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Customer Retention Model Using Machine Learning for Improved User-Centric Quality of Experience through Personalised Quality of Service

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Abstract

Customer retention remains a critical challenge in subscription-based industries, particularly in telecommunications, where customer dissatisfaction and poorly targeted retention strategies undermine long-term value creation. Existing churn prediction models typically rely on static behavioural data and overlook the emotional and contextual dimensions of customer experience. This study addresses these limitations by developing a Personalised Quality of Service (PQoS) framework, integrating advanced natural language processing (NLP) models-RoBERTa and BERT- with machine learning algorithms to analyse customer feedback and predict churn more effectively. The study utilises a novel approach that combines sentiment analysis, contextual embeddings, and predictive modelling to enhance churn prediction accuracy. The study analysed a large-scale customer dataset (n = 98,205), applying transformer-based embeddings to textual feedback, and evaluating five machine learning models. Stratified cross-validation and SMOTE were used to address class imbalance, and Expected Utility Theory (EUT) was then integrated to rank and personalise retention strategies based on predicted customer behaviour and sentiment. By incorporating Expected Utility Theory (EUT), the framework evaluates and prioritises retention strategies based on their expected impact on customer satisfaction and loyalty. The findings demonstrate that the Neural Network model with RoBERTa outperforms traditional methods, achieving 96% accuracy, 97% F1-score, 88% precision, and 95% recall. This research contributes to customer relationship management (CRM) Framework by re-conceptualising churn prediction as a sentiment-driven process and introducing EUT-based decision-making in customer retention. The findings offer businesses a scalable, data-driven strategy for enhancing customer engagement, reducing churn, and sustaining long-term value creation.

Keywords: Churn Management, Expected Utility Theory, Personalised Recommendation, RoBERTta, BERT, Machine Learning, Decision Support.

1. Introduction

Customer retention is a strategic priority for commercial organisations, particularly in industries where competition is fierce and acquisition costs are high. The subscription-based telecommunications sector exemplifies this challenge, as businesses must not only attract customers but also implement effective retention strategies to mitigate churn and sustain profitability (Ascarza et al., 2018). For example, in this context, a modest monthly churn rate of 2% can result in losing approximately 24,000 customers per year for a 100,000-subscriber service, translating to millions in lost annual revenue (Daria, 2025). Recent reports indicate that 45% of churn in mobile telecom services is due to poor network quality, and approximately 80% of all churn is voluntary, driven by dissatisfaction with the service (Sabrina, 2022). These figures underscore the urgency for businesses to adopt more sophisticated methods for retaining their customer base.

Despite advancements in customer relationship management (CRM), many traditional retention approaches rely on generalised models that fail to capture the dynamic nature of customer behaviour (Ibitoye et al., 2022). These models cannot often interpret the underlying sentiment in customer interactions, limiting their capacity to generate meaningful insights that could enhance engagement, improve service quality, and strengthen brand loyalty. For example, customer complaints about network performance often go unaddressed in traditional churn models, despite their direct impact on satisfaction and loyalty. Therefore, a more refined approach is needed to incorporate insights from customer feedback, moving beyond mere transactional data to a richer understanding of customer sentiment. Advancements in machine learning (ML) and natural language processing (NLP) offer significant opportunities to overcome these limitations. The ability to analyse vast amounts of structured and unstructured customer data, including feedback, service usage, and complaint logs, enables businesses to develop more personalised retention strategies. However, many existing churn prediction models remain constrained by a product-centric approach, which often results in misclassification errors and inadequate service personalisation (Ibitoye & Onifade, 2020).

Recent studies have incorporated sentiment analysis into churn models (Ibitoye & Onifade, 2022; Abdul-Rahman et al., 2024), but the application of advanced NLP techniques to understand customer feedback remains limited. These models also tend to rely on static data, rather than real-time customer experience metrics, leaving a significant gap in the industry's ability to proactively prevent churn. This limitation underscores the need for a more refined approach that integrates contextual customer insights with predictive analytics, ensuring that organisations can respond to churn risks with tailored interventions rather than one-size-fits-all retention measures. Telecommunication companies generate vast datasets from customer interactions, network usage, and service preferences. Leveraging big data analytics allows for deeper insights into customer preferences and dissatisfaction drivers (Hong et al., 2008). Yet, while structured data such as billing records and service usage patterns provide valuable signals, unstructured textual data, such as complaints and feedback, offers rich contextual information that traditional models often overlook (Nasr et al., 2018). Understanding customer sentiment through NLP techniques enables businesses to anticipate dissatisfaction, respond proactively, and refine customer experiences in ways that increase loyalty and engagement (Cambra-Fierro et al., 2021).

Customer feedback serves as an essential touchpoint for evaluating customer satisfaction, yet its full potential is rarely realised in predictive churn models (Lantos, 2015). Sentiment analysis and contextual embeddings extracted from customer feedback can illuminate underlying dissatisfaction patterns that quantitative metrics alone fail to capture. In highly competitive industries such as telecommunications, where consumers can switch providers with minimal friction, detecting these early warning signs is essential to pre-empt churn (Stahl et al., 2012). Despite this, most churn prediction models prioritise past transactional data over sentiment-driven insights, limiting their effectiveness in proactive customer engagement.

Machine learning algorithms have been widely adopted to enhance customer retention strategies by identifying churn patterns and predicting customer attrition risks (Bhujbal & Bavdane, 2021; Singh & Agrawal, 2019). These approaches enable companies to move beyond reactive retention tactics towards more predictive, data-driven strategies that anticipate customer concerns before they escalate. However, traditional ML models (Ahmad et al., 2019) often require extensive manual feature engineering and cannot process complex textual data effectively, neglecting user-centric QoE factors. Recent advances in natural language processing (NLP), particularly transformer-based models such as Bidirectional Encoder Representations from Transformers (BERT) and its optimised variant RoBERTa, offer powerful tools for extracting contextual meaning and sentiment from textual data. These models capture the subtleties in customer feedback and provide dense embeddings that reflect user intent and emotional tone, enabling more personalised and context-aware decision-making (Devlin et al., 2019; Bashir et al., 2024).

Despite progress in churn prediction, many current models fall short in translating predictions into personalised, actionable retention strategies. To address this gap, we propose a user-centric retention framework that links QoE measurements to adaptive Quality of Service (QoS) adjustments. Unlike traditional models that merely classify churn risk (Chihani et al., 2014), our approach combines structured service data with transformer-based embeddings derived from customer feedback, allowing for dynamic churn prediction and behaviourally informed segmentation. RoBERTa and BERT are used to generate sentiment scores and contextual embeddings from customer text, which are then combined with service metrics and behavioural features. These inputs feed into machine learning models, such as CatBoost, LightGBM, and Neural Networks, to detect churn patterns. To move beyond prediction into actionable decision-making, we apply EUT to evaluate and prioritise retention strategies. EUT enables the model to rank interventions based on both the predicted likelihood of customer acceptance and the perceived value of each action.

This study is guided by two central research questions:

i. How effective are transformer models such as BERT and RoBERTa in predicting churn and extracting insights from customer feedback in the subscription-based telecommunications sector?
ii. How can personalised, technology-enabled retention strategies enhance stakeholder value and organisational competitiveness?

The first question is empirical, evaluating model performance on customer feedback and structured service data. The second is strategic, exploring how personalised interventions can enhance value delivery and competitive positioning. By integrating sentiment analysis, behavioural segmentation, and utility-based prioritisation, this study bridges the gap between predictive analytics and decision support. It contributes both technically and practically by demonstrating how deep contextual embeddings and EUT-driven recommendations enable personalised, scalable retention strategies. These interventions are particularly relevant in telecommunications, where pricing, service quality, and support interactions significantly influence loyalty (Ibitoye & Onifade, 2020). The result is a comprehensive framework that supports dynamic, customer-centric decisions, ultimately improving satisfaction, reducing churn, and enhancing long-term competitiveness.

The remainder of this paper is structured as follows. Section 2 reviews the theoretical and empirical literature on customer retention, CRM strategies, and machine learning applications in churn prediction. Section 3 outlines the methodological framework, detailing the NLP techniques and predictive models used in the study. Section 4 presents the results of the empirical analysis, comparing the performance of RoBERTa models with traditional churn prediction methods. Section 5 discusses key findings and their implications for businesses, followed by a summary of contributions and recommendations for future research in Section 6.

2. Literature Review

2.1 CRM dimensions and cross-functional processes

Customer relationship management (CRM) is a strategic approach that entails the development of appropriate relationships with key customers and customer segments with the overarching goal of co-creating stakeholder value (Payne & Frow, 2005). CRM comprises four sequential and mutually reinforcing dimensions: customer identification, customer attraction, customer retention, and customer development (Guerola-Navarro et al, 2021). Customer identification focuses on actions, including target customer analysis and customer segmentation, aimed at finding individuals of interest to the company as potential customers. Customer attraction entails steps taken by the company to attract customer interest to their goods and/or services, through, say, marketing action planning. Building on this attraction, customer retention comprises strategic activities aimed at building customer loyalty through long-term, trustworthy business relationships that incentivise and reward repeated purchases from the company. Customer development includes activities, such as cross-selling and up-selling, that are aimed at expanding existing relationships with customers along new lines of business.

The CRM strategic process is data-driven, and it requires an integration of five cross-functional processes: strategy development process, value creation process, multi-channel integration process, information management process, and performance evaluation process (Singh et al., 2023). The strategy development process is broken into business strategy and customer strategy, the former focusing on the company's vision in light of the industry and competitive landscape; the latter focusing on understanding the existing customer base and identifying an appropriate strategy for segmentation. The value creation process entails the transformation of outputs from strategy development into programmes and products that deliver value to, and extract value from, customers. The successful management of this exchange often relies on an interdependent process of co-creation through which both the supplier and customer contribute unique and complementary resources (Sheth, 2020). The value co-creation process harnesses social capital between customers and companies to strengthen the knowledge sharing and information exchange necessary for co-production (Mishra & Maheshwari, 2024). The interactions among CRM dimensions and cross-functional processes are summarised in Figure 1.

Figure 1 to go here

The third functional process, multi-channel integrations, focuses on the selection and combination of appropriate channels through which customers can be reached for optimal, positive experiences of products and services (Payne & Frow, 2005). The multi-channel approach recognises and responds to the willingness of customers to explore and exploit more convenient options, online and offline, through which they can access products and services (Trenz, 2015). Multi-channel shopping captures the behaviour of a customer across the entire journey from search to purchase. It comprises phenomena such as channel lock-in, whereby the choice of a channel in an earlier phase of the journey influences the choice of that channel at the latter phase; and the augmentation effect, whereby the customer aggregates information from multiple channels before settling on one for purchase (Hu & Tracogna, 2020). More recently, scholars have noted a transition from multi-channel retailing to an omnichannel model in which the integration across multiple channels is the lynchpin of the service interface that creates a seamless experience for customers (Thaicon et al, 2022). The fourth process, information management, underlines the increasingly prominent role of data and information technology in CRM. Today, Large Language Models are being employed to analyse data and trends of customer behaviour to generate insights to create improved, including personalised, experiences for customers (Gil-Gomez et al, 2020). Finally, the performance evaluation process entails the evaluation and monitoring of shareholder results, which, in turn, is a function of employee value, customer value and cost reduction (Payne & Frow, 2005). Taken together, the five cross-functional processes are critical for effective customer relationship management, for which arguably the most important outcome is customer retention. The next section discusses how digital technologies play a key role in achieving this outcome.

2.2 Technological solutions for customer retention

In the digital age, customers have myriad options at their fingertips, making it easier for them to switch brands if their expectations aren't met. This dynamic environment necessitates the integration of technological solutions into customer retention strategies. Technology enables businesses to gather and analyse vast amounts of customer data, personalise interactions, and automate processes to deliver seamless experiences (Zaki, 2019). By harnessing the power of technology, companies can anticipate customer needs, resolve issues proactively, and cultivate lasting relationships. Similarly, technology-enabled customer retention strategies extend beyond cost-saving measures. By leveraging predictive models and personalised engagement, firms can enhance customer loyalty, which strengthens their competitive position and stakeholder value (Islam et al, 2021). For instance, companies employing AI-driven customer segmentation have reported a 20% increase in CLV (Nafez & Osama, 2024), underscoring the potential of advanced analytics as a strategic asset. Over the years, CRM systems have been the backbone of customer retention strategies. These platforms allow businesses to manage and analyse customer interactions throughout the customer lifecycle (Farhan et al., 2018).

With the introduction of machine learning and advanced techniques like transformer models, CRM systems have evolved to provide even more sophisticated insights and predictive capabilities. This evolution is significantly contributing to the improved user-centric quality of experience through the personalised quality of service (Anshari et al., 2019). Businesses are frequently concerned about customers' drop in customer engagement or the loss of customers. Different research activities have applied various customer exit-predictive models to optimise customer retention and business profits. Specifically, Machine learning algorithms (Gordini & Veglio, 2017; Gattermann-Itschert & Thonemann, 2022) analyse vast amounts of customer data, identifying patterns and trends that would be impossible for humans to detect manually. The attractive features of machine learning models include their ability to handle large volumes of data and their flexibility in adapting to different types of churn patterns. These models range from simple (e.g., logistic regression) to complex (e.g., GBMs) (Singh et al., 2024; Manzoor et al., 2024; De-Lima et al.,2022). They are generally less computationally intensive compared to deep learning models and can be scaled using techniques like ensemble learning. These models typically require extensive feature engineering, and domain knowledge is crucial to transform raw data into features that the model can understand.

The machine learning models are generally easier to train and are suitable for scenarios with well-defined and structured datasets where feature engineering can capture the relevant information (De Caigny et al., 2022). By integrating machine learning into CRM systems, businesses can predict customer behaviour more accurately, segment their audience more effectively, and tailor their marketing and support efforts to individual needs. On the other hand, transformer-based models offer improved performance in capturing complex dependencies within the data and have shown promising results in churn prediction tasks. The transformers, introduced by Vaswani et al. (2017), use self-attention mechanisms to process sequences of data efficiently. They have been predominantly successful in NLP tasks. Transformers can handle raw sequential data more effectively due to their self-attention mechanisms. They can automatically capture dependencies and interactions within the data, reducing the need for manual feature engineering (Kim et al., 2014). Although transformers are more computationally intensive due to their deep architecture and attention mechanisms, they potentially outperform traditional machine learning models, particularly in handling complex, high-dimensional data with temporal or sequential characteristics. Their ability to capture intricate patterns and dependencies can lead to superior performance in certain scenarios.

The integration of machine learning and transformer models into CRM systems enhances personalisation by providing a deeper understanding of customer sentiments and behaviours, improves predictive capabilities for anticipating customer needs and risks, automates routine tasks to increase efficiency, and contributes to a more user-centric quality of experience through tailored interactions, proactive support, and enhanced engagement. These advanced technologies enable businesses to offer a more personalised, efficient, and proactive quality of service, driving long-term customer loyalty. However, modelling customer dynamics is an important step in understanding customer retention, and designing marketing strategies based on this understanding using technology (Hoyer et al., 2020). The importance of technological solutions in customer retention cannot be overstated.

These tools serve as the backbone of modern businesses striving to retain their customer base. Customer Relationship Management (CRM) systems act as the nerve centre, housing invaluable customer data and insights necessary for personalised interactions. Predictive analytics empowers businesses to anticipate customer behaviour, enabling proactive retention strategies (Anshari et al.,2019). Personalisation engines elevate customer experiences by delivering tailored content and recommendations, fostering deeper connections (Behera et al., 2020). Omnichannel engagement platforms ensure consistency across touchpoints, enhancing brand perception and customer satisfaction (Rodríguez-Torrico, 2020). Lastly, customer feedback and sentiment analysis provide invaluable insights, guiding businesses in addressing concerns promptly and demonstrating their commitment to customer-centricity. Together, these technological solutions form a robust framework for effective customer retention strategies, essential for long-term success in today's competitive landscape.

2.3 Big data and competitiveness in the telecommunication sector

In the fiercely competitive landscape of the telecommunications sector, customer retention stands as a critical battleground for companies striving to maintain market share and profitability. Big data has emerged as a transformative force, empowering telecom companies to not only understand customer behaviour but also to craft personalised retention strategies that resonate with individual preferences and needs (Haudi, 2024). At the heart of this transformation lies the vast troves of data generated by telecommunications networks and customer interactions. From call records and text messages to app usage and browsing history, telecom companies possess a wealth of information that, when analysed effectively, can unlock actionable insights into customer churn patterns, preferences, and sentiment. By harnessing the power of big data analytics, telecom companies can identify early warning signs of customer dissatisfaction and proactively intervene to prevent churn (Kastouni & Lahcen, 2022).

Research by Ibitoye et al. (2022) addresses personalised customer relationships by introducing the Customer's Influence Degree (I) alongside the Recency, Frequency, and Monetary (RFM) metrics to improve churn prediction. This new factor reduces misclassification rates by considering socio-transactional affinities and enhancing targeted retention strategies. Predictive modelling techniques enable the anticipation of customer needs and the customisation of offers and promotions tailored to individual preferences, thereby increasing the likelihood of retention (Rosário & Dias, 2023). Moreover, big data facilitates the creation of holistic customer profiles, allowing telecom companies to gain a 360-degree view of each customer's journey across various touchpoints.

This comprehensive understanding enables more targeted and relevant marketing campaigns, service offerings, and customer service interactions, fostering stronger relationships and loyalty (Chen & Meyer-Waarden, 2021). In addition to enhancing customer retention efforts, big data also catalyses competitiveness within the telecom sector. Companies that leverage data-driven insights gain a strategic advantage by being able to respond swiftly to market trends, anticipate competitor moves, and innovate more effectively (Hossain et al., 20240. Moreover, big data analytics enables telecom companies to optimise network performance and resource allocation, leading to improved service quality and customer satisfaction (Akter et al., 2016). This, in turn, enhances brand reputation and differentiation in a crowded marketplace.

2.4 Machine learning approaches for customer retention

In today's business environment, retaining customers and enhancing their experience through personalised service quality are essential pillars of competitive organisational strategy. Customer retention, the practice of keeping existing customers, plays a critical role in business (Mathur & Kumar, 2013). This is evident when comparing the costs associated with acquiring new customers to those of retaining the existing customer base. Several studies have shown that acquiring a new customer is more expensive than retaining existing ones (Colgate & Danaher, 2000). Driven by profit considerations, Jiang et al. (2023) developed a hybrid predictive model, which integrated feature selection from a customised multi-objective atomic orbital search in combination with an extreme learning machine to predict customer churn, taking into account both potential returns and associated costs. Other scholars have provided contextual illuminations of the various factors that influence customer retention. Lai & Zeng, (2014) explored consumer churn behaviour within digital libraries and demonstrated that subsistence analysis is a valuable tool for comprehending customer churn dynamics.

While (Zhou et al. (2023) identified early warnings from customer characteristics, using four distinct ensembles ML (Adaboost, BPNN, RF, and RF-Adaboost) models and four classic ML (Decision Tree, Naive Bayes, K-Nearest Neighbor (KNN), Support Vector Machine) models for churn to deliver tailored marketing strategies and personalised services; from a real-world water purifier rental company, (Suh, 2023) analysed and harnessed the power of a machine learning algorithm on customer behaviour data to develop and validate a churn prediction model. Their objective was to identify potential churn among subscribers, understand the underlying causes for churn, and consequently, pinpoint the specific target audience with idea retention strategies. By analysing customer data, including feedback and behaviour, businesses can actively understand preferences and needs, enabling them to predict and address potential customer attrition effectively.

2.5 Toward personalised and prescriptive retention strategies

Despite the predictive advances, recent research on churn has largely focused on structured data sources such as usage logs, billing records, and service logs (Verbraken et al., 2014; Idris et al., 2021). While these models are effective in capturing historical churn patterns, they often miss early sentiment signals in unstructured feedback (Jayaswal et al., 2016). This is critical in subscription-based industries, where customer dissatisfaction is frequently voiced before actual churn occurs. Although sentiment analysis is increasingly adopted (Ranjan et al., 2018), it is often implemented using rule-based or binary classifications, overlooking context and depth. Recent NLP advancements, such as BERT (Devlin et al., 2019) and its variants, offer deeper contextual understanding. Yet, few models integrate these contextual embeddings with actionable business frameworks. Kilimci (2022), for instance, employed BERT among other deep learning models to process customer feedback but fell short of connecting predictions to prescriptive recommendations. Most existing frameworks stop at prediction and fail to answer: "What should we do next, and for whom?" As summarised in Table 1, sample models underutilise unstructured data and rarely incorporate strategy prioritisation based on customer-specific contexts

Table 1 to go here

As shown in Table 1, while progress has been made in churn prediction, fewer studies optimise retention interventions from a profit perspective. East et al. (2006) highlight the importance of linking retention incentives to revenue outcomes. For example, Schaeffer & Sanchez (2020) used sequence-based modelling of monthly client transactions to predict churn in B2B services, while Abou el Kassem et al. (2020) applied machine learning to survey-based sentiment to derive polarity scores for churn prediction. Additional research has explored loyalty modelling using clustering, deviation analysis, and association rule mining (Ng & Liu, 2000; Ullah et al., 2019), while others have implemented two-stage churn strategies combining prediction with proactive targeting (Milošević et al., 2017). Yang et al. (2022) examined the influence of brand equity on repurchase intent, and Ibitoye & Olufade (2023) used RoBERTa insights to support group-level decision-making.

Advanced analytics have also been applied in high-volume domains. Pepakayala & Kannan (2023) integrated an optimised deep learning classifier into Spark for telecom churn prediction. Shobana et al. (2023) used SVM and hybrid recommendation methods to manage e-commerce attrition. Lye & Teh (2021) combined Word2Vec and Random Forest to interpret Net Promoter Score (NPS) feedback, demonstrating how hybrid representations can enhance sentiment classification and churn forecasting. These contributions underline a shift toward more prescriptive, customer-aware retention strategies. This study builds upon these foundations by introducing a framework that integrates contextual NLP, segmentation, and decision theory to tailor interventions that reflect the needs of distinct customer segments. The following section details the methodology adopted to achieve this.

3. Research methodology

3.1 Data overview

This study integrates advanced machine learning techniques with behavioural science to develop a comprehensive personalised customer retention Quality of Service to Customers. In line with the research goal, here, customer interaction data, including customer feedback, behaviour, and other relevant information, were cleaned, structured, and stored. Overall, a total of 98205 anonymised Nigerian customers' telecommunications data was used in his research, which also contained 24 distinct features as presented in Table 2:

Table 2 to go here

The dataset comprises a mix of categorical, numerical, and unstructured textual features. CatBoost and LightGBM were selected for their ability to handle high-cardinality categorical variables with minimal preprocessing, while Neural Networks and XGBoost were chosen for their strength in modelling complex nonlinear relationships, especially when numeric features are normalised. Additionally, the inclusion of contextual embeddings and sentiment scores from RoBERTa/BERT required models capable of processing dense vector inputs. The data was randomly partitioned into 80% training and 20% testing sets. To ensure robust evaluation and prevent overfitting, stratified 5-fold cross-validation (repeated three times) was employed. Given the class imbalance (approximately 73% churn vs. 27% retained), Synthetic Minority Oversampling Technique (SMOTE) was applied during training to balance the classes. Model selection was informed by the heterogeneity of data types and the dual goals of predictive accuracy and interpretability. The model performance was assessed using averaged cross-validation scores and validated on the holdout test set.

3.2 Model design and workflow

The Personalised Quality of Service (PQoS) framework integrates advanced NLP models, RoBERTa and BERT, with machine learning algorithms, leveraging Expected Utility Theory (Mongin, 1998). Expected utility theory (EUT) is used to evaluate the effectiveness of retention strategies for each customer. Unlike traditional churn models, this approach prioritises actions with the highest potential to reduce churn based on individual behaviour and predicted responses, rather than a binary classification. By linking prediction to actionable strategies, the framework functions as a strategic decision-support system, optimising retention efforts and enhancing decision-making for customer retention. The empirical model includes the following key components:

i. D be the customer feedback dataset with N samples and M features.
ii. $BERT(D)$ and $RoBERTa(D)$ represent the embeddings obtained from BERT and RoBERTa models, respectively,

iii. X be the feature matrix obtained by combining $BERT\ (D)$, $RoBERTa(D)$, and other relevant features like customer demographics.

iv. S be the sentiment scores incorporated into X

v. C be the hierarchical clustering applied to BERT(D) and RoBERTa(D), resulting in customer segments.

vi. Y be the target variable representing customer behaviour, where $Y = 1$ indicates a customer has churned and $Y = 0$ otherwise.

vii. $Contexts$ be the set of five distinct contexts: Customer Support and Interaction, Plan and Billing, Service Quality and Network Performance, Marketing and Promotion, and Competitors Comparison and Preference

The predictive model for churn prediction can be formulated as follows:

$$Y = f(X, S, C) \qquad (1)$$

Where:

f is the predictive function incorporating machine learning algorithms, combining the embeddings, sentiment scores, Other features and clustered customer segments.

X is a matrix obtained by concatenating BERT(D), RoBERTa(D), and other relevant features

S is the sentiment scores.

C is the result of hierarchical clustering applied to embeddings.

The machine learning algorithms ML_{alg} include Random Forests, XGBoost, CatBoost, LightGBM, and Neural Networks. The final predictive function is an ensemble of these algorithms:

$$f(X, S, C) = \frac{1}{N_{alg}} \sum\nolimits_{alg} ML_{alg}\,(X, S, C) \qquad (2)$$

Before features like sentiment scores were incorporated into the models, they were derived using a systematic process to ensure their relevance and reliability as presented in Figure 2.

Figure 2 to go here

Sentiment scores were extracted from customer feedback, including text reviews, complaints, and survey responses. The raw textual data was preprocessed by removing noise, such as stop words and special characters. Using pre-trained transformer models like BERT or RoBERTa via the Huggingface Transformers library, the feedback was converted into contextual embeddings, which were then passed through a fine-tuned sentiment analysis model. This model assigned sentiment categories (e.g., Positive, Neutral, Negative) and corresponding numerical scores (e.g., +1 for positive, 0 for neutral, and -1 for negative). For customers with multiple feedback entries, an aggregated sentiment score, such as a weighted average, was computed. Then, hierarchical clustering was applied on BERT/RoBERTa embeddings of customer feedback to segment customers with similar concerns, preferences, or feedback patterns before each newly generated segment was profiled to analyse the characteristics and behaviour of customers within each cluster using machine learning algorithms. The extracted features, including BERT/RoBERTa embeddings and sentiment scores, were combined with other features across five contexts: Customer Support and Interaction, Plan and Billing, Service Quality and Network Performance, Marketing and Promotion, and Competitor Comparison and Preference, among other feature set to build a predictive model for churn prediction.

3.4 Motivations for model design

Based on the nature of the task, five distinct machine learning algorithms of Random Forests, XGBoost, CatBoost, LightGBM and Neural Networks were adopted here. The choice of machine learning algorithms and transformer-based models is rooted in their theoretical strengths and empirical effectiveness for customer retention. This integrated approach allows for accurate churn prediction, actionable insights, and improved organisational strategies. First, BERT and RoBERTa pre-trained models were utilised independently to convert customer feedback and textual interactions into high-quality embeddings. These embeddings capture the semantic meaning and context of the text and are later combined with other relevant features (e.g., customer ComplaintCategory, TotalCharges) on the customer feedback dataset to create a comprehensive set of features for analysis. Specifically, BERT is Ideal for extracting insights from customer feedback and helping identify dissatisfaction or sentiment trends linked to churn, while RoBERTa's robust generalisation ensures high-quality embeddings for more precise segmentation and predictive analysis. Machine learning models excel at handling structured data, such as customer demographics, subscription details, and usage patterns. They also provide interpretability, scalability, and robust predictions, which are crucial for decision-making. Together, these tools support the dual goals of the study: developing accurate churn models and demonstrating the strategic impact of advanced analytics on customer retention and stakeholder value. In Table 3, the justifications for using each of the ML algorithms are presented

Table 3 to go here

To complement the predictive capabilities of the selected models outlined in Table 3, this study integrates EUT as a decision-theoretic layer for personalised intervention. EUT provides a principled framework for translating churn predictions into ranked, value-based retention strategies**,** thereby bridging the gap between prediction and actionable decision-making.

Rooted in classical decision theory, EUT assumes that individuals make rational choices by selecting actions that yield the highest expected benefit. Applied to customer retention, this framework enables the system to evaluate multiple possible interventions per customer and select the one with the greatest potential impact. Three key constructs drive this process:

1. **Utility (U):** The estimated benefit of an intervention (e.g., discount, plan upgrade) to a specific customer, based on historical behaviour, preferences, and service usage.
2. **Probability (P):** The likelihood that the customer will respond positively, derived from predictive models using sentiment analysis, behavioural data, and contextual embeddings.
3. **Expected Utility (EU):** Calculated as:

$$EU = P \times U$$

This score enables prioritisation of interventions based on both the likelihood of success and the expected value delivered. By incorporating EUT into the modelling pipeline, alongside BERT/RoBERTa for feature extraction and machine learning for prediction, this study moves beyond traditional churn flagging. It delivers a prescriptive, customer-centric decision-support system that optimises both user experience and organisational outcomes by aligning service actions with predicted customer utility. The trained predictive model was used to estimate key behavioural dimensions, including churn probability, individual preferences, and the likelihood of response to specific retention interventions. These predictions form the basis for personalised recommendations, as detailed in the following section.

4. Analysis and findings

4.1 Analytical approach

Effective churn prediction models provide valuable insights into customer attrition risks, but their true utility lies in translating predictions into targeted retention strategies. Businesses need more than just churn probability scores; they require actionable frameworks that facilitate personalised interventions to sustain customer engagement. By integrating machine learning predictions with decision-support mechanisms, this study presents a structured retention approach that enhances customer segmentation and enables dynamic intervention strategies.

The Churn Risk Level Analysis (CRLA) model refines traditional churn prediction by incorporating three critical dimensions: churn probability (CP), engagement score (ES), and sentiment score (SC). This multidimensional approach ensures that customer segmentation goes beyond basic churn likelihood, offering a richer understanding of customer behaviour. Customers are grouped into three key categories, each requiring distinct retention measures:

i. **Low-risk customers:** Loyalty-building initiatives such as reward programmes and exclusive offers help sustain engagement.
ii. **Medium-risk customers:** Service enhancements, personalised promotions, and proactive support address emerging dissatisfaction signals.
iii. **High-risk customers:** Immediate, high-priority interventions, including direct customer outreach, personalised service plans, and targeted incentives, are necessary to prevent churn.

To quantify churn risk and prioritise interventions, the Churn Risk Level Analysis (CRLA) is formulated as:

$$CRLA = \alpha 1.\mathrm{CP} + \alpha 2.\mathrm{ES} + \alpha 3.\mathrm{SC} \tag{3}$$

Where $CRLA$ is the Churn's Risk Level Analysis, CP is Churn Probability, ES is the Engagement Score, SC is the Sentiment Score and $\alpha 1$, $\alpha 2$, $\alpha 3$ are weights determined by the business priorities.

This equation enables businesses to assign relative importance to each factor, ensuring that customer retention efforts align with actual service needs. For instance, a customer with high churn probability but positive sentiment and strong engagement may not require urgent intervention, whereas a customer with moderate churn probability but consistently negative sentiment could indicate dissatisfaction requiring proactive outreach.

To enhance decision-making, this study applies Expected Utility Theory (EUT) to retention strategies, allowing businesses to quantify the effectiveness of different intervention measures. Instead of reactive responses, companies can anticipate customer needs, ensuring that retention actions align with individual preferences and service expectations. A dissatisfied customer experiencing frequent network disruptions, for example, may receive an upgrade offer, while a price-sensitive customer might benefit more from targeted discount incentives.

This personalised, data-driven approach moves beyond static churn classification, integrating natural language processing (NLP) techniques with machine learning algorithms to analyse customer feedback and behavioural patterns. By leveraging models such as RoBERTa and BERT, this research extracts deeper insights from sentiment analysis and contextual embeddings, allowing for precision-driven retention efforts.

The findings that follow demonstrate how this approach improves churn prediction accuracy, enhances customer segmentation, and optimises retention strategies, providing a scalable and adaptable framework for businesses in the telecommunications sector.

4.2 Findings

During experiments and evaluations, the performance of the predictive models was assessed using appropriate evaluation metrics, such as accuracy, precision, recall, and F1-score. To assess the performance and effectiveness of the new Customer Retention Model:

$$Performance = Eval(f, D, Y) \tag{4}$$

These equations capture the essence of the Customer Retention Model, incorporating embeddings, sentiment analysis, hierarchical clustering, and machine learning algorithms to predict customer behaviour and provide personalised recommendations for improved user-centric quality of experience. First, by using the Agglomerative clustering model set to 5, the following contextual embedding was obtained for BERT in Figure 3

Figure 3 to go here

and RoBERTa in Figure 4, respectively, for all the features.

Figure 4 to go here

With sentiment analysis playing a major role in the build-up for the churn prediction model, in Figure 5, the visualised sentiments expressed in the customer feedback dataset is presented.

Figure 5 to go here

Then, the contextual distribution preference for BERT and RoBERTa was displayed in Figures 6 and 7, respectively.

Figure 6 to go here

Figure 7 to go here

Since churn prediction is a critical task for businesses to identify customers at risk of discontinuing their services. In this experiment, we applied various machine learning models for churn prediction on the preprocessed customer feedback dataset. The goal was to evaluate model performance and identify the most effective model for this specific task. Here, the dataset was randomly split into training (80%) and testing (20%) sets before we experimented with the following models: Random Forest, XGBoost, Neural Network, LightGBM and CatBoost, respectively. As illustrated in Figures 8 and 9, the models were evaluated using the following metrics:

i. **Accuracy:** The overall correctness of predictions.

ii. **Precision:** The accuracy of positive predictions. Here in the context of churn prediction, precision is relevant when the cost of making a false positive prediction (predicting a customer will churn when they won't) is high. This could result in unnecessary retention efforts or incentives being offered to customers who were not actually at risk of churning.

iii. **Recall:** The ability to capture all actual positives. Here In the context of churn prediction, recall is relevant when the cost of making a false negative prediction (missing an actual churning customer) is high. Missing a customer who is about to churn could result in revenue loss.

iv. **F1-Score:** The harmonic mean of precision and recall

Figure 8 to go here

Figure 9 to go here

Overall, the Neural Network model via RoBERTa outperformed other models, striking a balance between precision and recall. This suggested that the NN model was effective in identifying potential churners while minimising false positives. The Neural Network model was trained using TensorFlow and Keras. A multi-layer perceptron architecture was employed with ReLU activation functions for the hidden layers and a softmax activation function for the output. Dropout layers with a rate of 0.3 were included after each hidden layer to prevent overfitting, and batch normalisation was applied to standardise the inputs to each layer, accelerating the training process and improving stability. The model demonstrated superior performance across multiple metrics: Highest Accuracy (0.96), Highest F1-Score (0.97), High Precision (0.88) and Recall (0.95) when compared with other models in identifying potential churners while minimising false positives. From this, twenty (20) randomly selected customer feedbacks were experimented with the goal of personalised recommendations. Table 4 shows the obtained results from this exercise.

Table 4 to go here

From the sampled customers above, the heatmap in Figure 10 visualises the cosine similarity between the 20 customer feedbacks. Each cell in the heatmap represented the similarity score between two customers based on their corresponding feedback. The diagonal elements (top-left to bottom-right) represent the similarity of a customer's feedback with itself, and they are all 1.0

(maximum similarity). The colour intensity indicated the degree of similarity, with darker colours representing higher similarity, including churn status, churn category, aspect, and recommendation. This information is important in understanding patterns in feedback and making personalised recommendations for customers in different churn categories and aspects.

Figure 10 to go here

By visually representing the similarity between customer feedback, heatmap analysis provides a comprehensive understanding of customer sentiments and preferences. It serves as a powerful tool for telecom companies to identify clusters of customers with similar feedback, enabling targeted strategies to address common themes or sentiments. It also helps highlight outliers, providing valuable insights into diverse perspectives within the customer base. Moreover, heatmap analysis aids in gaining insights into customer segmentation, allowing companies to tailor their marketing campaigns and service strategies accordingly. By targeting specific customer segments with personalised offerings, telecom companies can enhance customer engagement and loyalty. Furthermore, heatmap analysis serves as a validation tool for analytical techniques, instilling confidence in the accuracy and effectiveness of the analysis. This validation reinforces the value of data-driven decision-making in the telecommunications sector.

5. Discussion

5.1 Empirical contributions

The findings of this study demonstrates the value of integrating machine learning (ML) and natural language processing (NLP) for proactive customer retention, particularly in the telecommunications sector. Traditional churn models relying solely on structured transactional data often miss critical sentiment and behavioural signals. By incorporating sentiment-aware analysis, this research shows that predictive models can more accurately identify at-risk customers and support tailored interventions. A key contribution is the introduction of CRLA, which combines churn probability, engagement metrics, and sentiment scores. This allows for refined segmentation, revealing that high churn probability doesn’t always align with negative sentiment, enabling more effective, personalised retention strategies.

RoBERTa's sentiment analysis outperformed BERT, achieving 96% accuracy and a 97% F1-score, empirically validating the effectiveness of deep contextual models over rule-based approaches. In addition, this study highlights the advantage of real-time churn detection, enabling businesses to respond dynamically before disengagement escalates. The personalised retention model presented is scalable beyond telecoms, offering practical applications in subscription-based sectors like streaming, finance, and SaaS, where understanding sentiment and engagement is crucial for reducing churn.

5.2 Theoretical contributions

This study advances the theoretical understanding of customer retention by expanding churn prediction beyond transactional data, introducing sentiment-aware models that integrate contextual feedback. While traditional models often assume churn is behaviourally driven, this research shows that customer sentiment, extracted via RoBERTa/BERT embeddings, plays a central role, aligning with emerging CRM perspectives that emphasise emotional engagement as a key loyalty factor. A second theoretical contribution is the re-conceptualisation of churn as a dynamic process. Unlike static models that classify churn risk at a single point, this study highlights the need for real-time monitoring of sentiment and engagement signals, reinforcing the necessity of adaptive, context-responsive retention strategies.

Third, the integration of EUT into predictive modelling introduces a decision-theoretic lens to churn management. EUT offers a structured method for prioritising interventions based on both their utility to the customer and the probability of a positive response, supporting efficient resource allocation and individualised action strategies. Finally, this research extends the CRM and AI literature by demonstrating how NLP and machine learning can operationalise customer feedback into actionable decision support. It encourages future work on hybrid churn models that combine real-time service metrics with adaptive personalisation to stay aligned with evolving customer expectations

5.3 Managerial implications

The findings also highlight key managerial implications. Businesses can benefit from automating customer engagement strategies based on real-time churn prediction insights. This would allow them to implement dynamic intervention models, where customer interactions are continuously analysed to determine the most effective engagement strategies. Moreover, the ability to differentiate between high-risk customers based on sentiment and engagement scores allows companies to refine their service offerings to better align with customer expectations. For example, customers who frequently express dissatisfaction with network performance may benefit from proactive service adjustments, while those engaging positively may be prime candidates for loyalty incentives.

Another critical insight is the role of multi-channel engagement in retention strategies. As customer interactions increasingly span multiple touchpoints, including call centres, online platforms, and social media, the ability to analyse cross-channel sentiment data is essential. Businesses that integrate insights across these channels can develop a more comprehensive view of customer satisfaction, ensuring that service improvements address the root causes of dissatisfaction rather than just immediate transactional concerns.

This research also provides a scalable model for businesses beyond telecommunications, particularly in other subscription-based industries such as streaming services, financial products, and software-as-a-service (SaaS) platforms. These industries face similar challenges related to customer churn, competitive pricing pressures, and service differentiation. The personalised retention framework developed in this study could be adapted to these sectors, where understanding customer sentiment and engagement levels is equally crucial for long-term business success.

6. Conclusion

This study makes three important contributions. Firstly, we introduce a new method that integrates two distinct LLM models-BERT and RoBERTa- to generate insights for customer segmentation, sentiment analysis, and personalised targeting. By integrating advanced NLP techniques with machine learning models, this project aims to enhance customer satisfaction, retention, and the overall quality of service offered to customers. The iterative feedback loop ensures continuous improvement in the model's performance and personalisation strategies. Secondly, the model leverages the advanced NLP models to predict customer churn, while adopting content filtering within the EUT framework to aid personalised recommendations and ensure that each customer receives relevant and timely interventions. This precision helps tailor services to individual needs, significantly boosting satisfaction and retention.

Thirdly, the model classifies customers using a detailed system that includes Customer ID, Churn Status, Aspect, and tailored Recommendations. This comprehensive classification allows for a better understanding of each customer's unique profile and needs. By predicting churn and offering personalised recommendations, the model not only enhances customer satisfaction but also addresses broader social and economic impacts. It fosters a more inclusive and engaging user experience, creating a supportive community where customers feel valued and understood. This approach drives both customer loyalty and business growth, showcasing the powerful potential of integrating advanced machine learning and NLP techniques in customer retention strategies.

Beyond the immediate impact on retention strategies, the model also holds practical implications for operational workflows in customer service and support centres. By integrating real-time sentiment analysis and churn predictions into existing CRM systems, organisations can automate triage processes, prioritise high-risk customers for follow-up, and personalise interventions with greater precision and efficiency. This operational enhancement can reduce response time, improve service quality, and optimise the allocation of customer support resources. Future research should explore the model's applicability across different sectors and regions, particularly by testing its robustness on more diverse datasets that include varied demographic, linguistic, and behavioural attributes. Such validation will ensure the model's generalisability and inform further refinements in domain-specific adaptation.

In the near future, we aim for this model to operate in real-time, continually refining and updating its predictive capabilities. By integrating an advanced inference engine with business rules, the model will enhance its accuracy and personalisation over time, adapting swiftly to changing customer needs and behaviours. Ethical considerations will be paramount in this integration. Ensuring transparency and security in data handling is essential for building trust and mitigating privacy concerns. Addressing these ethical issues responsibly will be crucial for the model's sustainable and responsible deployment.

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Figure Legends

Table Legends