VOL. 13 NO. 2,
AUGUST, 2026
E-ISSN 3027-1533
P-ISSN 3026-8648

African Scholar Publications & Research International
www.africanscholarpub.com

Journal of African Innovation & Advanced Studies (JAIAS)

Artificial Intelligence Applications, Customer Satisfaction, and Network Performance in the Telecommunications Sector: Evidence from Ikeji-Arakeji, Osun State, Nigeria

Tunde Elijah Ogundare; & Emmanuel Makanjuola Ogunjemilua

Department of Entrepreneurship, Joseph Ayo Babalola University, Ikeji Arakeji, Osun State
Corresponding Author: ogundaretundeelijah@gmail.com
DOI: https://doi.org/10.70382/ajaias.v13i2.0143

Abstract

Artificial intelligence (AI) is increasingly used in customer-facing telecommunications services and network management. This study examined the association between customers' perceptions of AI-enabled services and customer satisfaction, alongside observed network performance in Ikeji-Arakeji, Osun State, Nigeria. A mixed-methods design combined a questionnaire survey of 370 telecommunications subscribers with field-based speed tests of MTN, Globacom (Glo), and Airtel. The questionnaire data were analysed using descriptive statistics, Pearson's product-moment correlation, and simple linear regression in SPSS version 26. The analysis found a positive, statistically significant association between AI and customer satisfaction ($r = .412$, $p < .001$). The regression model was statistically significant, $F(1, 368) = 75.00$, $p < .001$, and explained 16.9% of the variance in customer satisfaction ($R^2 = .169$; adjusted $R^2 = .167$). The speed-test observations showed variation in download speed, upload speed, and latency across operators and observation periods. However, because the study did not measure operators' internal AI systems or control for infrastructure, traffic, and other network conditions, the speed-test results cannot establish that AI caused the observed differences. The findings suggest that customer-facing AI services are positively associated with customer satisfaction, while network performance should be interpreted as a separate descriptive outcome. Telecommunications operators should improve the usefulness and reliability of chatbots, personalized offers, and self-service tools, and monitor network quality continuously.

Keywords: Artificial Intelligence, Customer Satisfaction, Telecommunications, Network Performance, Ikeji-Arakeji.

Introduction

Artificial Intelligence (AI) has emerged as one of the most transformative technological innovations of the twenty-first century, with significant implications for the way organizations create value, make decisions, innovate and compete (Davenport & Ronanki, 2018; Raisch & Krakowski, 2021). Artificial Intelligence (AI) refers broadly to the ability of computer systems and machines to perform tasks that traditionally require human intelligence, including learning, reasoning, prediction, decision-making, problem-solving and pattern recognition (Russell & Norvig, 2021). Through technologies such as machine learning, deep learning, natural language processing and data analytics, AI enables organizations to process large volumes of data and generate insights that can improve the speed, quality and effectiveness of managerial and operational decisions. AI has consequently become an important driver of innovation and business transformation across sectors such as finance, healthcare, manufacturing, retail and telecommunications (UNESCO, 2021; OECD, 2023; World Economic Forum, 2023).

Beyond its technological applications, Artificial Intelligence (AI) has increasingly become an important resource for enhancing telecommunications service outcomes. Entrepreneurial performance refers to the extent to which an organization is able to achieve desired outcomes through innovation, opportunity exploitation, growth, competitiveness, efficient resource utilization and value creation. Entrepreneurial performance is multidimensional and may be assessed through indicators such as innovation performance, market performance, customer satisfaction, operational efficiency, growth and financial performance (Li et al., 2023; Fossen et al., 2024; Liu & Wang, 2024). The growing importance of AI to entrepreneurial activities is associated with its ability to support opportunity recognition and exploitation. Entrepreneurs and business organizations operate in increasingly dynamic and competitive environments where the ability to obtain, analyses and interpret information is critical to success. AI provides firms with advanced analytical capabilities that can assist in identifying market trends, predicting customer behavior, forecasting demand and discovering new business opportunities. By transforming large volumes of data into useful business intelligence, AI can enable firms to make more informed and timely entrepreneurial decisions. Scholars have increasingly argued that AI and other digital technologies are reshaping entrepreneurship by changing how opportunities are identified, evaluated and exploited and how new value is created within organizations (Obschonka & Audretsch, 2020; Nambisan, 2017; Nambisan et al., 2019). AI can also enhance innovation performance, which represents an important dimension of telecommunications service outcomes. Innovation performance concerns the ability of a firm to develop or improve products, services, processes and business models. AI can support innovation by providing insights from customer data, market trends and operational information. Firms can use AI to identify unmet customer needs, predict future demand and develop personalized products and services. In this regard, AI does not merely automate existing activities; it can also contribute to the generation of new ideas and business opportunities. Research on digital entrepreneurship has shown that digital technologies can significantly influence entrepreneurial processes by enabling firms to experiment, innovate and develop new forms of value creation (Nambisan et al., 2019; Obschonka & Audretsch, 2020). Another important dimension of telecommunications service outcomes influenced by AI is operational efficiency. Entrepreneurial firms require effective utilization of available resources in order to remain competitive and sustainable.

AI can improve operational efficiency by automating repetitive tasks, reducing human errors, improving forecasting and supporting predictive maintenance. Through AI-powered automation and analytics, firms can optimize their processes, reduce operational costs and improve the utilization of organizational resources. Studies examining the business implications of AI have suggested that organizations can derive value from AI through improved productivity, process optimization and enhanced decision-making capabilities (Davenport & Ronanki, 2018; Brynjolfsson & McAfee, 2017).

AI-enabled customer-service tools, including chatbots and data-driven service systems, are being studied as ways to support telecommunications service quality. In Nigeria, Busayo et al. (2023) examined data mining, machine learning and chatbots in relation to telecommunications service quality. This evidence supports examining AI-enabled services, but it does not justify assuming that every AI application automatically improves customer satisfaction.

AI also contributes to market performance and competitive advantage. In a rapidly changing business environment, organizations that can effectively utilize AI may be better positioned to respond to competitors and changing consumer preferences. AI enables firms to obtain real-time information about market developments, customer behavior and operational conditions. Such information can improve strategic decision-making and enable organizations to respond more quickly to market opportunities. Research on AI and firm strategy has emphasized that AI can influence organizational competitiveness by improving decision-making, innovation and the capacity of firms to create and capture value (Raisch & Krakowski, 2021; Wamba-Taguimdje et al., 2020). In addition, AI can influence financial performance, which represents another important dimension of telecommunications service outcomes. Through automation, predictive analytics, fraud detection and improved resource allocation, AI may assist organizations in reducing costs and improving revenue generation. AI can support firms in making better investment and pricing decisions, identifying profitable customers and reducing financial losses associated with fraud and operational inefficiencies. Studies on AI and organizational performance have suggested that the successful adoption of AI can generate economic value through productivity improvements, cost reduction, improved decision-making and innovation (Davenport & Ronanki, 2018; Wamba-Taguimdje et al., 2020).

Nigeria's telecommunications sector serves a large and geographically diverse customer base through operators including MTN, Airtel, Globacom and 9mobile. As network traffic and demand for digital services increase, operators must manage service quality, network congestion, reliability and customer support. Any claims about sector growth, subscriber totals or market share should be supported with a specific Nigerian Communications Commission (NCC) statistical release or annual report.

Artificial intelligence can support telecommunications operations through network monitoring, fault prediction, service automation and data-informed operational decisions. The International Telecommunication Union's framework for AI-enhanced telecommunication operation and management describes AI applications in operational efficiency, quality assurance, cost management and security assurance (International Telecommunication Union [ITU], 2021). The present study, however, did not directly measure operators' internal AI systems; therefore, such applications should be discussed as possible uses of AI rather than as confirmed interventions by the specific operators studied.

Empirical evidence specific to Nigerian telecommunications is available from Busayo et al. (2023), who examined data mining, machine learning and chatbots in relation to service quality. Separately, Olatokun and Ojo (2016) found that responsiveness, assurance and empathy were associated with customer satisfaction among mobile telecommunication users in Ibadan. The latter study concerns service quality rather than AI, so it should not be cited as direct proof of AI effectiveness. Together,

these studies support examining AI-enabled service quality while distinguishing measured evidence from broader expectations about AI.

Despite the potential applications of AI, successful implementation depends on data quality, suitable infrastructure, staff capabilities, governance and the ability to integrate AI into existing processes. These constraints should be supported with a specific source if the manuscript makes claims about their prevalence in rural Nigeria. The present study did not measure the level of AI adoption across rural and urban areas, so it cannot establish that rural locations have lower AI adoption.

Moreover, many existing studies focus on specific aspect of AI such as technical performance or customer service, without providing a holistic evaluation of its impact on telecommunication firm performance. There is also limited research that integrates operational efficiency, customer satisfaction, service reliability and financial performance into a single framework.

Therefore, this study examines the relationship between Artificial Intelligence and telecommunications service outcomes of telecommunications firms in Nigeria. Specifically, the study conceptualizes telecommunications service outcomes in terms of key outcomes such as customer satisfaction and non-financial performance. By examining these dimensions, the study seeks to provide a more comprehensive understanding of how the adoption and utilization of Artificial Intelligence contribute to value creation, opportunity exploitation, innovation, competitiveness and sustainable performance among telecommunication firms in Nigeria.

Statement of the Problem

The Nigerian telecommunications sector faces wider service-delivery challenges, and the effects of AI adoption should be evaluated rather than assumed. Connectivity, service availability and digital inclusion remain important contextual issues (International Telecommunication Union, 2022). The present study focuses specifically on customers' perceptions of AI-enabled services and descriptive network measurements in Ikeji-Arakeji.

Telecommunication companies in Nigeria continue to experience issues such as network congestion, service downtime, high operational costs, fraud and customer dissatisfaction. Although Artificial Intelligence have been introduced to address these challenges, the extent to which they have successfully improved performance across the sector remains unclear.

Existing empirical studies have shown that AI can enhance specific areas such as network reliability, customer service and fraud detection. However, most of these studies are fragmented, focusing on isolated aspects of performance rather than providing a comprehensive evaluation of the overall impact of AI on telecommunication firms. This creates a gap in understanding how AI contributes holistically to financial performance, non-financial performance and technical performance.

The verifiable literature located for this revision includes research on AI and telecommunications service quality in Nigeria (Busayo et al., 2023), Nigerian mobile telecommunications service quality and customer satisfaction (Olatokun & Ojo, 2016), and AI orientation and new-venture performance (Li et al., 2023). These works address related but different questions and should not be presented as interchangeable evidence. A defensible research gap is that the present study combines customers' reported perceptions of AI-enabled services with field measurements of download speed, upload speed and latency in one local setting. Because the study did not measure operators' AI systems directly, it examines the association between customer perceptions and satisfaction alongside descriptive network measurements, rather than establishing a causal effect of AI on network performance.

Research on AI and business performance includes Li et al. (2023), who examined AI orientation and new-venture performance, and Liu and Wang (2024), who studied generative-AI resources and

entrepreneurial performance. Fossen et al. (2024) review the emerging literature on AI and entrepreneurship and note that definitions and empirical approaches vary across studies. These sources concern entrepreneurial performance rather than telecommunications service outcomes specifically; they therefore provide general context, not direct evidence about network speed or customer satisfaction in Ikeji-Arakeji.

Research Questions

i. What are the types of AI adopted in telecommunication firms in Osun State Nigeria?
ii. What is the relationship between Artificial Intelligence (AI) and customer satisfaction of telecommunication firms in Osun State Nigeria?
iii. What is the influence of Artificial Intelligence (AI) on technical performance of telecommunication firms in Osun State Nigeria?

Literature Review

Resource Based View (RBV) Theory

The Resource Based View (RBV) Theory was propounded by Jay Barney in 1991 in the United States of America. The theory explains that organizations achieve competitive advantage and superior performance when they possess valuable, rare, inimitable and non-substitutable resources. According to the theory, internal organizational resources and capabilities are the major determinants of firm success and long-term sustainability. The central theme of the theory is that firms that effectively utilize strategic resources are more likely to outperform their competitors.

The Resource Based View theory is highly relevant to Artificial Intelligence because AI technologies are regarded as strategic organizational resources capable of enhancing operational efficiency, innovation, customer satisfaction and profitability. In telecommunication firms, AI applications such as machine learning, predictive analytics, automated systems and chatbots provide firms with competitive advantage by improving decision-making processes and reducing operational inefficiencies. Firms that successfully integrate AI into their operations are better positioned to improve telecommunications service outcomes and maintain market competitiveness.

Despite its relevance, the theory has received several criticisms. Critics argue that the theory pays excessive attention to internal resources while neglecting external environmental factors such as market competition, government regulations and technological changes. Others criticize the theory for failing to clearly explain how firms develop strategic resources over time. In addition, the VRIN framework has been considered difficult to measure practically in empirical studies.

Nevertheless, the theory is useful to this study because it provides a strong explanation of how Artificial Intelligence serves as a strategic resource capable of improving telecommunications service outcomes in telecommunication firms in Nigeria. The theory supports the argument that firms with advanced AI capabilities are more likely to achieve improved financial, non-financial and technical performance.

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) was developed by (Davis, 1989) to explain and predict users' acceptance and use of information technology. The model proposes that two fundamental beliefs determine technology acceptance: perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which an individual believes that using a particular technology will enhance his or her performance, while perceived ease of use refers to the extent to which an individual believes that using the technology will require little effort Davis, 1989. Davis empirically demonstrated that both

constructs were significantly associated with technology usage, with perceived usefulness showing a stronger relationship with usage than perceived ease of use.

The central proposition of TAM is that individuals are more likely to accept and use a technology when they perceive it as useful and easy to operate. In the context of Artificial Intelligence (AI), the model provides a useful explanation of how employees and customers may respond to AI-enabled technologies such as chatbots, automated customer service systems, machine learning applications and predictive analytics. For example, when telecommunications customers perceive AI-based customer service systems as useful for obtaining faster responses, resolving complaints and improving service experiences, they are more likely to accept and use such technologies. Similarly, when AI applications are perceived as simple, accessible and easy to interact with, users are more likely to adopt them.

The applicability of TAM to the present study is particularly relevant because the adoption and effective utilization of AI technologies within telecommunication firms depend partly on users' perceptions of the benefits and usability of such technologies. Where employees and customers perceive AI applications as useful and easy to use, their willingness to interact with and utilize such systems is expected to increase. Consequently, effective utilization of AI may contribute to improved service delivery, customer satisfaction and technical performance, which are dimensions of telecommunications service outcomes examined in this study. TAM has been criticized for providing an overly simplified explanation of technology adoption. (Bagozzi, 2007) argued that TAM has important conceptual limitations because technology acceptance cannot always be adequately explained through usefulness, ease of use and behavioral intentions alone. He noted that technology adoption can also involve emotional, social, cultural and contextual processes and argued for a broader approach to understanding technology-related decision making. Benbasat and Barki 2007 questioned the continued dominance of TAM in information systems research. Their criticism was that excessive concentration on TAM had diverted attention from other important issues surrounding information technology use and had encouraged repeated extensions of the model without sufficiently addressing broader theoretical issues. Their critique formed part of a special issue of the Journal of the Association for Information Systems devoted to examining the future direction of TAM research.

Another important limitation was identified by Straub, Keil, and Brenner 1997**,** who examined TAM across the United States, Switzerland and Japan. Their findings showed that TAM performed differently across the three national contexts. While the model was supported in the United States and Switzerland, it did not adequately predict technology use in Japan. This suggests that cultural and contextual factors may influence technology acceptance and that TAM should not necessarily be assumed to operate in the same way across all populations and environments.

The limitations of the original TAM also led to the development of extended versions of the model. For example, Venkatesh and Davis (2000) developed TAM2 by incorporating additional factors such as subjective norm, image, job relevance, output quality and result demonstrability. Their findings demonstrated that social influence and cognitive instrumental processes could significantly explain perceived usefulness and users' intentions to use technology.

Despite these criticisms, TAM remains relevant to the present study because perceived usefulness and perceived ease of use provide a simple and established basis for explaining users' acceptance of AI technologies. The theory is therefore useful in explaining why telecommunications employees and customers may accept or reject AI applications such as chatbots, machine learning and predictive analytics. Nevertheless, the present study recognises that AI adoption is not determined solely by individual perceptions. Organisational, social, cultural and technological conditions may also influence the effective implementation and utilization of AI. Thus, TAM is employed as a supporting theoretical

framework rather than as a complete explanation of all factors affecting AI adoption and its implications for telecommunications service outcomes.

Dynamic Capabilities Theory

Dynamic Capabilities Theory was formally articulated by Teece et al. 1997 to explain how firms achieve competitive advantage in rapidly changing business environments. The theory focuses on the ability of organizations to integrate, build and reconfigure internal and external competencies to address changing environments. According to Teece et al. 1997, competitive advantage in dynamic environments depends not only on the resources that a firm possesses but also on its ability to continuously renew, modify and deploy those resources in response to technological and market changes.

The major theme of Dynamic Capabilities Theory is organizational adaptability, innovation and strategic renewal**.** The theory suggests that firms operating in environments characterised by rapid technological development, changing customer preferences and intense competition must continuously modify their resources and capabilities to remain competitive Teece et al., 1997. In this regard, dynamic capabilities enable organizations to sense changes and opportunities in their environment, seize those opportunities and transform or reconfigure their resources and operations accordingly.

The theory is particularly relevant to the telecommunication industry because telecommunications firms operate in an environment characterized by rapid technological changes, evolving customer expectations, intense competition and continuous innovation. Artificial Intelligence (AI) can strengthen the dynamic capabilities of telecommunication firms by providing real-time information, predictive insights, automation and data-driven decision-making. For example, AI-powered predictive analytics can help firms identify changing customer preferences, anticipate network problems and make timely strategic decisions. Similarly, machine learning can assist firms in improving service processes, while AI-powered chatbots can enable firms to respond more quickly to customer enquiries and complaints. These applications demonstrate how AI can become an organizational capability that enables firms to adapt to changing environmental conditions.

Dynamic Capabilities Theory can therefore be linked to the telecommunications service outcomes of telecommunication firms. Through the effective deployment of AI, firms can identify new opportunities, develop innovative services, improve operational processes and respond more rapidly to customer needs. These capabilities can contribute to improved customer satisfaction and technical performance, which are the measures of telecommunications service outcomes adopted in this study. Thus, AI can be viewed not merely as a technological resource but as an enabler of organizational adaptation, innovation and strategic renewal.

Despite its relevance, Dynamic Capabilities Theory has attracted considerable criticism. (Winter, 2003) questioned the tendency to treat dynamic capabilities as a broad explanation for organizational change. He distinguished dynamic capabilities from ordinary operational capabilities and argued that not every organizational activity that produces change should automatically be regarded as a dynamic capability. This distinction is important because it implies that researchers need to clearly identify what constitutes a dynamic capability and how it differs from routine organizational activities. Eisenhardt and Martin 2000 argued that dynamic capabilities are not necessarily unique or idiosyncratic sources of sustained competitive advantage. They suggested that many dynamic capabilities take the form of identifiable and relatively common organizational processes, such as product development, strategic decision-making and resource allocation. Consequently, the possession of dynamic capabilities alone may not guarantee sustainable competitive advantage. Rather, their value may depend on the particular market

environment and the resources and positions of the firm. Arend and Bromiley 2009 provided a stronger critique, arguing that the dynamic capabilities literature had problems relating to conceptual clarity, empirical testing and operationalization. They questioned whether dynamic capabilities had been defined and measured sufficiently clearly to establish their independent effect on organizational performance. This criticism is particularly relevant to empirical studies because a concept that is too broad may be difficult to measure consistently.

Peteraf et al., 2013 noted that the dynamic capabilities literature contains different conceptualizations of what dynamic capabilities are and how they operate. They argued that greater conceptual clarity was necessary to distinguish dynamic capabilities from other organizational processes and capabilities. Their contribution helped refine the theoretical understanding of dynamic capabilities by identifying important commonalities and differences among existing perspectives. Despite these criticisms, Dynamic Capabilities Theory remains relevant to the present study because it provides a framework for explaining how telecommunication firms can use AI to adapt to technological and market changes. AI can enable firms to sense emerging customer needs and technological opportunities, seize those opportunities through innovative products and services, and transform organizational processes through automation and data-driven decision-making. The theory therefore supports the argument that effective deployment of AI can strengthen organizational adaptability and contribute to improved customer satisfaction, technical performance and overall telecommunications service outcomes.

The present study recognizes that the mere adoption of AI does not automatically create dynamic capabilities or guarantee improved organizational performance. The value derived from AI depends on how effectively firms integrate the technology with existing resources, processes, human capabilities and strategic objectives. Dynamic Capabilities Theory is therefore employed as a complementary theoretical lens for explaining how telecommunication firms can convert AI-related resources and technologies into adaptive and performance-enhancing capabilities.

Empirical Review

Busayo et al. (2023) examined the relationship between artificial intelligence and telecommunications service quality in Nigeria. Their study considered data mining, machine learning and chatbots and used survey data with descriptive and ordinary least-squares regression analyses. The authors reported positive associations for data mining and chatbots, while machine learning showed a negative relationship with service quality. This is directly relevant to the Nigerian telecommunications context. However, it examines service quality rather than measured network-speed outcomes, and its results should not be generalized automatically to every operator or location.

Olatokun and Ojo (2016) studied customer satisfaction with mobile telecommunications services in Ibadan, Nigeria, using a survey of 431 users and service-quality dimensions including reliability, responsiveness, assurance, empathy and tangibility. They reported that responsiveness, assurance and empathy were significant in explaining customer satisfaction. Although this study did not examine AI, it provides relevant local evidence that customer satisfaction depends on service experiences and should not be attributed to AI alone.

For technical network performance, Popoola et al. (2018) published data on quality-of-service indicators for GSM networks in Nigeria, including measures relating to call setup, dropped calls and congestion. Their work provides a Nigerian context for assessing operator performance with objective network indicators. The indicators in that study differ from the download-speed, upload-speed and latency measures used in the present research, so the studies are complementary rather than directly comparable.

At the international standards level, the International Telecommunication Union's Recommendation ITU-T M.3080 describes a framework for AI-enhanced telecommunication operation and management, including operational efficiency, quality assurance, cost management and security assurance (ITU, 2021). This provides a technical framework for discussing potential uses of AI in telecommunications. It is a standards document, not empirical proof that a particular Nigerian operator deployed these systems or that AI caused a measured performance change.

Broader research also considers AI and organizational performance. Li et al. (2023) examined AI orientation and new-venture performance using data from Chinese listed new ventures, while Liu and Wang (2024) examined generative-AI resources and entrepreneurial performance among startup founders. Fossen et al. (2024) reviewed research on AI and entrepreneurship, covering opportunities, decision-making, adoption and business performance. These studies help establish the wider organizational context for AI, but they are not direct evidence of AI's effect on telecommunications customer satisfaction or network performance in Osun State.

Taken together, the verifiable sources support investigating AI-enabled telecommunications services, customer satisfaction and technical network quality as related but distinct topics. A key contribution of the present study is its combination of customer questionnaire data and local speed-test observations. Because it did not measure the operators' internal AI systems or control for infrastructure, congestion, device characteristics and other network conditions, the technical results should be interpreted descriptively and should not be used to claim that AI caused the differences among operators.

Methodology

This study adopted a mixed-methods research approach, combining a questionnaire survey with a field-based technical performance assessment to examine the relationship between Artificial Intelligence (AI) and customer satisfaction and network performance in the telecommunications sector in Ikeji-Arakeji, Osun State, Nigeria. The telecommunications service outcomes of the firms were assessed using two dimensions, namely customer satisfaction and technical performance. The questionnaire survey provided perceptual evidence from telecommunication customers regarding AI applications and customer satisfaction, while the field-based speed test provided objective measurements of the technical performance of the selected telecommunication networks.

The questionnaire component employed a cross-sectional survey design. Data were collected from telecommunication customers at a single point in time using a well-structured questionnaire. The questionnaire was designed to obtain information on customers' perceptions and experiences concerning AI applications used by telecommunication firms, including chatbots, personalised SMS/data offers and predictive analytics, as well as their level of satisfaction with the services provided. The survey approach was considered appropriate because it enabled the researcher to obtain standardised information from a relatively large number of respondents and to statistically examine the relationship between AI and customer satisfaction (Creswell, 2014).

The second component involved a field-based technical performance assessment using network speed tests. Unlike the questionnaire, which relied on customers' perceptions, the speed test provided objective measurements of the actual performance of the selected telecommunication networks. The assessment focused on technical indicators such as download speed, upload speed and latency. Measurements were taken from the selected telecommunication operators over a specified period and under comparable conditions. These measurements were used to assess the extent to which AI-enabled network optimization was associated with technical performance.

The combination of questionnaire data and objective speed-test measurements enabled the study to examine telecommunications service outcomes from both the customer experience perspective and the technical performance perspective. The questionnaire captured customers' perceptions of AI and their satisfaction with telecommunication services, while the speed-test data provided measurable evidence of network performance. This combination was considered appropriate because customer satisfaction and technical performance represented different but complementary dimensions of telecommunications service outcomes in the telecommunications industry.

The mixed-methods approach therefore strengthened the study by reducing reliance on a single source of evidence. While questionnaire responses provided information about customers' experiences and perceptions, the technical assessment provided objective evidence concerning network performance. The integration of these findings provided a more comprehensive understanding of how AI applications related to customer satisfaction and technical performance in selected telecommunication firms in Osun State, Nigeria.

Methodological Details and Measurement

The study was carried out in Ikeji-Arakeji, Osun State, Nigeria. The area was selected because it is served by major telecommunication operators, including MTN, Airtel, Globacom (Glo) and 9mobile, allowing customers' perceptions and network performance to be examined. The manuscript states that the estimated population used for sample-size calculation was 5,000. The earlier citation to Babatola et al. (2023) could not be verified during this reference check, so the figure of 5,000 must be confirmed against the original local population source or replaced with an appropriate official estimate before submission.

The accessible population for the present study consisted of residents of Ikeji-Arakeji who used at least one of the selected telecommunication networks. These residents constituted the appropriate respondents because the study required customers who had experience with telecommunication services and could provide information on Artificial Intelligence applications and customer satisfaction.

Given the estimated population of 5,000 telecommunication subscribers in the study area, the sample size for the study was determined using the Taro Yamane (1967) formula, expressed as:

$n = N / [1 + N(e)^2]$

Where: n = sample size, N = population of the study, e = level of significance (0.05).

Substituting the values:

$n = 5,000 / [1 + 5,000(0.05)^2]$

$n = 5,000 / [1 + 12.5]$

$n = 5,000 / 13.5$

$n = 370.37 \approx 370$

Data obtained from the questionnaire were coded and analyzed using the Statistical Package for the Social Sciences (SPSS). Descriptive statistics, comprising frequency counts, percentages, means and standard deviations, were used to analyze the demographic characteristics of respondents and to describe the responses on Artificial Intelligence, the type Adopted by the telecommunication firms and non-financial performance.

The hypothesis relating to the relationship between Artificial Intelligence and non-financial performance was tested using Pearson Product-Moment Correlation to determine the direction and strength of the relationship, and simple linear regression analysis to determine the extent to which Artificial Intelligence explained variations in customer satisfaction. The decision rule adopted was that

the null hypothesis would be rejected where the probability value (p) was less than the 0.05 level of significance, and retained otherwise.

Data obtained from the network performance test were analyzed using descriptive and comparative statistics. The average upload speed, download speed and latency recorded for MTN, Globacom and Airtel were computed and compared across the three daily time periods and the three days of testing, in order to assess the extent to which the observed technical performance reflects the influence of Artificial Intelligence-driven network optimization on the technical performance of the telecommunication operators.

Technical performance was assessed using Speed Test Application to test the three core indicators upload speed, download speed, and latency measured across three data collection periods (9:00-11:00a.m., 2:00-4:00p.m., and 6:00-8:00p.m.) over three consecutive days. The tests covered MTN, GLO, and Airtel, with 9Mobile (Etisalat) included in the sampling frame but excluded from analysis due to unavailable data.

Discussion of Findings

The analysis of data collected from 370 respondents in Ikeji-Arakeji provided empirical evidence on the relationship between Artificial Intelligence (AI) and customer satisfaction in the Nigerian telecommunications sector. The findings are discussed in relation to the study objective and compared with findings from previous empirical studies. Particular attention is given to areas of agreement, disagreement and possible explanations for the differences observed.

Table1 presented the consolidated demographic and service-use characteristics of the respondents. The table showed that the respondents were fairly balanced by gender, with 186 males (50.3%) and 184 females (49.7%). This indicated that both male and female respondents were adequately represented in the study.

In terms of age, respondents aged 25-29 years constituted the largest group, with 109 respondents (29.5%), followed by those aged 30-39 years with 93 respondents (25.1%). Respondents aged 15-24 years accounted for 18.9%, while those aged 40-49 years and 49-60 years accounted for 15.9% and 10.5%, respectively. The distribution indicated that the sample contained a substantial proportion of younger respondents who were likely to have had regular exposure to telecommunication services.

Regarding marital status, single respondents formed the largest category, with 209 respondents (56.5%), while married respondents accounted for 131 respondents (35.4%). Widowed respondents represented 4.3%, while divorced respondents represented 3.8%. This showed that the respondents comprised individuals with different marital backgrounds, although single respondents constituted the majority.

The educational qualification distribution showed that respondents with B.Sc./HND constituted the largest category, with 147 respondents (39.7%). This was followed by OND/NCE holders with 76 respondents (20.5%) and SSCE holders with 74 respondents (20.0%). Respondents with M.Sc. accounted for 15.9%, while Ph.D. holders accounted for 3.8%. The result indicated that a considerable proportion of the respondents possessed tertiary educational qualifications.

With respect to occupation, private-sector employees constituted the largest group, with 110 respondents (29.7%), followed by students with 102 respondents (27.6%) and self-employed respondents with 93 respondents (25.1%). Civil servants accounted for 12.7%, while unemployed respondents represented 4.9%. The occupational distribution therefore indicated that the study included respondents from varied employment backgrounds.

For preferred telecommunication network, MTN had the highest representation, with 173 respondents (46.8%), followed by Airtel with 102 respondents (27.6%). Globacom (Glo) accounted for 70

respondents (18.9%), while 9mobile had the lowest representation, with 25 respondents (6.8%). The result showed that all four networks were represented among the respondents, although MTN was the most preferred network.

In terms of length of use of the preferred network, respondents who had used their preferred network for 1-3 years constituted the largest group, with 106 respondents (28.6%), followed by those who had used their network for 4-6 years with 92 respondents (24.9%). Those who had used their network for 7-10 years represented 18.9%, while those with more than 10 years of use represented 17.6%. Respondents who had used their preferred network for less than one year accounted for 10.0%. This suggested that most respondents had some level of experience with their preferred telecommunication network.

The frequency of telecommunication service use showed that 294 respondents (79.5%) used telecommunication services daily. Weekly users accounted for 58 respondents (15.7%), while 18 respondents (4.9%) used the services occasionally. The result demonstrated that telecommunication services were used frequently by the majority of the respondents. Personalized SMS or data offers were the most commonly reported AI-enabled service, with 118 respondents (31.9%). Chatbot/virtual assistant services accounted for 21.6%, while mobile app self-service accounted for 21.1%. AI-based customer support represented 16.5%, whereas 8.9% of respondents indicated that they were not aware of any AI-enabled service. This finding showed that personalized SMS or data offers were the most commonly experienced AI-enabled service among the respondents.

The consolidated demographic and service-use profile indicated that the respondents were diverse in terms of gender, age, marital status, educational qualification and occupation. The representation of different telecommunication networks and levels of network usage experience also provided a broad basis for assessing the respondents' perceptions of Artificial Intelligence and its relationship with telecommunication firms' performance.

Table 1: Demographic and Service-Use Characteristics of Respondents (N = 370)

Variable	Category	Frequency (f)	Percentage (%)
Gender	Male	186	50.3
	Female	184	49.7
Age Bracket	15–24	70	18.9
	25–29	109	29.5
	30–39	93	25.1
	40–49	59	15.9
	49–60	39	10.5
Marital Status	Single	209	56.5
	Married	131	35.4
	Widowed	16	4.3
	Divorce	14	3.8
Highest Educational Qualification	B.Sc/HND	147	39.7
	OND/NCE	76	20.5
	SSCE	74	20.0
	M.Sc	59	15.9
	Ph.D	14	3.8
Occupation	Private Sector Employee	110	29.7
	Student	102	27.6

Variable	Category	Frequency (f)	Percentage (%)
	Self-employed	93	25.1
	Civil Servant	47	12.7
	Unemployed	18	4.9
Preferred Telecommunication Network	MTN	173	46.8
	Airtel	102	27.6
	Globacom (Glo)	70	18.9
	9mobile	25	6.8
Length of Use of Preferred Network	Less than 1 year	37	10.0
	1–3 years	106	28.6
	4–6 years	92	24.9
	7–10 years	70	18.9
	More than 10 years	65	17.6
Frequency of Telecommunication Service Use	Daily	294	79.5
	Weekly	58	15.7
	Occasionally	18	4.9
AI-enabled Service Used Most	Personalized SMS or Data Offers	118	31.9
	Chatbot/Virtual Assistant	80	21.6
	Mobile App Self-Service	78	21.1
	AI-based Customer Support	61	16.5
	I am not aware of any AI-enabled service	33	8.9

Table 2 presented the descriptive statistics for Artificial Intelligence. The mean scores ranged from 3.5 to 3.6. Personalized offers or recommendations, ease of accessing telecommunication services, and improved overall experience each recorded a mean of 3.6, while accuracy and reliability recorded a mean of 3.5. The results indicated that the respondents generally expressed positive views concerning the use of AI-enabled services in telecommunication firms. The standard deviation values ranged from 0.8 to 0.9, indicating that there was relatively limited variation in the responses around their respective mean values.

Table 2: Descriptive Statistics of Artificial Intelligence

Item	N	Mean	Std. Deviation
Personalized offers/recommendations	370	3.6	0.8
Ease of accessing telecom services	370	3.6	0.8
Improved overall experience	370	3.6	0.8
Accuracy and reliability	370	3.5	0.9

Table 3 presented the descriptive statistics for customer satisfaction. The mean scores ranged from 3.9 to 4.0. Satisfaction with service quality and the extent to which AI increased satisfaction recorded the

highest mean of 4.0, while prompt complaint resolution, overall experience, intention to continue using the network, and recommendation to others each recorded a mean of 3.9.

The results indicated that the respondents generally had positive perceptions of the non-financial performance indicators measured in the study. The standard deviation of 0.8 across the items indicated relatively low variation in the responses.

Table 3: Descriptive Statistics of Customer Satisfaction

Item	N	Mean	Std. Deviation
Satisfaction with service quality	370	4.0	0.8
Prompt compliant resolution	370	3.9	0.8
Overall experience	370	3.9	0.8
Intention to continue using network	370	3.9	0.8
Recommendation to others	370	3.9	0.8
AI increased satisfaction	370	4.0	0.8

Table 4 presented the Pearson correlation analysis between Artificial Intelligence and customer satisfaction among telecommunication subscribers in Ikeji-Arakeji, Osun State. The result showed a positive relationship between Artificial Intelligence and customer satisfaction, with a correlation coefficient of $r = 0.412$. This indicated that higher levels of Artificial Intelligence adoption and utilization were associated with higher levels of customer satisfaction among the respondents. The significance value of $p < 0.001$ was less than the 0.05 level of significance. This indicated that the relationship between Artificial Intelligence and customer satisfaction was statistically significant. Therefore, the result provided evidence of a significant positive relationship between Artificial Intelligence and customer satisfaction among telecommunication subscribers in the study area.

Based on the result, the null hypothesis which stated that there was no significant relationship between Artificial Intelligence and customer satisfaction was rejected. The alternative hypothesis was therefore accepted, indicating that Artificial Intelligence had a significant positive relationship with customer satisfaction.

Table 4: Correlation Matrix of Artificial Intelligence and Customer Satisfaction

Variables	Artificial Intelligence	Customer Satisfaction	Sig. (2-tailed)	N
Artificial Intelligence	1.000	0.412	< 0.001	370
Customer satisfaction	0.412	1.000	< 0.001	370

Table 5 presented the regression model summary showing the relationship between Artificial Intelligence and customer satisfaction. The R-value of 0.412 indicated a positive relationship between Artificial Intelligence and customer satisfaction. The R-square value of 0.169 indicated that Artificial Intelligence explained 16.9% of the variation in customer satisfaction. This implied that changes in Artificial Intelligence were associated with changes in customer satisfaction, while the remaining 83.1% of the variation could be attributed to other factors not included in the model. The adjusted R-square provided a more conservative estimate of the explanatory power of the model after taking the model specification into account.

Table 5: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.412	0.169	0.167	0.6

Table 6 presented the analysis of variance (ANOVA) for the regression model examining the effect of Artificial Intelligence on customer satisfaction. The result showed that the regression model was statistically significant, $F(1, 368) = 75.000$, $p < 0.001$.

The significant F-statistic indicated that the regression model provided a statistically significant prediction of customer satisfaction based on Artificial Intelligence. In other words, Artificial Intelligence significantly contributed to explaining variations in the customer satisfaction scores of the respondents.

Since the probability value of $p < 0.001$ was less than the 0.05 level of significance, the null hypothesis that there was no significant relationship between Artificial Intelligence and customer satisfaction was rejected. The result therefore indicated that Artificial Intelligence had a statistically significant relationship with customer satisfaction among telecommunication subscribers in Ikeji-Arakeji, Osun State.

Table 6: ANOVA of Regression Model

Model	Sum of Squares	Df	Mean Square	F	Sig.
Regression	27.000	1	27.000	75.000	< 0.001
Residual	132.500	368	0.360		
Total	159.500	369			

Table 7 presented the regression coefficients for Artificial Intelligence and customer satisfaction. The result showed that Artificial Intelligence had a positive unstandardized regression coefficient (**$\beta = 0.4$**) and a positive standardized beta coefficient (**$\beta = 0.4$**). This indicated that Artificial Intelligence made a positive contribution to customer satisfaction.

The t-value of **8.7** and the significance level of **$p < 0.001$** indicated that the regression coefficient for Artificial Intelligence was statistically significant at the 5% level. This suggested that Artificial Intelligence significantly predicted customer satisfaction among telecommunication customers in Ikeji-Arakeji, Osun State.

The regression equation was expressed as:

$$CS = 2.6 + 0.4AI + e$$

Where:

CS = Customer Satisfaction

AI = Artificial Intelligence

2.6 = Constant/intercept

0.4 = Unstandardized regression coefficient of Artificial Intelligence

e = Error term

The equation indicated that, holding other factors constant, a one-unit increase in Artificial Intelligence was associated with an estimated 0.4-unit increase in customer satisfaction. The positive coefficient therefore indicated that greater utilization of Artificial Intelligence was associated with higher customer satisfaction among the respondents.

Table 7: Regression Coefficients of Artificial Intelligence and Customer Satisfaction

Model	B	Std. Error	Beta	t	Sig.
(Constant)	2.6	0.2		15.8	0.0
Artificial Intelligence	0.4	0.0	0.4	8.7	0.0

The hypothesis was tested using the Pearson Product-Moment Correlation analysis at the 5% level of significance. The result presented in Table 4.6 showed a Pearson correlation coefficient of $r = 0.412$ and a significance value of $p < 0.001$. The positive correlation coefficient indicated a positive relationship between Artificial Intelligence and customer satisfaction among telecommunication subscribers in the study area.

Since the significance value of $p < 0.001$ was less than the 0.05 level of significance, the relationship between Artificial Intelligence and customer satisfaction was statistically significant. Therefore, the null hypothesis was rejected.

The regression analysis further supported the correlation result. The model summary showed an R-value of 0.412 and an R-square value of 0.169, indicating that Artificial Intelligence explained approximately 16.9% of the variation in customer satisfaction. The ANOVA result showed that the regression model was statistically significant, $F(1, 368) = 75.000$, $p < 0.001$. Furthermore, the regression coefficient for Artificial Intelligence was positive and statistically significant ($\beta = 0.4$, $\beta = 0.4$, $t = 8.7$, $p < 0.001$).

Based on these findings, the null hypothesis, which stated that there was no significant relationship between Artificial Intelligence and customer satisfaction among telecommunication subscribers in Ikeji-Arakeji, Osun State**,** was rejected. The study therefore concluded that Artificial Intelligence had a statistically significant positive relationship with customer satisfaction**.**

Table 8: Test of Hypothesis

Hypothesis	Test	R	Sig. (2-tailed)	Decision
H_{01}: There is no significant relationship between AI and customer satisfaction.	Pearson Product-Moment Correlation	0.412	< 0.001	Reject H_{01}

Researcher's Computation 2026

Table 9 presents the technical performance of the three major telecommunication operators (MTN, GLO, and Airtel) based on upload speed, download speed, and latency measured at three different periods of the day (9:00-11:00a.m., 2:00-4:0 p.m., and 6:00-8:00p.m.).

The results indicate that MTN (Operator 1) recorded an average upload speed of 0.10Mbps, an average download speed of 5.21Mbps, and an average latency of 325.67ms. The upload speed was highest in the morning (8.98Mbps) but declined significantly during the afternoon and evening. Although MTN achieved the highest average download speed among the operators on Day 1, its latency was relatively high, indicating slower network responsiveness.

GLO (Operator 2) recorded an average upload speed of 2.12Mbps, an average download speed of 0.85 Mbps, and an average latency of 207.67ms. Compared with MTN, GLO demonstrated better upload performance but considerably lower download speed. However, its latency was lower than that of MTN, suggesting relatively faster response time.

Airtel (Operator 3) recorded the highest average upload speed of 5.74Mbps, an average download speed of 0.85Mbps, and the lowest average latency of 51.00ms. The low latency indicates superior network

responsiveness, making Airtel the best-performing network in terms of response time during the first day of testing. The Day 1 results suggest that while MTN provided superior download performance, Airtel exhibited the best overall technical performance due to its high upload speed and significantly lower latency. GLO demonstrated moderate performance, particularly in upload speed, but lagged behind in download performance.

Table 9: The Technical Performance Test Result (Day 1)

No.	Operators	9–11 am	2–4 pm	6–8 pm	Average
1	A	0.10	8.98	6.24	0.40
1	B	5.21	0.19	0.05	0.06
1	C	325.67	53	79	845
2	A	2.12	0.87	0.04	1.64
2	B	0.85	3.56	1.57	1.23
2	C	207.67	52	184	387
3	A	5.74	0.81	0.69	1.04
3	B	0.85	8.74	7.98	10.1
3	C	51.00	37	35	81
4	A	–	–	–	–
4	B	–	–	–	–
4	C	–	–	–	–

Legends: Operators 1= MTN, Operator 2= GLO, Operator 3= Airtel, Operator 4= 9Mobile (Etisalat) A= Upload Speed, B= Download Speed, C= Latency.

Table 10 presents the technical performance test conducted on the second day. The findings reveal that MTN achieved the highest average upload speed of 6.86Mbps, an average download speed of 3.86Mbps, and a latency of 46.67ms. The improvement in upload speed compared to Day 1 indicates more stable network performance, while the lower latency reflects faster communication between devices and network servers.

GLO recorded an average upload speed of 1.97Mbps, an average download speed of 2.18Mbps, and a latency of 221.33ms. Although its download speed improved compared with Day 1, the relatively high latency suggests slower network responsiveness.

Airtel recorded an average upload speed of 1.56Mbps, the highest average download speed of 4.57Mbps, and the lowest latency of 37.33ms among all the operators. These results indicate that Airtel maintained excellent network responsiveness while also providing strong download performance.

The second-day findings demonstrate fluctuations in network performance across the operators. MTN recorded the best upload performance, Airtel achieved the highest download speed and the lowest latency, while GLO continued to record relatively higher latency. This suggests that Airtel maintained the most balanced technical performance during the second day of testing.

Table 10: The Technical Performance Test Result (Day 2)

No.	Operators	9–11 am	2–4 pm	6–8 pm	Average
1	A	6.86	8.98	3.83	7.78
1	B	3.86	4.65	0.16	6.76
1	C	46.67	72	30	38
2	A	1.97	2.86	1.01	2.03
2	B	2.18	2.30	2.37	1.88

No.	Operators	9–11 am	2–4 pm	6–8 pm	Average
2	C	221.33	298	192	174
3	A	1.56	1.51	2.00	1.16
3	B	4.57	1.98	8.14	3.58
3	C	37.33	37	32	43
4	A	–	–	–	–
4	B	–	–	–	–
4	C	–	–	–	–

Legends: Operators 1= MTN, Operator 2= GLO, Operator 3= Airtel, Operator 4= 9Mobile (Etisalat) A= Upload Speed, B= Download Speed, C= Latency.

Table 11 presents the technical performance results obtained on the third day of the network speed tests. The results show that MTN recorded an average upload speed of 1.23 Mbps, an average download speed of 2.18Mbps, and a latency of 1,596.33ms. Although download performance remained moderate, the extremely high latency indicates severe delays in network responsiveness during the testing period. GLO recorded an average upload speed of 0.97Mbps, an average download speed of 2.81Mbps, and a latency of 456.00ms. Compared with MTN, GLO experienced lower latency but recorded slower upload speed.

Airtel recorded an average upload speed of 1.50Mbps, the highest average download speed of 7.26Mbps, and the lowest latency of 40.00ms. This indicates that Airtel consistently provided the fastest download service and the quickest network response among the operators tested on Day 3.

The Day 3 findings indicate that Airtel maintained the best technical performance by combining the highest download speed with the lowest latency. In contrast, MTN experienced unusually high latency, which negatively affected its technical performance despite moderate download speeds. GLO maintained average performance but did not outperform Airtel in any of the technical indicators.

The three-day technical performance assessment reveals noticeable variations in network performance among the telecommunication operators. Airtel consistently demonstrated the most stable technical performance by maintaining comparatively low latency and competitive upload and download speeds across the three testing days. MTN generally performed well in download and upload speeds but experienced substantial fluctuations in latency, particularly on the third day, indicating periods of network congestion. GLO displayed moderate performance throughout the testing period, with acceptable upload and download speeds but relatively higher latency than Airtel.

These findings imply that the technical performance of telecommunication firms differs across operators and time periods. The observed variations support the view that network quality is dynamic and influenced by factors such as traffic congestion, infrastructure capacity, and network management practices. Since technical performance is a key indicator of entrepreneurial performance in this study, the results suggest that greater application of AI-driven network optimization and predictive maintenance could improve upload speed, download speed, and latency, thereby enhancing overall service quality and customer experience.

Table 11: The Technical Performance Test Result (Day 3)

No.	Operators	9–11 am	2–4 pm	6–8 pm	Average
1	A	1.23	0.01	0.62	3.07
1	B	2.18	0.40	0.24	5.90
1	C	1,596.33	4,135	604	50

No.	Operators	9–11 am	2–4 pm	6–8 pm	Average
2	A	0.97	1.32	1.32	0.27
2	B	2.81	1.40	5.48	1.54
2	C	456.00	465	190	713
3	A	1.50	0.93	1.97	1.60
3	B	7.26	5.39	6.10	10.3
3	C	40.00	42	42	36
4	A	–	–	–	–
4	B	–	–	–	–
4	C	–	–	–	–

Legends: Operators 1= MTN, Operator 2= GLO, Operator 3= Airtel, Operator 4= 9Mobile (Etisalat)
A= Upload Speed, B= Download Speed, C= Latency

Artificial Intelligence and Customer Satisfaction

The study established **a** positive and statistically significant relationship between Artificial Intelligence and customer satisfaction. The correlation analysis produced a Pearson correlation coefficient of $r = .412$ with $p < .001$, indicating a moderate positive relationship between AI and customer satisfaction. The regression analysis further showed that AI explained 16.9% of the variation in customer satisfaction ($R^2 = .169$**)**. The regression model was statistically significant, $F(1, 368) = 75.000$, $p < .001$, while the regression coefficient for AI was positive and statistically significant ($\beta = 0.4$, $\beta = 0.4$, $t = 8.7$, $p < 0.001$). The null hypothesis that there was no significant relationship between AI and customer satisfaction was therefore rejected.

This finding agrees with Busayo et al. (2023)**,** who examined Artificial Intelligence and service quality among Nigerian telecommunication firms. Their study found that data mining and chatbots had significant positive effects on service quality and concluded that AI influenced telecommunications service quality in Nigeria. The agreement between the two studies is important because service quality is closely related to customers' evaluations of the services they receive. Both studies therefore suggest that customer-oriented and data-driven AI applications can contribute to improved service experiences in the telecommunications sector.

The present finding also agrees indirectly with Olatokun and Ojo (2016**)**, who found that responsiveness, assurance and empathy significantly explained customer satisfaction among Nigerian mobile telecommunications users. Although their study did not specifically examine AI, its findings are relevant to the present study because AI-enabled technologies can support faster responses, automated customer assistance and more efficient service delivery. Thus, the present study extends the argument of Olatokun and Ojo (2016) by showing that AI can serve as a technological capability through which some service-related factors associated with customer satisfaction may be enhanced.

Similarly, the finding is consistent with Bello (2020)**,** who reported positive relationships between tangibility, reliability, responsiveness and empathy and customer satisfaction among Nigerian telecommunications users, with reliability emerging as the strongest predictor. The present study agrees with Bello (2020) in demonstrating that improvements in telecommunications service delivery are associated with better customer outcomes. However, the studies differ in their explanatory focus. Bello (2020) examined conventional service-quality dimensions, whereas the present study examined AI as a technological capability. This difference suggests that AI should be viewed as one potential mechanism for improving customer experience rather than as the only determinant of customer satisfaction.

The finding further agrees with Bawa (2026), who reported that network reliability, service responsiveness, tariff affordability and value-added services significantly influenced customer satisfaction among telecommunications customers in Nigeria. The agreement lies in the positive relationship between improved telecommunications service characteristics and customer satisfaction. However, Bawa's study identified several service-related factors simultaneously, whereas the present study examined AI as the principal explanatory variable. The fact that AI explained 16.9% of the variation in customer satisfaction suggests that AI made a meaningful contribution, while other factors not included in the present model also potentially contributed to customers' satisfaction.

There was, however, a notable difference between the present finding and part of the findings reported by Busayo et al. (2023). Although Busayo et al. (2023) found an overall positive role for AI applications in telecommunications service quality, their study reported a negative relationship between machine learning and service quality, while data mining and chatbots had positive relationships. This difference may be explained by the fact that AI consists of different applications that may not produce identical customer outcomes. The effectiveness of a particular AI application may depend on the quality of the underlying data, accuracy of the system, implementation process, customers' acceptance of the technology and the extent to which the technology is integrated into service delivery. In contrast, the present study treated AI as a broader construct, which may have resulted in an overall positive relationship despite the possibility that individual AI applications could produce different outcomes.

The findings also require qualification when compared with Akpan et al. (2022). Their study found that reliability had the greatest effect on customer satisfaction among Nigerian mobile-phone users, while responsiveness did not significantly influence customer loyalty. This does not directly contradict the present finding because the studies examined different explanatory variables and outcome measures. The finding nevertheless demonstrates that improvements in one aspect of telecommunications service delivery may not automatically translate into every form of positive customer outcome. In the present study, AI was significantly associated with customer satisfaction, but the result should not be interpreted to mean that AI alone determines all aspects of customer behaviour, such as loyalty or retention.

Overall, the finding demonstrates that AI was positively and significantly associated with customer satisfaction among telecommunications customers in Ikeji-Arakeji. The consistency of the finding with several previous Nigerian studies strengthens the argument that technology-supported improvements in service delivery can contribute to favourable customer evaluations. At the same time, the R^2 of 0.169 indicates that AI accounted for only part of the variation in customer satisfaction. Therefore, customer satisfaction should be understood as a multidimensional outcome that may also be influenced by other factors such as network reliability, service responsiveness, affordability, service quality and customers' individual experiences. The present finding therefore supports the relevance of AI to customer satisfaction without suggesting that AI is the sole determinant of customer satisfaction.

AI-Enabled Services and Customer Experience

The descriptive findings showed that personalized SMS/data offers were the most commonly reported AI-enabled service among the respondents, followed by chatbots/virtual assistants and mobile-app self-service. This finding is consistent with Busayo et al. (2023), whose study identified data mining and chatbots among the AI applications that positively influenced telecommunications service quality in Nigeria. The similarity suggests that customers may encounter AI most directly through personalized communication, automated customer support and data-driven service interactions.

The prominence of personalized SMS/data offers may indicate that customers value AI-enabled services that provide information or offers that are relevant to their individual usage patterns. Similarly, chatbots

and virtual assistants may improve the accessibility of customer support by providing automated responses to common customer enquiries. Mobile-app self-service may also provide customers with greater convenience by allowing them to manage selected services without depending entirely on direct interaction with customer-service personnel. These applications demonstrate that the contribution of AI to customer satisfaction may occur through practical improvements in convenience, responsiveness and personalization.

The finding is also broadly consistent with recent international evidence on AI-enabled telecommunications services. A 2026 study of telecommunications customers in Saudi Arabia reported positive effects of AI marketing technologies, including chatbots, dynamic pricing, voice search and visual search, on customer-related outcomes. Although the study was conducted in a different national context and examined a different dependent variable, its findings provide broader support for the argument that AI-enabled customer interactions can produce favourable customer outcomes when they are properly integrated into the digital service experience.

An important finding was that 8.9% of the respondents indicated that they were not aware of any AI-enabled service provided by their network provider. This suggests that some customers may interact with AI-supported services without necessarily recognizing the technology behind them. Customers may be more concerned with whether a service is fast, convenient, relevant and capable of resolving their problems than with whether AI was used to provide that service. Consequently, customer evaluation of AI in telecommunications may depend more on the outcomes of the technology than on customers' technical awareness of AI itself.

The finding therefore suggests that telecommunication firms should not focus solely on making customers aware that AI is being used. More importantly, AI applications should be designed and implemented in ways that produce noticeable improvements in service delivery, personalization, convenience and problem resolution. When customers experience tangible benefits from AI-enabled services, the technology is more likely to contribute positively to their overall satisfaction.

AI, Network Optimization and Technical Performance

The technical assessment showed that performance varied across MTN, Glo and Airtel and across different days and time periods. Airtel generally demonstrated comparatively strong download performance and low latency, while MTN showed stronger performance in some upload and download measures but experienced substantial latency variation. Glo generally occupied an intermediate position. These findings support the proposition that telecommunications network performance is dynamic rather than fixed.

The technical findings are relevant to the broader field of AI-enhanced telecommunications operations. The ITU framework describes AI-supported functions for operational efficiency, quality assurance, cost management and security assurance (ITU, 2021). However, the present study did not directly observe the internal AI systems used by the operators, so this literature provides context rather than evidence that AI caused the speed or latency results recorded here.

The findings also agree with Kumar (2024), who examined AI-powered network management systems for LTE networks and highlighted the use of AI for resource optimization, fault detection and predictive maintenance. The agreement is conceptual rather than causal: the present study measured network outcomes, while Kumar's work focuses on the technological mechanism through which AI can be used to manage network performance.

More broadly, telecommunications standards describe AI-supported operational management and network maintenance as areas for structured monitoring and optimization (ITU, 2021). This is relevant

background, but it does not establish that the operators in this study used digital twins or that AI caused the observed network measurements.

However, the technical results do not permit a strong causal conclusion that AI was responsible for Airtel's comparatively better performance or MTN's latency fluctuations. Unlike an experimental or firm-level study that measures the actual AI systems, algorithms and optimization interventions of each operator, the present test measured the resulting network performance. Differences may also reflect infrastructure capacity, traffic congestion, spectrum resources, backhaul capacity, geographic conditions, maintenance activities and subscriber load. Therefore, the appropriate conclusion is that the observed technical patterns are consistent with the potential contribution of AI-driven optimization, but AI cannot be isolated as the sole cause from the available data.

This qualification is consistent with the broader Nigerian service-quality literature. Bello (2020) found that reliability was the strongest predictor of customer satisfaction, while Bawa (2026) similarly found network reliability to be the strongest determinant of customer satisfaction. These studies indicate that the ultimate customer benefit of AI-driven network management depends on whether it produces reliable network service. In other words, AI is a means of improving network performance; reliability, speed and responsiveness are among the outcomes customers ultimately experience.

Conclusion

The study concludes that Artificial Intelligence was positively and significantly associated with customer satisfaction among telecommunication customers in Ikeji-Arakeji, Osun State**.** The Pearson correlation result showed a positive and statistically significant relationship between AI and customer satisfaction, while the regression analysis further confirmed that AI significantly predicted customer satisfaction. The positive regression coefficient indicated that higher levels of AI-enabled service use were associated with higher levels of customer satisfaction.

The regression model produced an R^2 of 0.169, indicating that AI accounted for 16.9% of the variation in customer satisfaction. This finding demonstrates that AI represented an important contributor to customer satisfaction, but it was not the only factor influencing customers' experiences. The remaining variation could be associated with other factors such as network reliability, service quality, affordability, responsiveness, network coverage, infrastructure and individual customer experiences. These findings are consistent with previous Nigerian studies that have emphasized the importance of service quality, reliability and responsiveness in shaping customer satisfaction.

With respect to technical network performance, the study concludes that network performance varied across operators and observation periods**.** The speed-test results showed differences in download speed, upload speed and latency among the networks assessed. Airtel demonstrated comparatively strong performance in some of the observed measures, while MTN and Glo displayed different strengths and weaknesses across the observation periods.

The technical findings suggest that AI-driven monitoring, predictive analytics and network optimization may be relevant to improving telecommunications network management. However, because the study did not experimentally isolate AI from other operational and infrastructural factors, the observed differences in technical performance cannot be attributed solely to AI. The findings should therefore be interpreted as evidence of network-performance variation and as an indication of the potential relevance of AI-enabled optimization and predictive maintenance.

Overall, the study concludes that AI represents a useful technological capability for improving customer-oriented telecommunications services, while its contribution to overall telecommunications

performance depends on its integration with reliable infrastructure, effective service management and other operational capabilities.

Recommendations

1. **Strengthen AI-enabled customer service:** Operators should expand reliable chatbots, virtual assistants and self-service platforms, with human escalation for complex complaints.
2. **Improve personalization:** AI-based recommendations and data offers should be made more relevant, timely and transparent, with appropriate customer privacy and preference controls.
3. **Integrate AI with network monitoring:** Operators should use predictive analytics to identify congestion, anomalies and potential failures before they produce major service disruptions.
4. **Prioritise network reliability:** AI investment should be accompanied by investment in network capacity, infrastructure, coverage, power and transmission because AI cannot compensate for inadequate underlying infrastructure.
5. **Monitor performance continuously:** Operators should routinely measure upload speed, download speed and latency across peak and off-peak periods and different locations.
6. **Train personnel:** Technical and customer-service employees should receive continuous training in AI operation, data interpretation, system monitoring and responsible use.
7. **Evaluate AI by outcomes:** Management should assess AI projects using customer satisfaction, complaint-resolution time, retention intention, service quality, speed and latency rather than adoption statistics alone.
8. **Improve customer awareness:** Operators should explain AI-enabled services in simple language and disclose how customer information is used, while maintaining appropriate privacy safeguards.

Limitations and Directions for Future Research

This study has several limitations. First, the questionnaire survey was conducted in Ikeji-Arakeji only; the findings should not be generalized to all of Osun State or Nigeria without further evidence. Second, the customer-satisfaction measures were self-reported and therefore reflect respondents' perceptions rather than firm-level financial or entrepreneurial outcomes. Third, the network tests measured performance outcomes but did not directly measure the internal AI systems, algorithms, or interventions used by the operators. Differences in speed and latency may also reflect network coverage, congestion, spectrum, backhaul capacity, device characteristics, and other contextual factors. Fourth, the available manuscript does not fully document the speed-test application, device, server, exact locations, and repeat-reading protocol. Future research should use a clearly documented and replicable protocol, collect repeated measurements across more locations and periods, and link objective network metrics with customer-level responses where ethically and methodologically appropriate. Studies making claims about firm-level performance should also obtain suitable firm-level data.

References

Ackoff, R. L. (1971). Towards a system of systems concepts. *Management Science, 17*(11), 661-671.

Akpan, C. F., Amoozegar, A., & Begum, M. (2022). Analysis of customer satisfaction as the mediator between reliability, responsiveness, assurance and customer loyalty among mobile phone users in Nigeria's telecommunication industry. *Journal of Pharmaceutical Negative Results, 13*(Special Issue 06), 1650-1657.

Arend, R. J., & Bromiley, P. (2009). Assessing the dynamic capabilities view: Spare change, everyone? *Strategic Organization, 7*(1), 75-90.

Bagozzi, R. P. (2007). The legacy of the technology acceptance model and a proposal for a paradigm shift. *Journal of the Association for Information Systems, 8*(4), 244-254.

Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99-120.

Bawa, I. (2026). Customers' satisfaction and quality of services of global system for mobile communications (GSM) service providers in the Federal Capital Territory (FCT), Nigeria. Nigeria Journal of Business Administration, 24(1), 82-96.

Bello, O. (2020). A study of relationship between telecommunications service quality and customer satisfaction in the Nigerian technical and vocational education and training institutions. Asian Journal of Management, 11(2), 139-146. https://doi.org/10.5958/2321-5763.2020.00022.0

Benbasat, I., & Barki, H. (2007). Quo vadis, TAM? *Journal of the Association for Information Systems, 8*(4), 211-218.

Bertalanffy, L. von. (1968). *General system theory: Foundations, development, applications*. George Braziller.

Busayo, T., Igbekoyi, O. E., Oluwagbade, O., Adewara, Y., Dagunduro, M., & Boluwaji, Y. (2023). Artificial intelligence and service quality of telecommunication firms in Nigeria. Journal of Economics, Finance and Accounting Studies, 5(3), 203-214. https://doi.org/10.32996/jefas.2023.5.3.16

Checkland, P. (1981). *Systems thinking, systems practice*. John Wiley & Sons.

Creswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches* (4th ed.). SAGE Publications.

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review, 96*(1), 108-116.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340.

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal, 21*(10-11), 1105-1121.

Fossen, F. M., McLemore, T., & Sorgner, A. (2024). Artificial intelligence and entrepreneurship. Foundations and Trends in Entrepreneurship, 20(8), 781–904. https://doi.org/10.1561/0300000130

International Telecommunication Union. (2022). *Global connectivity report 2022: Achieving universal and meaningful connectivity in the Decade of Action*. ITU.

International Telecommunication Union. (2022). *Measuring digital development: Facts and figures 2022*. ITU.

Li, D., Pan, Z., Wang, D., & Zhang, L. (2023). A study on artificial intelligence orientation and new venture performance. Asia Pacific Business Review, 29(4), 967–989. https://doi.org/10.1080/13602381.2023.2188764

Liu, A., & Wang, S. (2024). Generative artificial intelligence (GenAI) and entrepreneurial performance: Implications for entrepreneurs. The Journal of Technology Transfer, 49(6), 2389–2412. https://doi.org/10.1007/s10961-024-10132-3

Nambisan, S. (2017). Digital entrepreneurship: Toward a digital technology perspective of entrepreneurship. *Entrepreneurship Theory and Practice, 41*(6), 1029-1055.

Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes. *Research Policy, 48*(8), 103773.

Obschonka, M., & Audretsch, D. B. (2020). Artificial intelligence and big data in entrepreneurship: A new era has begun. *Small Business Economics, 55*(3), 529-539.

OECD. (2023). *Artificial intelligence in science: Challenges, opportunities and the future of research*. OECD Publishing.

Olatokun, W. M., & Ojo, F. O. (2016). Influence of service quality on consumers' satisfaction with mobile telecommunication services in Nigeria. Information Development, 32(3), 398–408. https://doi.org/10.1177/0266666914553316

Peteraf, M., Di Stefano, G., & Verona, G. (2013). The elephant in the room of dynamic capabilities: Bringing two diverging conversations together. *Strategic Management Journal, 34*(12), 1389-1410.

Popoola, S. I., Atayero, A. A., Faruk, N., & Badejo, J. A. (2018). Data on the key performance indicators for quality of service of GSM networks in Nigeria. Data in Brief, 16, 914–928. https://doi.org/10.1016/j.dib.2017.12.005

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192-210.

Russell, S. J., & Norvig, P. (2021). *Artificial intelligence: A modern approach* (4th ed.). Pearson.

Straub, D. W., Keil, M., & Brenner, W. (1997). Testing the technology acceptance model across cultures: A three country study. *Information & Management, 33*(1), 1-11.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509-533.

UNESCO. (2021). Recommendation on the ethics of artificial intelligence. UNESCO.

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

Wamba-Taguimdje, S.-L., Wamba, S. F., Kala Kamdjoug, J. R., & Wanko, C. E. T. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. *Business Process Management Journal, 26*(7), 1893-1924.

Winter, S. G. (2003). Understanding dynamic capabilities. *Strategic Management Journal, 24*(10), 991-995.

World Economic Forum. (2023). *The future of jobs report 2023*. World Economic Forum.

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