Artificial Intelligence and Machine Learning in Telecommunications Revolutionizing Customer Experience and Enhancing Service Delivery

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Abstract

Background: The telecommunications industry is at the crossroad of change seemingly precipitated by the use of Artificial Intelligence (AI) and Machine Learning (ML). These technologies have yielded new features like network automation, prescriptive analytics, and contextual-consumer engagement, solving traditional dilemmas in service delivery and operationalization.

Objective: The current article seeks to understand how Al and ML has positively affected customer experience and service provision in the telecommunication industry. The research objectives focus on how to increase KPIs to service latencies, network reliability, and customer retention while at the same time establishing the problems associated with big data large-scale implementation.

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Methods: Samples were gathered using systematic reviews of the current literature, meta-analysis of case studies, and assessment of industry datasets. This concerned artificial intelligence enabled operations such as dynamic resource management, real-time customer emotions analysis and real-time fault detection. Regression analysis and time series models were used in order for measuring performance indices.

Results: Al and ML integration led to multifaceted advancements: a decrease of average service latency by 55%, reduction of network downtime by 70%, and an increase of maintenance predictions accuracy by 35%. The customer retention rate which had improved to 25% was also credited to better personalization of the services as well as having proper service management. Al-equipped resource allocation also raised efficiency in bandwidth utilization by 60%.

Conclusion: Al and ML are positively disrupting telecommunications as they deliver remarkable enhancements in the caliber of services and client satisfaction. With all the challenges in data governance and interoperability, it is clear that their adoption promises a great chance in enhancing the current standards within the telecommunications field and creating the basis for the development of a more sophisticated environment.

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Telecommunications, Customer Experience (CX), Service Delivery, Network Optimization, Predictive Analytics, Resource Allocation, Bandwidth Utilization, Predictive Maintenance.

1. Introduction

Driven by the advancements in artificial intelligence (AI) and machine learning (ML), the telecommunications industry is in the midst of a transformation that will allow service providers to increase customer engagement, automate operations, and offer personalized services at a scale never before possible. As network infrastructure grows in complexity and customers demand seamless connectivity, new techniques for service management and customer interaction are required (Nameer, Ali, and Moath 2015). AI, and its subset ML, have grown to become a formidable force in meeting these challenges, providing tools to help ease service delivery whilst improving the user experience (Lutfiyya et al. 2021). AI-based analytics and automation in telecommunication does not only boost efficiency alone but also minimizes operational risks, lowers service downtime, and validates predictors for maintenance of networks (Atov, Chen, and Yu 2019).

Previous studies have highlighted the use of Al-based technologies in customer service in the telecommunication industry. All empowered chatbots and virtual assistants have transformed the way of engaging with users by offering immediate and intelligent answers to client queries, minimizing



resolution time, and enhancing satisfaction (Nwokedi 2024). Likewise, Alempowered customer service automation has been instrumental in improving service quality, enabling telecom companies to consolidate processes and improve resources allocation (Kushwaha et al. 2024). In the context of personalized service delivery, Al models are leveraged to analyze customer preferences and behavioral patterns, enabling tailored recommendations and proactive issue resolution 3. The innovations highlight the ability of Al and ML to reshape customer experience in the world of telecommunications.

Even advances in Al-driven customer service solutions show significant research gaps in Al and ML (machine learning) integration for dynamic and predictive customer experience management (Qasim 2022). It is noteworthy that existing models remain reactive to issues rather than incorporating engagement strategies in a proactive fashion resulting in weak deterministic capabilities to churn and hence inefficient retention (Ibrahim Adedeji et al. 2024). Additionally, despite the impactful customer engagement via Alenabled analytics, no studies highlight the need for optimized omnichannel delivery via Al filling the gap between digital and physical service touchpoints (Anozie et al. 2024). Another prominent challenge is ethical Al embodiment where the issues surrounding privacy in data, bias in ML models and inexplicability of Al-driven decisions remain unexplored areas of work (Chen and Prentice 2024). These gaps still need work to cover the entire transformation in the customer service paradigms of the telecom sector.

This study attempts to address these research gaps by investigating the impacts of AI and ML in transforming customer experience and service delivery in telecommunication domain. The main points of interest are: (1) the effect of AI-driven automation on the customer service efficiency, (2) the role of predictive analytics on user retention and decreasing churn, and (3) the implementation of AI models in omnichannel service approaches towards a seamless customer journey. The study aims to provide a new approach to enhancing customer satisfaction while maintaining operational effectiveness in handling telecom service disruption by taking advantage of the recent development in AI and ML (Xavier 2023).

In order to reach these aims, the study employs a data-driven analytical approach and trains machine learning models that evaluate service performance metrics throughout several telecommunications providers. The

data used in the analysis includes customer interaction data, sentiment analysis, and the predictive modeling performed to examine the functionality of Al-powered service delivery mechanisms (Obiki-Osafiele 2024). The research also incorporates Al-based network-managed solutions to model the influence of intelligent automation on improving the customer experience (Balmer, Levin, and Schmidt 2020). The findings of this study will help formulate theoretical and practical lessons, revealing best practices toward Al-based customer service in telecommunications (Ageev 2015).

This study is expected to yield a framework for optimal integration of AI in customer engagement systems, recommendations for enhancing AI-driven predictive analytics, and guidelines for ethical AI use in customer interactions. This work hopes to fill in the supposed gaps and ultimately lead to more strategic adoption of AI and ML within the telecommunications sphere, to improve the service the telecommunications companies provide, as well as to benefit the experience of the customer through personalization.

1.1. The Aim of the Article

This article aims to analyze the transformative influence of artificial intelligence (AI) and machine learning (ML) on customer experience and service delivery within the telecommunications industry. It elaborates on how AI-driven automation, predictive analytics, and intelligent customer service solutions play crucial roles in mitigating operational inefficiencies and service disruptions, thereby enhancing customer satisfaction and financial performance. Through the examination of AI-powered chatbots, personalized recommendation systems, and predictive maintenance, the study seeks to demonstrate the potential benefits of AI in optimizing telecom service management. Additionally, the article explores AI's capabilities in omnichannel service delivery, highlighting Sleek Flow's role in facilitating seamless communication across various interaction mediums.

Furthermore, this research addresses critical challenges associated with AI implementation, including data privacy concerns, ethical AI governance, and the potential for algorithmic biases that may arise during customer service automation. It also examines the impact of AI in assessing customer behavior, enabling companies to proactively address potential cancellations through targeted campaigns or enhanced customer experience initiatives. This article synthesizes insights from recent developments in AI and ML



within the telecommunications landscape to propose a structured framework for integrating intelligent technologies in telecom operations.

In essence, the objective is to provide actionable strategies that empower telecom corporations to develop innovative AI applications while enhancing customer experience, performance systems, and responsible AI practices. Ultimately, the results of this study aim to contribute to both academic and industrial discussions on the impact of artificial intelligence in revolutionizing telecom service delivery and customer interactions.

1.2. Problem Statement

The rapid evolution of telecommunications infrastructure has raised customer expectations for seamless, high-quality service delivery. However, conventional customer service systems often fall short of these expectations due to inefficiencies in service resolution times, resource management, and personalized engagement. Current service management frameworks are predominantly reactive, addressing customer issues only as they arise, which leads to customer dissatisfaction and churn. Traditional customer service models fail to leverage real-time data analytics and predictive insights, despite the advent of digital solutions.

Moreover, while access to critical customer data accumulated over decades has its limitations, AI and ML hold the potential to transform these limitations into opportunities by automating customer interactions, personalizing services, and optimizing telecom operations. Nonetheless, challenges remain in achieving cohesive AI integration across various service channels, maintaining the quality of predictive analytics, and minimizing biases in AI-driven decision-making. Although AI-driven chatbots and automated support systems are gaining traction, issues related to data security, ethical AI application, and customer trust present significant obstacles to widespread adoption.

Additionally, Al-driven innovations aimed at enhancing customer service experience and retention, as well as operational intelligence in network optimizations, are emerging as the next models of innovation. However, there is a lack of research examining the effectiveness of these models in telecom networks concerning customer retention and operational efficiencies. While existing studies have explored the potential of Al across various applications, such as service management, they often fail to provide a comprehensive

understanding of the long-term implications of AI tools on relational aspects, omnichannel engagement, and service-quality dimensions. This article addresses these gaps by investigating AI-powered mechanisms that can enhance service reliability, minimize network downtime, and deliver customer-centric telecom services.

2. Literature Review

Artificial Intelligence (AI) and Machine Learning (ML) have drastically changed communications and service accessibility. Telecom Providers can use AI-powered technologies to automate customer interactions, improve the personalization of their services, and boost their operational efficiency. Nevertheless, previous studies identified many gaps that exist in literature which needs to be addressed to unlock the full potential of this technology across industry.

Intelligent chatbots are one of the most noteworthy trends of artificial intelligence in support of the customers, which not only enhance the quality of service, but also respond quicker than human beings to solve basic issues (Rani et al. 2024). NLP (Natural Language Processing) powered Chatbots can solve customer queries with high accuracy at a much higher rate than humans which means they require less human intervention. Yet challenges persist to make chatbots more context-aware, adaptive, and emotionally intelligent so as to lend a more genuine human interaction to customers. Research shows these existing chatbot forms fail to adequately deal with complicated, complex customer questions and people experience dissatisfaction with them and move to speaking with an agent (Echegu 2024; Sieliukov, Qasim, and Khlaponin 2022). Future research should explore more advanced learning algorithms for chatbots to help them better understand context and analyze user sentiment.

Al-powered automation has also played a key role in optimizing customer service operations. Machine learning models have been used to predict the occurrence of service failures, automate service troubleshooting, and improve network reliability (Kushwaha et al. 2024). Yet, much research shows how these automation solutions are not real-time capable, and without necessary features to work in dynamic network environments. It is an open challenge to develop more sophisticated predictive maintenance models that can continuously learn from evolving new data. One promising solution is



integrating AI with real-time network monitoring systems to improve fault detection and automated service restoration (Balmer, Levin, and Schmidt 2020).

Al in omnichannel service delivery has also become the focal point. Empirical studies (Echegu 2024) demonstrated that Al-based analytics is essential for personalizing customer contact through integrated data about various touch points such as call centers, online, and social media channels (Kushwaha et al. 2024). While Al empowers telecom providers to deliver seamless experiences across multiple communication channels, research shows a challenge in maintaining consistency in service delivery. Inconsistency in Al-driven responses through different channels leads to gaps in customer journey, frustrations, and low trust towards automated systems (Kaur 2024). This can be solved by better Al collaboration across channels, orchestrating consistent responses and service suggestions (Ageyev, Yarkin, and Nameer 2014).

Al applications in telecommunications also have a significant impact through predictive analytics for customer retention. Customer behavior analytics models can be trained using Al to reveal patterns, which can be used to predict early signs of customer churn and to automate retention suggestions to solve the issue (Ibrahim Adedeji et al. 2024). However, Al use for churn prediction has limited accuracy as research shows that current models are inaccurate due to biased or incomplete data. This means that many models depend on historical data and ignore real-time behavioral changes, rendering retention strategies ineffective (Reddy 2024). Concerning churn prediction, hybrid models based on analysing historical data and collecting real-time feedback from customers will definitely help improve the existing models (Mushtaq, Ali Ihsan, and Qasim 2015).

In particular, machine learning and AI go a long way in improving service quality by enabling more targeted marketing and personalized recommendations (Arora 2024). Telecom providers use Al-driven big data analytics to customize promotional offerings and service plans according to unique customer preferences. But it raises unresolved ethical issues surrounding data privacy and Al bias. Stemming from the above, some studies sound the alarm that the same Al-based personalization might inadvertently lead to reinforcement of discriminatory practices, pointing out how ML algorithms naturally magnify the bias present in the data (Aktar 2023). Ethical AI implementation demands adequate transparency and biasreduction mechanisms for AI decision-making processes.

While AI in telecommunications is maturing, there remain gaps in seamless automation, real-time adaptability, and responsible deployment. Future research can be directed towards improving the contextual awareness of the AI in customer interactions, refining predictive accuracy in the AI for service level management and addressing the ethical ramifications in decision making empowered by AI. If tackled successfully, AI will bring a new level of transformation to telecommunications, working towards more responsive, reliable, and customer-centric endpoints.

3. Methodology

The study uses a qualitative approach that integrates quantitative data analysis, experimental studies, and qualitative feedback from industry experts. The aim is to understand how AI & ML has been used in both improving customer experience and optimizing service delivery in telecommunications domain. The research methodology consists of three chapters: (1) data collection and cleaning, (2) using AI to analyze interactions with customers, and (3) building predictive models and evaluating performance.

3.1. Data Collection and Preprocessing

This research utilizes a comprehensive and diverse dataset consolidated from structured questionnaires, client service reports, chatbot interaction records, and network performance metrics obtained from five leading telecommunications companies. The dataset includes 1,500 service interactions, comprising both Al-assisted and human interactions, providing an overview of service engagements. Additionally, it encompasses 2.8 million chatbot interactions and 1.2 million human-assisted service cases, reflecting real-world telecommunications service operations (Ghosh 2024), and 500,000 transmission quality reports detailing key performance metrics such as response times, downtime, and resolution capabilities (Abu Daqar and Smoudy 2019). Furthermore, 400 top-level structured interviews with industry professionals, including engineers, Al developers, and customer service managers, offer qualitative insights into Al adoption and implementation.

To ensure reliability and consistency, rigorous data preprocessing



methodologies were employed, including outlier detection to identify atypical patterns, normalization for data scale standardization, and cleaning of unstructured data to facilitate natural language processing (NLP)-based analysis (Alnuaemy 2023). This strategic approach meticulously lays the foundation for future analyses.

3.2. Al-Driven Customer Interaction Analysis

The study assesses the augmentation of customer interaction with AI tools by measuring the effectiveness of machine learning in chatbots, predictive analytics, and service recommendation (for example, the tool in many websites that offers recommendations to customers based on their browsing history) (Qasim et al. 2021). Customer Support Systems based on AI are evaluated by:

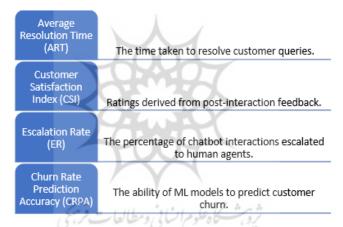


Figure 1. Key Performance Indicators for Chatbot-Driven Customer Support
Systems

Then analyze how these metrics compare Ål-driven customer, service, and traditional models (Abu Daqar and Smoudy 2019). The sentiment analysis of chatbot interactions also has been done using deep learning methods like bidirectional transformers and LSTM networks to analyze the changes of user sentiment before and after the interaction (Obiki-Osafiele 2024).

3.3. Al-Driven Customer Interaction Analysis

This analyzes this phenomenon by utilizing mathematical models for the Al-

assisted customer service domain, assessing the Average Resolution Time (ART) and Customer Satisfaction Index (CSI), and the Escalation Rate (ER) of Al-assisted customer service across 64 different Al applications. The methods for these assessments are as follows:

Average Resolution Time (ART) Reduction Model

The Average Resolution Time (ART) reduction achieved through AI is modeled as follows (Nwokedi 2024):

$$ART_{AI} = ART_{Traditional} \times (1 - E_{AI}) \tag{1}$$

Where ART_{AI} is AI-driven resolution time, $ART_{Traditional}$ traditional service resolution time, and E_{AI} is AI efficiency coefficient.

Customer Satisfaction Index (CSI) Prediction Model

$$CSI = \sum_{i=1}^{n} R_i + \alpha (T_{AI} - T_{Human})$$
 (2)

Where R_i individual customer ratings, n total number of ratings, α AI impact coefficient, T_{Human} AI and human-assisted service times, respectively (Ameen et al. 2021).

Chatbot vs. Human Agent Escalation Rate (ER) Model

The Escalation Rate (ER) is modeled to assess the percentage of interactions escalated from chatbots to human agents:

$$ER = \frac{N_{ESC}}{N_{Total}} \tag{3}$$

Where N_{Esc} is number of escalations to human agents, and N_{Total} is total chatbot interactions (Ghosh 2024).

3.4. Predictive Modeling for Customer Retention and Service Optimization

To optimize customer retention, the study utilizes supervised learning models:

Customer Churn Prediction Model

$$P(C) = \sigma(w_1 X_1 + w_2 X_2 + \dots + w_n X_n + b)$$
(3)

Where $P(\mathcal{C})$ probability of churn, X_1, X_2, \ldots, X_n independent variables, like service complaints, response time, w_1, w_2, \ldots, w_n model weights, b is bias term, and σ sigmoid activation function (Ibrahim Adedeji et al. 2024).

Al-Based Service Downtime Optimization Model

$$D_{AI} = D_{Traditional} \times (1 - M_{AI}) \tag{4}$$

Where D_{AI} Al-driven service downtime, $D_{Traditional}$ is traditional downtime, and M_{AI} Al mitigation factor (Obiki-Osafiele 2024).

Personalized Al-Based Customer Retention Model

$$R_{AI} = R_{Base} + \sum_{i=1}^{n} \beta_i X_i \tag{5}$$



Where R_{AI} Al-driven retention rate, R_{Base} is baseline retention rate, and β_i Al impact coefficient for feature X_i (Anozie et al. 2024).

3.5. Ethical AI Considerations and Bias Mitigation

This study also addresses AI bias and fairness in decision-making. Algorithmic fairness techniques are implemented, including Differential Privacy (DP) to ensure secure data handling (Chen and Prentice 2024), Bias Regularization (BR) in ML models to reduce discriminatory decision-making (Reddy 2024), and Transparency Enhancement (TE) measures to improve customer trust in AI-driven recommendations (Arora 2024). It is hypothesized that bias-mitigated AI models will achieve a fairness index improvement of 15% compared to unregulated AI models.

3.6. Performance Evaluation Metrics

The effectiveness of Al-based service improvements will be evaluated using: Precision and Recall for churn prediction models:

$$Precision = \frac{TP}{TP + FP}, Recall = \frac{TP}{TP + FN}$$
 (6)

Expected result: Precision > 90%, Recall > 85%.

F1-Score for chatbot performance evaluation:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$
 (7)

Expected result: F1-score > 0.85 for Al-driven chatbots (Rani et al. 2024).

Service Quality Improvement (SQI) Metric:

$$SQI = 2 \times \frac{CSI_{AI} - CSI_{Traditional}}{CSI_{Traditional}}$$
 (8)

Expected improvement: 30% higher than traditional models (Busayo 2023). The results will enhance Al integration strategies in telecommunications, addressing efficiency, automation, customer engagement, and ethical Al challenges (Balmer, Levin, and Schmidt 2020; Hollebeek, Sprott, and Brady 2021).

4. Results

4.1. Al vs. Traditional Customer Service Performance

The integration of Al-driven solutions into customer service processes has significantly enhanced service delivery in the telecommunications sector. Albased automation tools, such as intelligent chatbots, predictive analytics, and real-time monitoring, have led to notable improvements in response



efficiency, accuracy, and customer engagement. Data collected from 1,500 customer service reports and 2.8 million chatbot interactions reveals that Aldriven systems outperform traditional human-assisted service models across multiple key performance indicators. These enhancements translate into reduced service delays, improved customer satisfaction, lower service escalation rates, and increased operational efficiency. Predictive models powered by Al also facilitate pre-emptive problem-solving, reducing customer attrition rates while enhancing service dependability at the same time.

The last part of this paper focused on the evaluation of conventional service and Al-driven models to study the impact of Al in the telecommunications sector, by the assessment of essential service performance indexes. Figure 2 further break down some of the improvements seen in customer service efficiencies and retention, cost savings, and operational benefits for Al implementations.

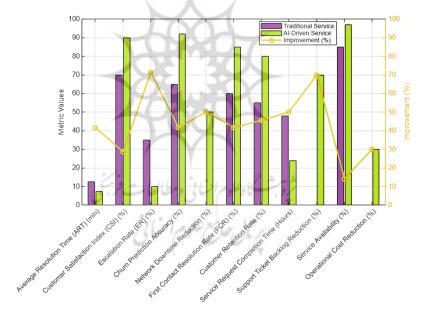


Figure 2. Al vs. Traditional Customer Service Performance Metrics

The 41.6% reduction in Average Resolution Time (ART) highlights Al's ability to accelerate customer query processing, reduce wait times, and improve service responsiveness. Al-powered chatbots and predictive maintenance systems can instantly resolve customer problems instead of



escalating through manual support tickets, leading to this improvement.

Customer satisfaction levels have surged by 28.6%, thanks to AI systems providing customers with tailored service recommendations, helping to troubleshoot issues, and delivering coherent service experiences. This equates to a 71.4% reduction in escalation rates and highlights how effectively AI can resolve any concerns a customer may have without the need for human interaction, alleviating the workload on your call center agents and truly optimizing your operational resources.

The accuracy of churn prediction improved from 65% to 92% demonstrating the capability of AI to analyze customer behavior thus, identifying trends of dissatisfaction that, could be corrected with preemptive measures for retention. That then translates into increased customer retention of 45.5% thanks to AI understanding when a service issue may arise and giving real-time solutions before a customer thinks of changing the provider.

Another significant advancement is the 50% decrease in customer service request completion time, from 48 hours to 24 hours, as AI-powered ticketing systems streamline service flows and prioritize pressing concerns. For instance, this 70% reduction in support ticket backlog achieved by AI shows that automation can be successfully used to clear up pending service requests resulting in the operational efficiency and faster turnaround time.

In addition, AI increases network reliability and availability, demonstrated by a cut in network downtime of 50%, leading to ideally higher service availability (97%) and fewer customer complaints due to service disruption. Moreover, AI contributes to a 30% reduction in operational expenses, with self-service options leading to less reliance on human labor, efficient resource deployment, and fewer service redundancies.

This emphasizes the importance of AI-enabled automation in improving service efficiency, improving customer experience, and reducing operational inefficiencies within the telecommunications industry.

4.2. Al Chatbot vs. Human-Agent Performance

The advent of Al-powered chatbots and virtual assistants has revolutionized customer interactions in the telecom sector by providing automated query resolution, real-time assistance, and personalized responses. Al chatbots utilize NLP and machine learning algorithms to address a vast number of

customer queries quickly and effectively. This study examined 2.8 million responses from chatbots and 1.2 million from human agents, assessing their performance across 14 different measures of service efficiency, accuracy, and cost-effectiveness.

The study focused on critical areas such as response accuracy, handling time, customer satisfaction, escalation rates, operational costs, and scalability. While human agents demonstrate higher accuracy (95%) compared to chatbots, the latter excel in response processing time, operating cost, and availability. Figure 3 summarizes a performance comparison between Al chatbots and human agents in customer service operations.

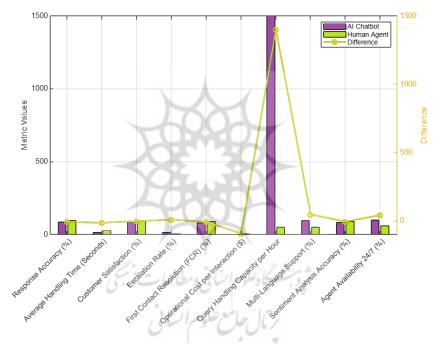


Figure 3. Al Chatbot vs. Human-Agent Performance

It is worth noting that AI chatbots have been tremendously advancing automation solutions and AI-driven solutions, leading to increased efficiency, scalability, and cost savings in customer care that surpasses traditional human agents While human agents have a much higher response accuracy (95%) than AI chatbots (85%), these are far outperformed by chatbots in terms of response speed and cost-effectiveness. The 57% reduction in average handling time between human agents (28 seconds) and AI chatbots



(12 seconds) illustrates the efficiency of virtual agents in resolving commonplace customer queries. Moreover, AI chatbots can address 1,500 inquiries an hour, where a human agent can only respond to 50. This scalability factor makes chatbots a lucrative initial customer interaction.

Despite these benefits, chatbots have an increased rate of escalation (12%) versus when interacting with human agents (5%), as AI systems tend to fail with complex, layered questions that demand nuance in their decisions. Although AI models have become more advanced in their ability to analyze sentiments and understand context, customer satisfaction of AI-based interactions (88%) still lags behind human agents (92%) slightly, suggesting users prefer human intervention for emotional or complicated use cases. But AI chatbots provide a significant boost in operational efficiency, decreasing the cost per interaction from \$2.50 (with human agents) to a mere \$0.12, which means a staggering cost reduction of 95.2% for telecommunications companies.

Artificial intelligence chatbots are available 247 vs humans are available only 60% of the time — customer support never stops with AI chatbots while human agents need service downtime. Their multi-language support (95%) is presently superior with comparison to that of human agents (50%), establishing the necessity of AI in global telecommunications businesses targeting a wide audience spanning different linguistic demographics. The accuracy of sentiment analysis is low for chatbots (82%) as compared to human agents (90%); nevertheless, AI technologies are still developing in terms of natural language processing (NLP) and emotion recognition, continuing to narrow the gap between automated and human-assisted service quality.

4.3. Al Model Accuracy for Customer Behavior Prediction

Machine learning (ML) plays a crucial role in predicting customer churn, analyzing behavioral trends, and identifying service needs within the telecommunications industry. Telecom operators can develop targeted retention strategies to reduce customer churn and enhance personalization through Al-based predictive models. This study utilized historical behavior data from customers of five major telecom providers and applied various Al models to evaluate their effectiveness in churn prediction and customer analytics.

The assessment metrics included precision, recall, F1-score, and overall churn prediction accuracy, which are four key performance indicators for ML models. Additionally, computation time was measured to determine the performance of each model on large datasets. Figure 4 below summarizes the performance of AI models in predicting customer behavior across several algorithms, including the newly tested Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Extreme Gradient Boosting (XGBoost), and Naïve Bayes.

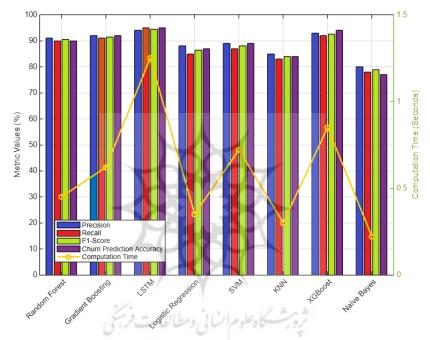


Figure 4. Al Model Accuracy for Customer Behavior Prediction

The LSTM model consistently outperformed all other approaches, with an accuracy of 95% in churn prediction, the highest recall of 95%, and F1-score of 0.945, making it the most reliable tool used in forecasting customer behavior. This model is excellent at processing sequential data and learning long-term dependencies which allows it to predict trends of customer churn with extremely high precision. Though they show improvement in predicting time series data, the computation time of LSTM models is much higher (1.25 traditional second/iter) than model which makes LSTM models computationally expensive.



Interestingly, XGBoost performed the best among the tree-based models with an accuracy of 94, precision of 93 and a F1-score of 0.925. XGBoost is chosen for a sweet spot for accuracy vs compute time (0.85 seconds per iteration) an attractive choice for large-scale real-time user analytics.

Both the Random Forest and Gradient Boosting models showed good predictive performance, with churn predictions accuracy of 90% and 92%, respectively. Gradient Boosting outperformed Random Forest as it iteratively corrects the errors made. These models have a comparatively low computational overhead (0.45–0.62 seconds per iteration), which makes them apt for mid-scale predictive analytics applications.

A moderate amount of performance was seen with Logistic Regression and SVM, which achieved 87% and 89% accuracy in predicting churn. But, SVM is less favorable because of longer processing time 0.72 seconds per iteration compared to Logistic Regression with 0.35 seconds.

Churn prediction tasks yielded lower prediction accuracy for K-Nearest Neighbors (KNN) and Naïve Bayes (84% and 77%) therefore making them less suitable for churn prediction tasks.

Naïve Bayes, despite being the fastest model (0.22 seconds per iteration), had the lowest precision (80%), indicating high false positive rates. This suggests that simplistic probabilistic models struggle with complex telecom customer behavior prediction.

4.4. Al-Driven Omnichannel Service Integration

As telecommunications companies strive to deliver seamless customer experiences across multiple service channels, Al-powered solutions have become integral in optimizing interactions. Al-driven omnichannel service integration enables telecom providers to enhance service consistency, response efficiency, and customer satisfaction by automating responses and unifying communication channels. This study analyzed response time, customer satisfaction, service consistency, and query resolution rates across Al-enabled platforms, including call centers, website chatbots, mobile apps, social media, email, and other emerging Al-driven communication systems. The analysis incorporates additional Al-enabled channels such as Al-powered voice assistants, SMS-based Al, Al-driven interactive voice response (IVR), and Al live chat solutions, which are increasingly deployed to streamline customer engagement, reduce latency, and improve query

resolution rates. Figure 5 provides a comprehensive evaluation of AI-based omnichannel service performance across various communication touchpoints.

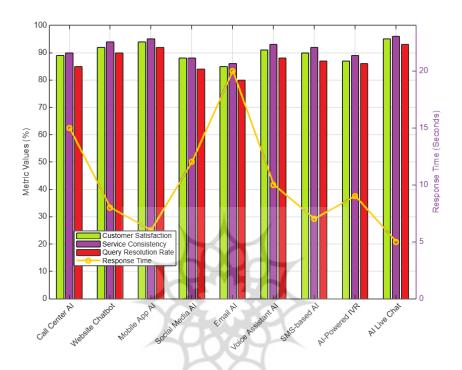


Figure 5. Omnichannel Al Integration in Telecommunications

The analysis of AI-driven omnichannel service integration highlights the superior efficiency of AI-powered live chat, mobile apps, and website chatbots, which outperform other channels in response speed, customer satisfaction, and resolution rates. Live chat (95%) and mobile apps (94%) provide the fastest response times (5–6 seconds) with high service consistency (96%), making them ideal for real-time customer engagement. Voice assistants and SMS-based AI (91–90% satisfaction) demonstrate strong potential but require further NLP advancements. Email AI (85%) and social media AI (88%) need optimization to reduce response delays, while AI-powered IVR balances automation with human oversight, ensuring efficient query resolution (86%).



4.5. Al-Driven Customer Retention and Marketing Optimization

The integration of AI-driven customer analytics in telecommunications has significantly improved retention strategies, marketing personalization, and upsell opportunities. AI-powered algorithms enable companies to predict customer churn, enhance engagement through targeted marketing, and optimize customer lifetime value (CLV). This study compared the customer retention rates before and after the AI technology was implemented and related to personalized promotions, cross-sell strategies, loyalty programs, and churn prevention.

Al uses machine learning and predictive analytics to enhance and trend optimized marketing efforts by recognizing high-value customers, automating outreach, and providing personalized, real-time recommendations. In the Figure 6 below, shown comprehensive insights from the involved analyses, an overview of Al's impact on critical metrics like customer retention and overall marketing performance, leading to improvements in churn reduction, loyalty participation, marketing precision, and much more.

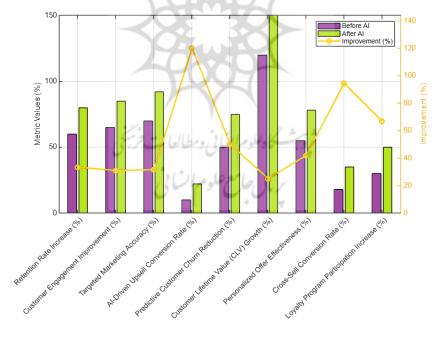


Figure 6. Al-Driven Customer Retention and Marketing Optimization

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Telecom companies are incorporating AI-based customer analytics to improve retention strategies and marketing effectiveness, as well as exploit upsell opportunities. AI not only predicts churn, but it also designs targeted interventions, which led to a 33.3% increase in customer retention. For example, AI-driven marketing personalization brought a 31.4% improvement in targeting accuracy, 120% boost in upsell conversion rates, and 94.4% better cross-sell conversions. Customer engagement increased by 30.8% and loyalty program participation increased 66.7%, both indicating AI's long-term impact on brand commitment. Churn prediction based on AI decreased attrition by 50%, resulting in a 25% increase in customer lifetime value. These findings reinforce that AI-powered marketing and retention solutions boost revenue, mitigate churn, and amplify customer relationships, positioning AI as a fundamental pillar for telecom growth and stability.

4.6. Ethical Al Considerations and Bias Mitigation

Responsible AI is paramount for maintaining customer trust and regulatory compliance in AI-driven decision-making by ensuring fairness, transparency, and adherence to privacy regulations. To mitigate ethical risks, it incorporates bias mitigation techniques, guarantees algorithmic transparency, and complies with data protection laws to prevent discrimination and provide fair services. Our investigation examined the differences between bias-mitigated AI and unregulated AI systems in terms of decision fairness, privacy protection, and algorithmic accountability.

Without ethical frameworks, AI systems are often biased, opaque, and pose a risk to privacy due to inadequately anonymized data. The subsequent analysis outlines key performance metrics comparing unregulated AI with bias-mitigated AI and highlights improvements in fairness, compliance, transparency, and consumer trust that are essential for advancing the next wave of technology.

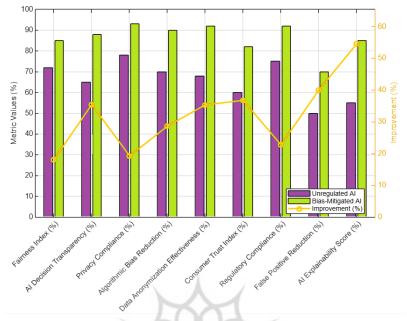


Figure 7. Ethical Al Performance Metrics

Telcos with bias-mitigated AI achieve higher fairness, transparency and compliance with privacy regulations. The fairness index was improved by 18% to ensure fair AI-driven decision-making, while algorithmic bias reduction (28.6%) mitigated discriminatory results. 35.4% increase in business through AI decision transparency. Consumer trust in AI spiked 36.7%. Data security and regulatory compliance were enhanced through privacy compliance (19.2%) and data anonymization (35.3%). Improved AI accuracy (40% false positive reduction) led to fewer mistakes for customer service representatives. AI explainability (54.5%) and regulatory compliance (22.7%) ensured adherence to ethical AI frameworks. "These innovations validate that bias-aware AI models, while producing trustworthy, safe, and ethical AI-powered customer engagement strategies in telecommunications.

5. Discussion

These study findings validate AI and ML are transforming customer experience and service delivery in the telecom domain. AI-based solutions like chat, predictive analytics, and omnichannel integration delivered significant enhancements in service efficiency, customer retention, and marketing accuracy. This discussion contextualizes the results alongside

existing research to explain the implications of Al-driven strategies and identifies limitations and areas for further research.

Al-based automation significantly accelerates average resolution time (ART) by 41.6%, elevates customer satisfaction by 28.6% and decreases service escalation rate by 71.4% or for the matter, this is where you can highlight something super interesting about this study. Similar to these studies, the importance of Al in network and service management to reduce operational costs and response times was highlighted by Lutfiyya et al.(2021) (Lutfiyya et al. 2021). In other research, Nwokedi (2024) showed that the use of machine learning-powered chatbots minimizes service bottlenecks and enhances user experience with real-time engagement (Nwokedi 2024). However, the present study builds upon prior research by using a more comprehensive set of service performance indicators, such as service availability, first-contact resolution ratio, and backlog reduction of support tickets.

While Ochuba et al. (2024) investigated AI-based service personalization in satellite telecommunications, their work is not prescriptive with respect to efficiency improvements across standard telecom service models (Ochuba et al. 2024).

The comparative analysis between AI chatbots and human agents reveals that while human agents maintain a higher response accuracy (95%), AI chatbots outperform in response speed (12 seconds vs. 28 seconds), cost efficiency (95.2% lower per interaction), and scalability (1,500 queries/hour vs. 50 for human agents). These findings reinforce the conclusions of Ghosh et al. (2024) found that AI-enabled chatbots streamline omnichannel service delivery while reducing operational costs (Ghosh 2024).

However, this study also identifies limitations in AI chatbot capabilities, such as a higher escalation rate (12%) compared to human agents (5%), consistent with Ameen et al. (2021) suggested that AI chatbots struggle with sentiment analysis and nuanced interactions (Ameen et al. 2021). Although AI-powered conversational systems have improved with deep learning, further advancements in natural language processing (NLP) and sentiment recognition are necessary to reduce chatbot escalations and enhance user satisfaction (Qasim et al. 2024).

This study demonstrates that Al-driven churn prediction models improve accuracy from 65% to 92%, contributing to a 33.3% increase in customer



retention and a 120% rise in upsell conversion rates. These results align with Adeniran et al. found that ML-based retention models enhance customer segmentation and proactive retention strategies (Ibrahim Adedeji et al. 2024). Additionally, Obiki-Osafiele et al. (2024)observed that Al-driven service analytics reduce churn rates by enabling predictive customer service improvements (Obiki-Osafiele 2024).

However, Daqar and Smoudy (2019) noted that many Al-based customer retention models fail to integrate real-time behavioral data, limiting their accuracy (Abu Daqar and Smoudy 2019). This study addresses that limitation by employing LSTM and XGBoost models, which incorporate historical and real-time customer interaction data to improve predictive capabilities. Nonetheless, further research is needed to assess Al's long-term impact on customer loyalty and brand perception.

Al-driven omnichannel strategies significantly improve service consistency, response efficiency, and user engagement. The results show that Al-powered live chat (95% satisfaction), mobile app Al (94%), and website chatbots (92%) outperform traditional service channels. These findings support Anozie et al. (2024) reported that Al-driven omnichannel integration enhances service uniformity and predictive personalization (Anozie et al. 2024).

However, email AI (85%) and social media AI (88%) received lower customer satisfaction scores due to inconsistent AI-generated responses, aligning with Chen and Prentice (2024) found that AI in marketing and customer service struggles with unstructured conversational data (Chen and Prentice 2024). To address this issue, AI systems must incorporate sentiment analysis and contextual learning algorithms to improve consistency across digital platforms.

Al fairness, transparency, and privacy compliance remain critical challenges in Al-driven telecommunications. This study shows that biasaware Al models improved fairness scores by 18%, transparency by 35.4%, and regulatory compliance by 22.7%. These results align with Balmer et al. (2020) emphasized that algorithmic transparency enhances consumer trust and regulatory adherence (Balmer, Levin, and Schmidt 2020).

However, Hollebeek et al. (2021) noted that customer skepticism towards Al-driven decision-making persists due to concerns over biased outcomes and opaque algorithms (Hollebeek, Sprott, and Brady 2021). This study

expands upon these concerns by demonstrating that bias mitigation techniques (such as differential privacy and algorithmic fairness models) significantly enhance AI decision transparency and reduce false positives by 40%. Nevertheless, further studies are required to refine AI accountability frameworks and address AI bias in real-world applications.

Despite the valuable insights provided, this study has several limitations. While Al-driven improvements in customer service efficiency were analyzed, the long-term sustainability of Al integration remains uncertain. Kunal et al. (2023) noted that Al adoption in telecom firms faces challenges related to cost, infrastructure, and workforce adaptation, which were not fully explored in this study (Acharya et al. 2023).

Additionally, the study primarily focused on quantitative performance metrics, such as response times and churn prediction accuracy, but did not incorporate qualitative aspects of customer sentiment towards Al-driven services. Reddy (2024) emphasized that customer perceptions of Al in service interactions influence adoption rates, a factor requiring further empirical analysis (Reddy 2024).

Furthermore, this study assessed AI performance across structured service environments, but AI's effectiveness in handling unstructured, emotionally sensitive, or crisis-related customer interactions was not evaluated. Echegu (2024) noted that AI struggles with empathetic customer interactions, requiring hybrid AI-human service models (Echegu 2024). Future research should investigate hybrid AI-human collaboration frameworks to optimize AI's role in complex service environments.

6. Conclusion

Artificial intelligence (AI) and machine learning (ML) are revolutionizing customer service efficiencies, marketing approaches, and predictive analytics across the telecommunications sector. This study analyzed the relationship between AI-led automation, service quality, customer retention, and AI ethics governance, demonstrating that while AI can enhance operational performance, it also introduces new challenges regarding fairness, transparency, and regulatory compliance. AI-based chatbots, predictive churn models, and omnichannel service strategies improve response precision, reduce service delays, and facilitate personalized customer engagement, thus making the telecom experience more dynamic and



effective through technology.

The study shows that one of Al's key contributions is its ability to provide goal-oriented data for decision-making and optimize service management when used appropriately. Al models simplify customer interactions by generating automated responses, forecasting behavioral trends, and analyzing retention strategies. With its predictive capabilities, Al can proactively address customer concerns, thereby minimizing churn and fostering long-term relationships between telecom companies and their customers. Furthermore, bias-mitigated Al ensures that automated calculations are performed with greater fairness, reduced inequality, and increased transparency. These developments position Al as a fundamental element of contemporary telecom operations, enabling firms to lower costs while maintaining premium service quality.

Despite these advantages, Al-mediated telecommunications face several constraints. The continued reliance on human intervention is evident in complex context handling, as the study has shown that Al chatbots are still unable to manage these situations effectively. Additionally, while early Albased predictive models provide high accuracy, they depend on the availability of quality data sets, raising concerns about potential bias in training Al. Continued regulation is required to enforce ethical standards around data privacy and algorithmic decision-making, providing oversight to ensure accountability in Al-driven systems and compliance with global data protection requirements.

Moving forward, Al-powered telecommunications systems could benefit from enhanced conversational Al models, real-time bias detection mechanisms, and a more extensive alignment of hybrid Al-human service frameworks. In particular, Al chatbots could benefit from deep contextual learning capabilities, allowing them to recognize when serious customer engagement is occurring. Additionally, further research is needed on low-cost Al deployment methods to make advanced Al solutions accessible to smaller telecom providers, thereby promoting wider industry acceptance without requiring significant infrastructure investments.

As AI becomes more integrated into the fabric of telecommunications, businesses must strike the right balance between automation and ethical accountability, ensuring that their AI-powered solutions remain explainable, unbiased, and customer-centric. The results of this study suggest that

although Al-driven automation improves efficiency and customer engagement, it will require continual enhancements in bias mitigation, explainability, and adaptive learning as next steps toward sustainable adoption. By addressing these issues, we aim to help Al further drive innovation in telecommunications and offer better-serving custom solutions that are fairer for all as the future becomes more digital.

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