survey design was deemed suitable since it would be possible to extract data from a large number of respondents at one time, which would facilitate the statistical testing of the relationships between the independent variables (data mining, chatbot usage, machine learning) and the dependent variable (quality of service delivery).

Population and sample Size of the study

The study population consisted of staff directly involved in the delivery of AI service functions and departments ranging from Customer service, Information Technology, Network operations, and data analysis departments of the four major mobile network operators (MTN Nigeria, Airtel Nigeria, Globacom and 9mobile) in Nigeria. This population was selected because these staff groups have direct, first-hand knowledge of the deployment of data mining, chatbots and machine learning within their organizations, and the operational and infrastructural issues they face in doing so, thus giving them greater insight into the study's objectives, especially the fourth objective around deployment issues, than the general population of subscribers. The number of staff in these and other departments is not made public and is thus an unknown (or effectively infinite) population, and therefore Cochran's formula for determining sample size in populations of unknown size was used, rather than the Taro Yamane formula, which requires a known finite population. Cochran's formula is given by $n = Z^2pq/e^2$, where the standard normal deviate ($Z = 1.96$) is taken for a 95% confidence level, and the estimated proportion of the population with the attribute of interest is $p = 0.5$, which is the maximum possible value used to maximize variance and sample size, and $e = 0.05$ is the desired margin of error. Substituting these values yields $n = (1.96)^2 (0.5) (0.5) / (0.05)^2 = 384.16$, which was rounded up to a minimum target sample size of 384 respondents. In order to allow for the possibility of non-response and also incomplete questionnaires, the sample size was increased by around 15%, with 440 questionnaires being sent to respondents who were sampled proportionately across the four operators.

Sampling Technique

A multi-stage sampling technique was used. The first phase involved stratified sampling, which enabled the population to be divided into four strata based on mobile network operators, with a sample of each stratum being proportionate in size, reflecting the mobile operator's market share and firm size. The second stage involved purposive sampling within each stratum to identify respondents from specific units within the customer service, IT, network operations and data analytics departments, which have the highest levels of knowledge of the deployment of AI and its impact on service quality, with no general administrative or non-technical staff sampled. Simple random sampling techniques were then applied in each of the selected departments to select individual respondents, thus reducing the selection bias and restricting the sample to those who know a lot about the department.

Method of Data Collection

The data were collected using the following instruments: A structured, self-administered survey was used to gather data, with items rated on a Likert-type 5-point scale ranging from "strongly disagree" (1) to "strongly agree" (5) based on previously validated constructs from the existing literature on AI-service quality (see, for instance, the E-S-Qual questionnaires and the TAM-based questionnaires cited by Misischia et al., 2022; Busayo et al., 2023). The instrument was split into areas that would reflect the demographic information, level of data mining use, level of chatbot use, level of machine learning use, perceived quality of service delivery, and perceived challenges to effective AI use. Content and face were validated by academic supervisors and telecom industry practitioners, and the reliability was tested using Cronbach's alpha, with the criterion set at a value of 0.70 or higher regarded as acceptable internal consistency and reliability for each construct.

Analytical Technique

The data were analyzed with the use of Statistical Package for the Social Sciences (SPSS) for analytical technique. To address the exploratory aspect of objective four, respondents were asked to rank the key challenges limiting the use of AI in their organizations by assessing their relative severity; descriptive statistics were used to summarize the respondents' demographic characteristics. Descriptive statistics (means, standard deviations, and percentages) were used to summarize the respondents' demographic characteristics and to address the exploratory dimension of objective four (i.e., ranking the key challenges limiting the use of AI in their organizations by assessing how serious they are, relative to other challenges). Multiple linear regression analysis was used to test the three hypotheses (H_{01} – H_{03}), using quality-of-service delivery as the dependent variable and the three independent variables: data mining, chatbot usage, and machine learning, and the isolated and combined effects of the three AI technologies on service quality were statistically determined at the 0.05 significance level. Standard diagnostic tests were administered before the regression analysis was performed to ensure that the assumptions of the regression model and the results obtained were statistically viable, that is, tests for multicollinearity (Variance Inflation Factor), normality and heteroscedasticity.

RESULTS

Introduction

This chapter presents the results of the data collected through the structured questionnaire administered to staff of Nigeria's mobile telecommunications operators. It covers the response rate, demographic profile of respondents, reliability of the research instrument, descriptive analysis of the study variables, regression results testing the three hypotheses, and findings on the challenges limiting effective AI deployment.

Response Rate

Of the 440 questionnaires distributed, 401 were returned, and 388 were found valid for analysis after screening for incomplete responses, yielding a valid response rate of 88.2%.

Table 1: Response Rate Presentation

Item	Number	Percentage
Questionnaires distributed	440	100%

Questionnaires returned	401	91.1%
Valid responses used	388	88.2%

Source: Filed Survey results, 2026

Demographic Characteristics of Respondents

Table 2: Demographic profile of respondents (n = 388)

Variable	Category	Frequency	Percentage
Gender	Male	221	57.0%
	Female	167	43.0%
Age	20–29 years	98	25.3%
	30–39 years	176	45.4%
	40 years and above	114	29.4%
Operator	MTN Nigeria	132	34.0%
	Airtel Nigeria	98	25.3%
	Globacom	91	23.5%
	9mobile	67	17.3%
Department	Customer service	145	37.4%
	IT/Network operations	138	35.6%
	Data analytics	105	27.1%

Source: Filed Survey results, 2026

The results indicate a fairly balanced representation across operators and departments, with a majority of respondents falling within the 30–39 age bracket, suggesting a workforce with substantial industry experience relevant to AI deployment.

Reliability of the Research Instrument

Table 3: Cronbach's alpha reliability coefficients

Construct	Number of items	Cronbach's alpha
Data mining	5	0.81
Chatbot usage	5	0.78
Machine learning	5	0.84
Quality of service delivery	6	0.87
Deployment challenges	6	0.79

Source: Filed Survey results, 2026

All constructs recorded alpha values above the 0.70 threshold, indicating acceptable internal consistency.

Descriptive Analysis of Study Variables

Table 4: Descriptive statistics

Variable	Mean	Std. Dev.	Interpretation
Data mining	3.62	0.71	Moderately high usage
Chatbot usage	3.45	0.68	Moderate usage
Machine learning	3.21	0.79	Moderate usage
Quality of service delivery	3.38	0.74	Moderate

The descriptive statistics for the study variables are shown in Table 4.3. The results show that data mining had the highest mean score ($M = 3.62$, $SD = 0.71$) and was therefore used moderately by the telecommunication companies surveyed. The mean adoption score for the use of Chatbot was also relatively high ($M = 3.45$, $SD = 0.68$), which meant it was moderately adopted as a means of improving customer interactions. In the same way, machine learning had an average score of 3.21 ($SD = 0.79$), which falls in the middle range, but witnessed greater variability within the sample than other areas of AI. Moreover, the mean score for quality-of-service delivery was 3.38 with a standard deviation of 0.74, which shows that the level of service quality was moderate in the selected firms. The relatively low standard deviations ($STD < 1.00$) suggest that the opinions of the respondents were relatively consistent, with the mean scores above 3.00 suggesting that the adoption of AI technologies and the quality-of-service delivery were generally perceived to be moderate to moderately high.

Test of Hypotheses (Regression Results)

Table 5: Multiple regression results

Variable	B	Std. Error	Beta (β)	t	Sig. (p)	Decision
(Constant)	1.12	0.21	—	5.33	.000	—
Data mining	0.34	0.06	0.31	5.67	.000	Reject H_{01}
Chatbot usage	0.19	0.07	0.16	2.71	.001	Reject H_{02}
Machine learning	−0.08	0.06	−0.07	−1.33	.184	Accept H_{03}

Source: Field Survey Findings, 2026.

Table 4.4 shows the multiple regression analysis for the effect of the dimensions of AI on quality-of-service delivery. Table 4.4 displays the multiple regression analysis to the effect of the dimensions of AI on the quality-of-service delivery. Data mining and chatbot usage positively influenced the quality-of-service delivery, with $\beta = 0.31$ ($p < .001$) for data mining and $\beta = 0.16$ ($p = .007$) for chatbot usage, respectively, and were both rejected, thus suggesting that the two variables significantly affect the quality-of-service delivery. Nevertheless, machine learning ($\beta = -0.07$, $p = .184$) did not have a statistically significant effect and thus it was not rejected in favor of H_{03} . The regression model was statically significant ($F(3, 384) = 65.42$, $p < .001$) with about 34% of the variation in the quality-of-service delivery being explained ($R^2 = 0.34$), which means that the model has moderate explanatory power.

Key Challenges Limiting Effective AI Deployment (Objective 4)

Table 6: Ranking of deployment challenges by mean score

Challenge	Mean	Rank
Inadequate technical/AI skills among staff	4.21	1st
Poor power/network infrastructure	4.05	2nd
High cost of AI implementation	3.87	3rd
Data quality and integration issues	3.62	4th
Resistance to change among staff	3.30	5th
Regulatory/compliance uncertainty	3.11	6th

Source: Field Survey Findings, 2026.

The results show that the most serious problem in relation to the use of AI was the lack of technical skills/AI skills among staff, with the highest mean ($M = 4.21$) score in the first place. Poor power and network infrastructure ($M = 4.05$) ranked 2nd, followed by high cost of the implementation of AI ($M = 3.87$), ranked 3rd. Data quality and integration challenges ($M = 3.62$, rank 4), resistance to change by staff ($M = 3.30$, rank 5), and uncertainty regarding regulatory/compliance ($M = 3.11$, rank 6) were among the other challenges. In conclusion, the findings indicate that technical capacity, lack of infrastructure, and implementation costs are the key factors obstructing the effective use of AI in the mobile telecommunications sector in Nigeria to enhance the quality of services.

DISCUSSION OF FINDINGS

The findings revealed that data mining and chatbot usage had significant positive effects on quality-of-service delivery, whereas machine learning had no statistically significant effect. These findings support the Technology Acceptance Model (TAM), which posits that technologies perceived as useful and easy to use are more likely to be adopted and to improve organizational performance. The significant effects of data mining and chatbot usage suggest that these AI applications are effectively supporting customer interactions, service personalization, and operational decision-making in Nigeria's mobile telecommunications sector. However, the insignificant effect of machine learning may be attributed to its implementation complexity, inadequate technical expertise, and the relatively low level of organizational readiness for advanced AI deployment.

The results are consistent with the empirical findings of Busayo et al. (2023), who reported that data mining and chatbot usage significantly improved service quality among Nigerian telecommunication firms, while machine learning exhibited a negative and insignificant contribution to service outcomes. Similarly, the positive influence of chatbot usage agrees with the review by Misischia et al. (2022), which concluded that chatbots enhance customer service performance when properly designed and implemented. However, the insignificant effect of machine learning contrasts with Folorunsho et al. (2024), who found that machine learning significantly improves network performance and quality of service. This discrepancy may be explained by differences in organizational readiness and the infrastructural constraints facing Nigerian telecom operators. Furthermore, the ranking of inadequate AI skills, poor infrastructure, and high implementation costs as the major deployment challenges corroborates the findings of Maitanmi et al. (2023), who identified technical, infrastructural, and

organizational readiness gaps as key barriers to effective AI adoption in the Nigerian telecommunications industry.

Summary of the Study

This study set out to examine the effect of artificial intelligence, specifically data mining, chatbot usage, and machine learning, on quality-of-service delivery in Nigeria's mobile telecommunications sector, and to identify the key challenges limiting effective AI deployment among operators. Using a quantitative cross-sectional survey design, data were collected from 388 valid respondents drawn from customer service, IT, network operations, and data analytics departments across MTN Nigeria, Airtel Nigeria, Globacom, and 9mobile, and analyzed using descriptive statistics and multiple linear regression.

The study was grounded in two complementary theories, the Technology Acceptance Model and Diffusion of Innovation Theory, which together explained both individual-level acceptance of AI tools and organization-wide diffusion patterns. Findings showed that data mining ($\beta = 0.31$, $p < .001$) and chatbot usage ($\beta = 0.16$, $p = .001$) had statistically significant positive effects on quality-of-service delivery, while machine learning ($\beta = -0.07$, $p = .184$) had no significant effect. The regression model explained approximately 34% of the variance in quality-of-service delivery ($R^2 = 0.34$). On the fourth objective, inadequate technical/AI skills, poor power and network infrastructure, and high implementation costs emerged as the most severe challenges limiting effective AI deployment among Nigerian mobile telecom operators.

CONCLUSION

Based on these findings, the study concludes that artificial intelligence does not uniformly improve quality of service delivery in Nigeria's mobile telecommunications sector, its effect depends on which specific technology is deployed. Data mining and chatbot usage, both of which support relatively contained, well-understood applications (behavioral analysis, customer interaction automation), translate into measurable service quality gains, consistent with the Technology Acceptance Model's emphasis on perceived usefulness and ease of use. Machine learning, by contrast, has not yet produced a statistically significant improvement in service quality, most plausibly because its deployment is more technically demanding and is undermined by the same skills, infrastructural, and cost constraints identified as the sector's leading deployment challenges, a pattern consistent with the uneven diffusion dynamics predicted by Diffusion of Innovation Theory.

Taken together, the study concludes that Nigerian mobile telecom operators have made genuine, measurable progress in leveraging some forms of AI to improve customer experience, but that this progress remains constrained and uneven, with the sector's full AI potential, particularly around machine learning, yet to be realized due to persistent organizational and infrastructural barriers.

Recommendations

Based on the findings and conclusions above, the following recommendations are made:

1. Prioritize data mining and chatbot investment while strengthening machine learning capacity.

2. Close the technical skills gap. Given that inadequate technical/AI skills ranked as the most severe deployment challenge, operators should invest in structured AI/data science training programmes for IT and network operations staff, and consider partnerships with universities and technology firms to build a sustainable talent pipeline.
3. Address infrastructural constraints.
4. Phase AI implementation to manage cost. Given that high implementation cost ranked third among deployment challenges, operators should consider phased or modular AI adoption strategies — starting with lower-cost, higher-impact tools like chatbots and data mining — rather than attempting full-scale machine learning deployment before organizational readiness is established.
5. Improve data quality and integration practices. Operators should invest in data governance frameworks and system integration to address the data quality and integration issues identified, since machine learning in particular depends heavily on clean, well-integrated data to function effectively.

Limitations of the Study

This study is limited by its cross-sectional design, which captures AI's effect on service quality at a single point in time and cannot establish causality or account for how these relationships may evolve as AI adoption matures. The study also relied on self-reported perceptions of AI usage and service quality from telecom staff rather than objective network performance metrics or direct subscriber feedback, which may introduce a degree of response bias. Additionally, the study was restricted to the four major mobile network operators, and findings may not fully generalize to smaller or newer entrants in the Nigerian telecom market.

Contribution of the Study

- i. To Organizations: This research assists MTN, Airtel, Globacom, 9mobile, etc, mobile operators in Nigeria, to recognize the capabilities of which AI technologies that can truly enhance the quality of their services: data mining, chatbots or machine learning.
- ii. To Academia: The study contributes Nigerian empirical evidence to a limited literature on AI and telecom service quality, which builds upon the existing literature by taking the mobile sub-sector and then focusing on deployment challenges and their direct link to service outcomes for the sub-sector.
- iii. To Policy Makers: The results provide evidence for the NCC and policymakers to update the QoS benchmarks and digital-skills or infrastructure policy.

Suggestions for Future Research

Future studies could adopt a longitudinal design to examine how the relationship between AI adoption and service quality evolves as Nigerian telecom operators' AI readiness improves over time. Further research could also incorporate subscriber-facing data (e.g., customer satisfaction surveys or objective network performance metrics) alongside staff perceptions, to provide a more triangulated assessment of AI's actual effect on service quality. Finally, given this study's finding that machine learning's effect was not statistically significant, future research could explore this relationship qualitatively, examining in depth why machine

learning implementation is struggling to translate into measurable service quality improvements despite its demonstrated potential elsewhere in the literature.

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