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Explaining Telecom Customer Churn through Communication-Oriented Machine Learning and SHAP Analysis

Nutnicha Janchai[1], Warawut Narkbunnum[1]

[1]Mahasarakham Business School, Mahasarakham University, Thailand

Correspondence: Warawut Narkbunnum, Mahasarakham Business School, Mahasarakham University, Mahasarakham, Thailand.

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Abstract

In subscription-based communication markets, customer churn threatens both revenue and long-term audience relationships. Although machine learning models are widely used to target at-risk subscribers, many implementations remain opaque and difficult to translate into communication strategies. This article analyzes an anonymized telecom customer churn dataset to examine how communication-related attributes of the customer relationship shape churn risk and how explainable machine learning can support retention communication. Logistic regression, random forest, and gradient boosting models are estimated on secondary data for 7,032 subscribers, with class imbalance handled through weighted training and performance evaluated on a held-out test set. Shapley Additive Explanations (SHAP) are then applied to the best-performing tree-based model, with predictors grouped into four constructs: relationship and contract attributes, digital communication and billing channels, support and value-added services, and demographic and household characteristics. The models achieve good discrimination, and SHAP analyses show that contract type, tenure, and billing-related monetary variables dominate churn prediction, followed by support and value-added services and digital billing channels, while demographics play a limited role. Aggregating explanations at the construct level yields stage-specific insights into early versus late relationship drivers of churn and illustrates how churn analytics can be aligned with media and communication theory to design more targeted retention communication.

Keywords: customer churn, explainable AI, machine learning, retention communication, telecommunications

1. Introduction

1.1 Introduce the Problem

Customer churn remains a strategic challenge for telecommunications providers, particularly in the mobile and bundled service sectors, characterized by intense competition and relatively low switching barriers. Empirical research and comprehensive literature reviews demonstrate that the decision to terminate or switch service providers is influenced by variables such as fluctuations in service quality, customer satisfaction levels, perceived switching costs, and structural characteristics of the bundled service market. These factors can expedite customer migration among service providers (Gerpott et al., 2001; Grzybowski et al., 2021; H. Ribeiro et al., 2024).

When a customer terminates their relationship with a service provider, the impact extends beyond immediate revenue loss to include a reduction in Customer Equity, which reflects the long-term value of the customer relationship and the organization's capacity to retain its customer base through acquisition, management, and data analytics (Hogan et al., 2002). Furthermore, in highly competitive service markets, the allocation of resources between acquiring new customers and retaining existing ones bears significant economic implications. The costs associated with customer retention cannot be directly substituted by those related to customer acquisition, as these activities respond differently to competitive positioning and market dynamics in the wireless telecommunications sector (Min et al., 2016).

From the perspective of managerial control and decision support systems, these dynamics underscore a growing reliance on data analysis systems to support customer retention decisions in complex service environments. Specifically, the deployment of intelligent analytics systems and artificial intelligence to assist managerial decision-making and to regulate communication processes within organizations (Tsotniashvili, 2025).

Consequently, telecommunications and digital communication service providers have enhanced their deployment of churn analysis and customer retention programs by utilizing Predictive Risk Scores to prioritize proactive measures such as targeted discounts, personalized communications, and restructuring service packages. Nonetheless, empirical evidence from real-world operations indicates that targeting exclusively based on risk levels may yield adverse outcomes if retention offers do not correspond to the genuine needs of customers or if responses vary among high-risk customer groups, thereby highlighting the limitations inherent in employing predictive technology without an appropriate communication strategy (Mallek et al., 2025; Ascarza, 2018).

This challenge demonstrates that managing customer attrition transcends predictive modeling; it also involves control and communication challenges, requiring an analytical framework that can be explicitly articulated and strategically directed to support managerial decision-making.

1.2 Explore the Importance of the Problem

The significance of churn goes beyond merely controlling costs. In communication and media markets, maintaining subscription continuity is crucial for ensuring consistent audience engagement and ongoing brand relationships, especially as more digital content and media services rely on recurring subscription models. Recent evidence in digital content subscription markets shows a growing tension between adopting innovation and resisting change, which leads to fluctuations in subscription continuation decisions and makes it harder to build long-term relationships through communication strategies alone (Yang & Kwon, 2024). From a media and communication perspective, churn analytics should be viewed not only as a predictive task but also as a decision-support tool for creating relationship-focused communication throughout the customer lifecycle. This involves providing explanations that align with how managers think about customers, rather than presenting fragmented lists of technical predictors. Theory-based explanation research highlights that human explanations are contrastive, selective, and audience-dependent, which means churn explanations should be structured into meaningful constructs aligned with communication strategy, channel management, and relationship building (Miller, 2019). In marketing and management research, explainable AI is similarly seen to translate complex models into transparent, decision-relevant insights (Rai, 2020).

Explainable artificial intelligence (XAI) methods offer practical options for such translation. Model-agnostic local explanation techniques, like LIME, are used to estimate feature contributions around individual predictions (M. T. Ribeiro et al., 2016). Similarly, SHAP-based methods for tree models allow a seamless shift from local explanations to a broader understanding of the entire model, supporting both managerial interpretation and model governance (Lundberg et al., 2020). Telecom-focused research increasingly combines predictive models with local and global explanations to identify churn drivers and make results understandable for stakeholders (Poudel et al., 2024). Overall, these advances highlight the need for a communication-focused framework that connects technical model explanations with theoretically grounded concepts of relationships and communication to guide segmentation, messaging, and service redesign.

1.3 Describe Relevant Scholarship

A substantial and multidisciplinary body of literature has examined why subscribers discontinue telecommunications and other subscription-based communication services. Evidence from systematic syntheses indicates that churn results from a combined influence of customer socio-demographics, service quality and value perceptions, switching costs and barriers, and tariff or contract characteristics, with the field often fragmented across studies of behavioral intention and observed switching behavior in operational datasets (Ribeiro et al., 2024). Within this area, contractual frictions and lock-in mechanisms remain consistently prominent. Minimum contract duration and related commitment structures have been shown to shape retention behavior by changing the perceived cost of leaving and the timing of re-evaluation decisions, thereby helping to explain why shorter or more flexible contracts are typically associated with higher churn propensity (Becker et al., 2014). Empirical evidence from bundled telecommunications settings further suggests that customer experience and loyalty processes function as nearby mechanisms linking service encounters to churn outcomes, reinforcing the importance of relationship and service design factors in strategies aimed at reducing churn (Ribeiro et al., 2024).

In addition to behavioral explanations, churn prediction has become a mature field in analytics, where supervised learning models estimate each customer's likelihood of churning and prioritize retention efforts. Recent surveys and comparative studies show that logistic regression remains a strong benchmark, while tree-based ensemble methods and boosting techniques often provide better discrimination in complex telecom data environments, typically assessed using metrics such as AUC and related ranking measures (Manzoor et al., 2024; Wagh et al., 2024). However, the existing literature remains largely focused on algorithms. Even when performance improves, many studies highlight accuracy but fail to translate model outputs into decision-relevant insights about customer relationships, communication touchpoints, or service bundle design, thereby reducing managerial adoption in communication-focused retention initiatives (Manzoor et al., 2024; Wagh et al., 2024).

This gap has driven the increased use of explainable artificial intelligence (XAI) in churn analytics. Model-agnostic local explanations, exemplified by LIME, and game-theoretic attribution methods, such as SHAP, are widely used to link predictions to input factors, thereby supporting scrutiny and actionable insights (Lundberg & Lee, 2017; M. T. Ribeiro et al., 2016). Conceptual work also suggests that, especially for important business decisions, explanations should be viewed as a core component of trustworthy deployment and to prevent overreliance on opaque predictors (Rudin, 2019; Miller, 2019). In telecom churn analysis, recent studies show that SHAP-based methods can identify key churn drivers and allow segment-level interpretation, though explanations are often shared as feature lists rather than as higher-level constructs aligned with customer relationship management and communication strategies (Asif et al., 2025; Chang et al., 2024; Poudel et al., 2024).

Building on this scholarship, the current study adopts a communication-focused interpretive layer to explain churn. Predictors from a widely used anonymized telecom churn dataset are grouped into four categories based on customer relationship and communication research: (1) relationship and contract attributes, (2) digital communication and billing arrangements, (3) support and value-added services, and (4) demographic and household characteristics. This construct-based organization, combined with SHAP explanations, generates both global and segment-specific insights that are easier to interpret for retention communication decisions than solely feature-level outputs (Lundberg & Lee, 2017; Poudel et al., 2024; Rudin, 2019).

1.4 State Hypotheses and Their Correspondence to Research Design

To address the theoretical and practical issues identified above, this study employs a quantitative explanatory design using only secondary data. The empirical analysis relies on the widely used Telco Customer Churn dataset (publicly available on Kaggle), which contains anonymized customer-level information on contract terms, billing and payment arrangements, subscribed services, and basic demographic and household characteristics for 7,032 subscribers. The modeling pipeline estimates three supervised classifiers that are commonly used in churn analytics: logistic regression, random forest, and gradient boosting. Model comparison is conducted under a standardized preprocessing workflow, with explicit attention to class imbalance and to evaluation using both discrimination-oriented metrics and calibration-oriented diagnostics, consistent with current best practice in predictive churn research (Manzoor et al., 2024; Wagh et al., 2024).

Because the goal is not only prediction but also explanation, the study applies an XAI layer after model selection. SHAP values are computed for the best-performing tree-based model and summarized in two complementary ways. First, feature-level SHAP attributions identify which observable attributes contribute most to churn predictions at both the population and individual levels (Lundberg & Lee, 2017). Second, SHAP outputs are aggregated into the four construct groups to support communication-relevant interpretation, reducing the risk that managerial conclusions remain trapped at the level of technical variables (Chang et al., 2024; Poudel et al., 2024; Rudin, 2019).

Guided by communication and customer relationship theory, the study is structured around three research questions:

RQ1: Which communication-related attributes of the customer relationship are most strongly associated with churn risk in the Telco Customer Churn dataset?
RQ2: How do churn drivers differ across contract tenure segments that represent distinct stages of the customer relationship?
RQ3: How can SHAP-based explanations be translated into retention communication insights that are actionable for media and communication managers?

These questions correspond directly to the research design. RQ1 is addressed through model training and SHAP-based ranking of drivers at both feature and construct levels (Lundberg & Lee, 2017; Poudel et al., 2024). RQ2 is examined via segmentation by contract type and tenure, motivated by evidence that contract structures and commitment horizons shape retention dynamics and churn timing (Becker et al., 2014; H. Ribeiro et al., 2024). RQ3 is addressed by interpreting construct-level patterns in the context of communication-oriented decision needs, emphasizing that billing channels, support touchpoints, and service configurations can be reframed as actionable levers for targeted retention messaging rather than as isolated predictors (Chang et al., 2024; Miller, 2019; Rudin, 2019).

2. Method

2.1 Identify Subsections

This study adopts a quantitative, explanatory research design based entirely on secondary data from a publicly available telecommunications churn dataset. The primary aim is to quantify how communication-related attributes of the customer relationship are associated with the probability of churn and to generate explanations that can inform communication and retention strategies. Supervised machine learning models are used to estimate individual churn risk, and explainable artificial intelligence techniques are employed to interpret model predictions in relation to theoretically motivated constructs. The models are not intended to automate individual-level decisions. Instead, they serve as analytical tools for deriving segment-level insights for media and communication managers.

2.2 Data Source and Sample

The empirical analysis uses the Telco Customer Churn dataset, a widely cited benchmark hosted on Kaggle. The dataset contains customer-level records for 7,032 subscribers of a telecommunications service provider. For each subscriber, the data include a binary churn indicator and a set of predictors that capture contract terms, billing arrangements, service bundles, and basic demographic and household characteristics. All records are fully anonymized, and no direct identifiers or sensitive personal information are available.

In this study, the dataset is treated as an analytical case study that is representative of subscription-based communication and media services. The goal is not to produce population-level estimates for a specific operator but to investigate how communication-related attributes in a typical telecom setting relate to churn risk and to demonstrate a transparent modelling and explanation pipeline that can be transferred to other contexts. Any potential sampling bias in the original dataset is acknowledged as a limitation, and the findings are interpreted in terms of patterns within this customer base.

2.3 Measures and Construct Grouping

The dependent variable is a binary indicator of churn, taking the value 1 if the customer discontinued service during the observation period and 0 otherwise. The predictors are organized into four conceptual construct groups grounded in the customer relationship management and communication literature:

1) Relationship and contract attributes. This group captures the depth and economic terms of the relationship between the customer and the provider. It includes tenure (in months), the type of contract (month-to-month, one-year, two-year), and billing-related monetary variables such as MonthlyCharges and TotalCharges. These variables reflect both contractual lock-in and accumulated relationship value.

2) Digital communication and billing channels. This group reflects the degree to which the relationship is mediated through digital self-service channels and the convenience of billing arrangements. It includes indicators such as PaperlessBilling and the payment method categories (for example, electronic check versus automatic bank or credit card transfer).

3) Support and value-added services. This group represents the breadth and quality of the service bundle and the availability of technical support. It includes variables indicating the presence or absence of internet service, multiple lines, and add-ons such as online security, online backup, device protection, tech support, and streaming services.

4) Demographic and household controls. This group captures basic characteristics of the subscriber and their household that may correlate with communication needs and switching behavior. It includes gender, SeniorCitizen status, Partner status, and whether the customer has Dependents.

These construct groups are used not only to structure the description of the variables but also to organize the interpretability analysis, in which feature-level importance scores are aggregated to the construct level.

2.4 Data Preprocessing

Data preprocessing was implemented in Python using a reproducible workflow. The raw dataset was first inspected for internal consistency, invalid codes, and missing values. Records with missing or non-parsable values in key numeric variables were removed. Categorical predictors were encoded as binary indicator variables using one-hot encoding, ensuring well-defined reference categories and controlling for multicollinearity by omitting one level per factor.

Continuous variables such as tenure, MonthlyCharges, and TotalCharges were standardized to have a mean of zero and unit variance for models that assume scale homogeneity, particularly logistic regression. For tree-based models, which are invariant to monotonic transformations of predictors, raw scales were retained after basic cleaning. All preprocessing steps were encapsulated in scripts that take raw data as input and produce a single analysis-ready table as output, ensuring that the entire pipeline from raw data to model input can be reproduced.

To evaluate out-of-sample performance, the dataset was partitioned into training and test sets using a random split. A fixed random seed was used to enable reproducible sampling, and stratification on the churn indicator was applied to approximately preserve the churn proportion across both subsets. The training data were used to estimate the model and tune hyperparameters, whereas the held-out test data were reserved exclusively for final performance assessment.

2.5 Modeling Strategy

Three supervised learning models were used to predict churn probability: logistic regression, random forests, and gradient boosting. Logistic regression provides a transparent, parametric baseline that is widely used in churn research and allows direct interpretation of coefficient signs and magnitudes. Random forests are bagging-based ensembles of decision trees that can capture nonlinearities and interaction effects without requiring manual specification of interaction terms. Gradient boosting builds an additive ensemble of shallow trees in a stagewise manner, focusing sequentially on observations that are poorly predicted by the current ensemble.

The churn rate in the dataset is approximately 25%, indicating a moderate class imbalance between churners and non-churners. To address this, class-balanced loss functions were used in the tree-based models, and class weights were applied in logistic regression to penalize misclassifications of churners more heavily. Hyperparameters for the random forest and gradient boosting models, such as the number of trees, maximum tree depth, and learning rate, were selected through cross-validation on the training set within a constrained search space that favoured parsimonious configurations and avoided overfitting. The final configurations are documented in the supplementary material.

2.6 Model Evaluation

Model performance was assessed on the held-out test set using a combination of threshold-independent and threshold-dependent metrics. Discrimination was evaluated using the area under the receiver operating characteristic curve and the area under the precision-recall curve, which are standard measures for imbalanced classification problems and quantify how well the models rank churners ahead of non-churners by predicted probability. In addition, accuracy, precision, recall, and F1 score were calculated at a conventional probability threshold to provide more interpretable summary measures for practitioners.

Calibration of predicted probabilities was assessed using the Brier score as an overall measure of probabilistic accuracy and by graphical inspection of reliability plots comparing predicted and observed churn rates across probability bins. These calibration diagnostics are critical because retention decisions often rely on absolute risk thresholds rather than on relative ranking. The combination of discrimination and calibration metrics enables a nuanced assessment of model quality in terms relevant *to* communication and retention planning.

2.7 Explainable Modeling and Construct-Level Aggregation

In this study, the SHAP (Shapley Additive Explanations) values were calculated for a Random Forest model, which serves as a benchmark classifier for interpretive analysis. The primary emphasis was placed on the Churn class = 1, with positive SHAP values indicating an elevated probability of customer churn, and negative values representing a diminished risk. To facilitate the pragmatic application of the algorithm's findings within communication strategies, the researcher advanced the analysis from summarizing the influence of factors at the aggregate level (Global Feature-level Summary) to clustering based on conceptual frameworks (Construct-level Aggregation). Additional details have been incorporated to better align with the communication context as follows

1) The transformation of statistical data into communicative contexts involves, rather than merely reporting the significance of variables in a technical manner, interpreting the SHAP value as a representation of the Touchpoint Influence Index. This methodology aims to demonstrate how interactions across touchpoints, such as contractual arrangements or digital communication channels, affect the relationship's fluidity or tension between the brand and the customer.

2) The comparative analysis for decision-making involves integrating variables aligned with the four conceptual dimensions as delineated in Section 2.3. This approach facilitates the generation of contrastive explanations in accordance with Miller's (2019) framework. Such an approach enables communication executives to precisely identify which lever within the communication ecosystem exerts the greatest influence on shaping customer opinions.

3) The support for strategic communication involves a process of aggregation aimed at reducing Data Simplification by converting dispersed variable lists into a Risk Trajectory diagram. This diagram enables the corporate communications department to meticulously design messaging and select communication channels to sustain the customer base.

2.8 Ethical Considerations and Reproducibility

The dataset used in this study is fully anonymized and publicly available, with no attempt made to re-identify individuals or link records to external sources. The analysis is limited to aggregated patterns and model-based summaries, and no operational decision support tool was deployed. As a result, a formal ethics review was not required. Nonetheless, the study addresses broader debates on responsible and transparent use of predictive models in customer management in the discussion section.

To ensure reproducibility, all analyses were performed using open-source software within a scripted environment. The workflow is structured as a numbered pipeline that includes data ingestion, preprocessing, model training, evaluation, and explainability analysis. Each step uses the outputs of the previous step as inputs and saves results to versioned files with descriptive names. A detailed runbook in the Appendix documents the software environment, key commands, input and output file paths, and the relationship between scripts, tables, and figures in the manuscript, enabling other researchers to replicate or extend the analysis using the same dataset.

3. Results

3.1 Descriptive Overview of the Sample

3.1.1 Churn Prevalence

Among the 7,032 customers in the analytical sample, churn is non-trivial. Table 1 reports the distribution of customers who churned versus those who did not. The churn prevalence is 0.27, indicating that approximately 27% of customers discontinued service during the observation period. This outcome distribution is moderately imbalanced, suggesting that a sizeable share of the customer base is at risk and that predictive models should account for class imbalance in both training and evaluation.

Table 1. Churn prevalence in the analytical sample (N = 7,032)

Churn status	count	proportion
No (0)	5,163	0.73
Yes (1)	1,869	0.27

Note. Churn status is coded as 1 for churners and 0 for non-churners. Proportions may not sum to 1 due to rounding.

The breakdown shows that churners are more likely to have shorter relationships with the provider and to be concentrated in specific contract types and service bundles. In contrast, non-churners tend to have longer-standing contracts and higher total charges accumulated, reflecting longer tenure and more stable relationships.

3.1.2 Contract and Service Characteristics

Tables 2a–2c report selected contract, billing, and service characteristics in the analytical sample. Overall, month-to-month contracts constitute the largest share of customers (0.55), followed by two-year (0.24) and one-year contracts (0.21) (Table 2a). Paperless billing is relatively common (0.59), and payment methods are distributed across automatic payments and check-based channels, with electronic check representing a sizeable segment (0.34) (Table 2a). Regarding core services, fiber optic internet is the most prevalent internet service category (0.44), and most customers subscribe to phone service (0.90) (Table 2b). Value-added and support services exhibit substantial variation, with "No internet service" consistently capturing the subgroup without internet subscriptions (Table 2c). To complement these compositional patterns, Figures 1–2 compare churn outcomes across contract types and tenure, highlighting how contract commitment and relationship length relate to churn risk

Table 2a. Contract and billing characteristics in the analytical sample (N = 7,032)

variable	level	count	proportion
Contract	Month-to-month	3,875	0.55
Contract	One year	1,472	0.21
Contract	Two year	1,685	0.24
PaperlessBilling	No	2,864	0.41
PaperlessBilling	Yes	4,168	0.59
PaymentMethod	Bank transfer (automatic)	1,542	0.22
PaymentMethod	Credit card (automatic)	1,521	0.22
PaymentMethod	Electronic check	2,365	0.34
PaymentMethod	Mailed check	1,604	0.23

Table 2b. Core telecom service characteristics in the analytical sample (N = 7,032)

variable	level	count	proportion
InternetService	DSL	2,416	0.34
InternetService	Fiber optic	3,096	0.44
InternetService	No	1,520	0.22
MultipleLines	No	3,385	0.48
MultipleLines	No phone service	60	0.10
MultipleLines	Yes	2,967	0.42
PhoneService	No	680	0.10
PhoneService	Yes	6,352	0.90

Table 2c. Support and value-added services in the analytical sample (N = 7,032)

variable	level	count	proportion
DeviceProtection	No	3,094	0.44
DeviceProtection	No internet service	1,520	0.22
DeviceProtection	Yes	2,418	0.34
OnlineBackup	No	3,087	0.44
OnlineBackup	No internet service	1,520	0.22
OnlineBackup	Yes	2,425	0.34
OnlineSecurity	No	3,497	0.50
OnlineSecurity	No internet service	1,520	0.22
OnlineSecurity	Yes	2,015	0.29
StreamingMovies	No	2,781	0.40
StreamingMovies	No internet service	1,520	0.22
StreamingMovies	Yes	2,731	0.39
StreamingTV	No	2,809	0.40
StreamingTV	No internet service	1,520	0.22
StreamingTV	Yes	2,703	0.38
TechSupport	No	3,472	0.49
TechSupport	No internet service	1,520	0.22
TechSupport	Yes	2,040	0.29

Figure 1a shows a stacked bar chart of churn by contract type, emphasizing the clear difference in churn rates across categories. Churn is mostly seen in the month-to-month segment, which offers high flexibility but little contractual commitment. Figure 1b displays boxplots of tenure by churn outcome, revealing that churners generally have much shorter tenures than non-churners. Many churners leave within the first year of service, while customers with longer tenures are mostly retained. These patterns suggest that contract type and relationship length are key factors in explaining churn.

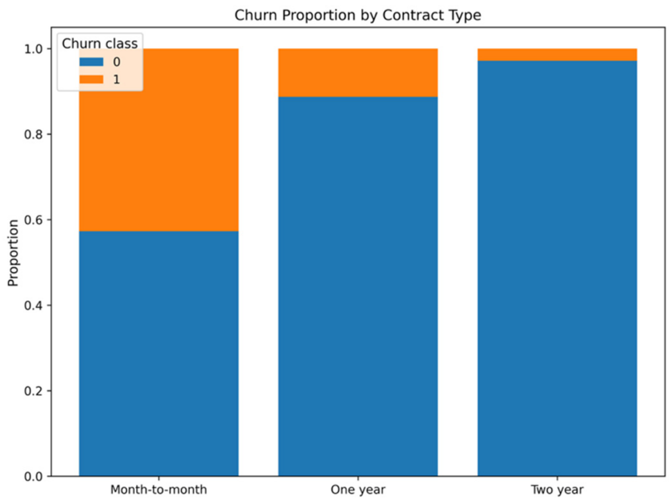

Figure 1a. Churn prevalence by contract type

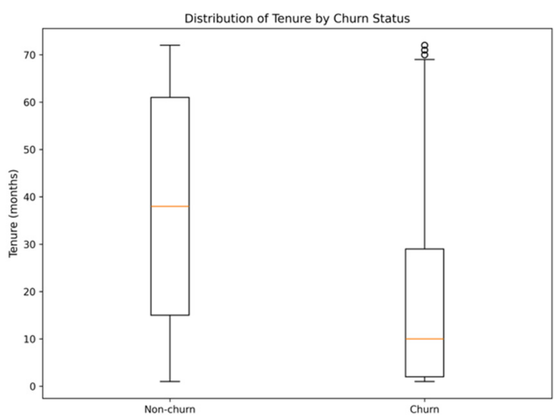

Figure 1b. Boxplots of tenure by churn status (0 = non-churners, 1 = churners)

3.1.3 Numeric Attributes

Table 3 presents summary statistics for key numeric attributes in the analytical sample, including tenure, MonthlyCharges, and TotalCharges. The sample shows considerable variation, especially for tenure and TotalCharges, indicating differences in relationship duration and total payments made. The median tenure is 29 months (IQR: 9–55), while TotalCharges display a wide range (median = 1,397.48; IQR: 401.45–3,794.74). MonthlyCharges are also quite diverse (median = 70.35; IQR: 35.59–89.86), reflecting notable differences in ongoing service costs among customers. These descriptive distributions offer useful context for the modeling analyses discussed in the following sections.

Table 3. Summary statistics for key numeric attributes

	N	Mean	std	min	25%	50%	75%	max
tenure	7,032	32.42	24.55	1.0	9.0	29.0	55.0	72.0
MonthlyCharges	7,032	64.80	30.09	18.25	35.59	70.35	89.86	118.75
TotalCharges	7,032	2,283.30	2,266.77	18.8	401.45	1397.48	3794.74	8684.80

The dispersion of tenure and charges is also insightful. The distribution of tenure among churners skews toward very short relationships, while tenure among non-churners covers a broader range. Total charges show a similar trend, with a heavy right tail among non-churners that indicates accumulated payments over longer relationships. These descriptive contrasts provide a solid context for the modeling results discussed in the next subsections.

3.2 Model Performance

Table 4 compares the performance of three supervised learning models: logistic regression, random forest, and gradient boosting on the held-out test set. The models are evaluated using threshold-independent discrimination metrics, including the area under the receiver operating characteristic curve and the area under the precision-recall curve, as well as threshold-dependent measures such as accuracy, precision, recall, and F1 score at a standard probability threshold.

Table 4. Model performance across algorithms

model	accuracy	precision	recall	f1	roc_auc	average_precision
logistic_regression	0.726	0.490	0.797	0.607	0.835	0.618
random_forest	0.788	0.631	0.489	0.551	0.813	0.591
gradient_boosting	0.734	0.500	0.807	0.618	0.839	0.654

All three models demonstrate solid discrimination between churners and non-churners (Table 4). Gradient boosting attains the highest ROC AUC and average precision, indicating strong ranking performance under class imbalance. Random forest yields the highest precision at the chosen threshold and provides a competitive overall profile among the evaluated classifiers. For the subsequent explainability analyses, we use the random forest model as the benchmark tree-based classifier to ensure consistency with the SHAP computation, and the construct-level aggregation pipeline used in this study. Threshold-dependent metrics (accuracy, precision, recall, and F1) are reported at a probability threshold of 0.50.

3.3 Feature-Level Determinants of Churn

Feature-level determinants of churn are analyzed using SHAP values computed for the benchmark random forest model. Figure 2a presents a SHAP beeswarm plot summarizing the distribution of SHAP values for the top-ranked features across customers. In contrast, Figure 2b reports mean absolute SHAP values as a bar chart. Positive SHAP values indicate higher predicted churn risk (class = 1), whereas negative SHAP values indicate lower predicted churn risk.

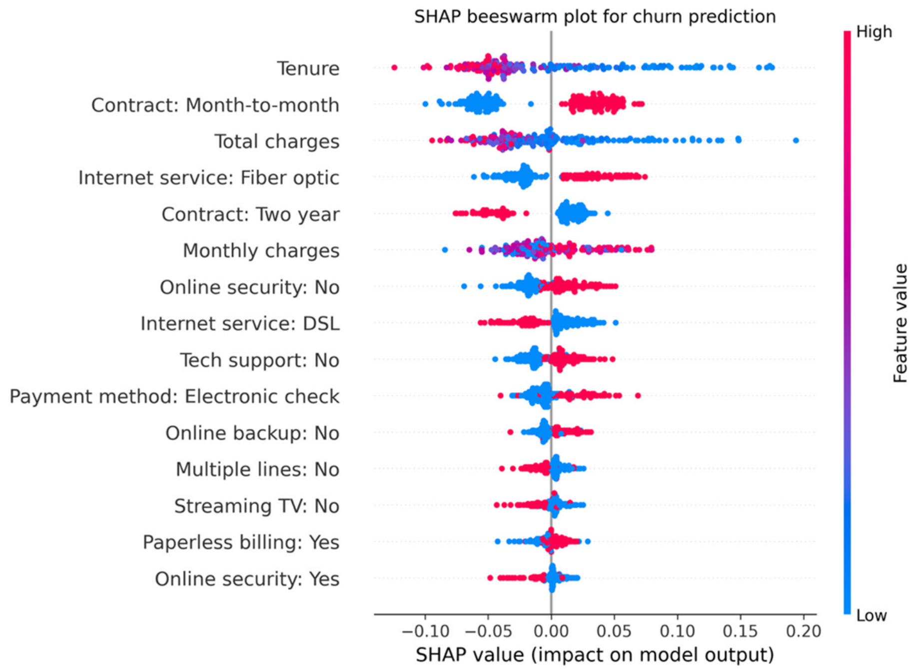

Figure 2a. Global feature-level SHAP values for churn from the random forest model (beeswarm plot)

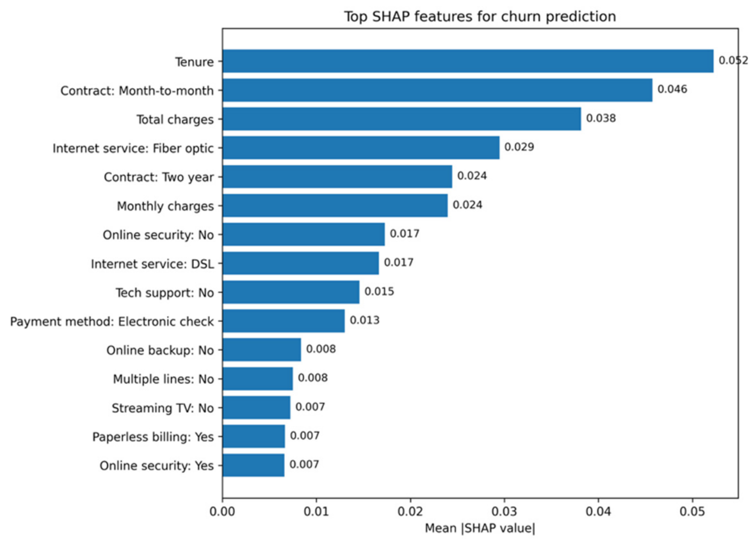

Figure 2b. Global feature importance by mean absolute SHAP value from the random forest model

Across both visualizations, tenure emerges as the most influential predictor. Shorter tenure is associated with positive SHAP values, indicating elevated churn risk, whereas longer tenure is associated with negative SHAP values, consistent with more stable customer relationships. Contract structure is similarly salient. Month-to-month contracts are linked to higher churn risk, while longer-term contracts, particularly two-year contracts, contribute negative SHAP values and therefore reduce the predicted probability of churn. TotalCharges also ranks highly; lower accumulated charges tend to increase churn risk, which is consistent with early-stage relationship termination and limited accumulated spending.

Billing and service attributes contribute additional explanatory power. Higher MonthlyCharges generally increase churn risk, and electronic check payments and paperless billing are associated with higher predicted churn risk relative to more stable automatic payment methods. Several service-related features also appear among the top drivers. The absence of OnlineSecurity and TechSupport is associated with increased churn risk, suggesting that the lack of supportive service components can destabilize retention. Taken together, Figures 2a–2b indicate that relationship duration, contract commitment, and a subset of billing and service features jointly shape churn risk at the global level.

3.4 Construct Level Importance

To translate technical predictors into communication-focused constructs, SHAP values from the benchmark random forest model are aggregated into four construct groups defined in the Methods: relationship and contract attributes, digital communication and billing channels, support and value-added services, and demographic and household controls. Table 5 reports the total mean absolute SHAP value and the share of total SHAP importance for each construct group, whereas Figure 3 visualizes the within-construct SHAP importance patterns using radar and bar charts.

Table 5. Construct-level SHAP importance from the random forest model.

Construct group	Total mean absolute SHAP	Share of total importance
Relationship and contract attributes	0.19	0.43
Support and value-added services	0.18	0.40
Digital communication and billing	0.04	0.09
Demographic and household controls	0.03	0.08

At the construct level, relationship and contract attributes make up the largest portion of total importance (share = 0.43), followed closely by support and value-added services (share = 0.40) (Table 5). This pattern shows that churn predictions are mainly influenced by relationship duration and contractual commitment, as well as the presence or absence of service features that affect perceived reliability and support. Digital communication and billing channels have a smaller but still significant contribution (share = 0.09), indicating that billing arrangements and payment behaviors are still important for retention efforts. Demographic and household controls contribute the least to the model's predictions (share = 0.08), suggesting that churn risk in this dataset is more strongly linked to relationship and service configurations than to basic demographic traits.

3.5 Within-Construct Patterns: Radar and Bar Charts

Within-construct patterns are examined using visualizations that summarize within-group SHAP importance for the benchmark random forest model. For construct groups with three or more variables, radar charts are used to capture multidimensional importance patterns, whereas for groups with fewer variables, bar charts are employed to preserve visual clarity and interpretability. Figure 3 presents these visualizations, where larger values indicate variables that contribute more strongly to predictions within each construct.

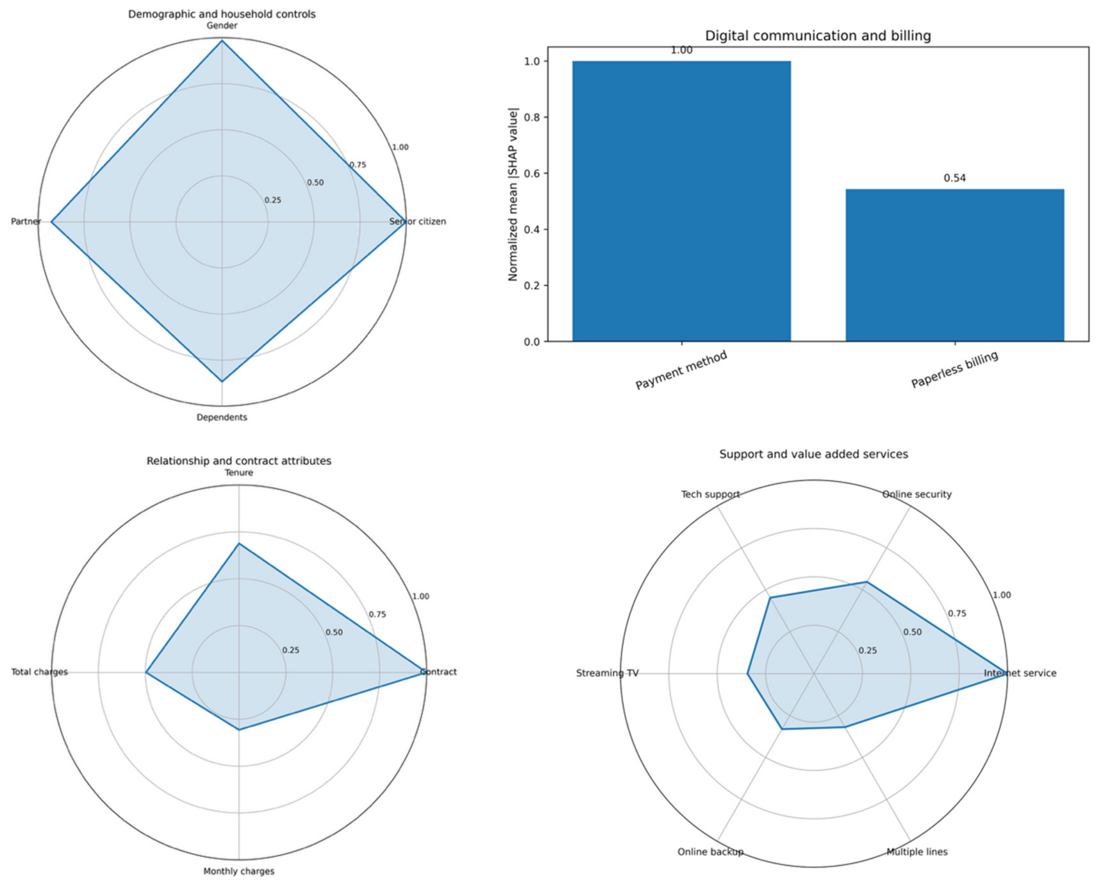

Figure 3. Within-construct SHAP importance patterns from the random forest model (radar and bar charts)

For relationship and contract attributes, the radar chart highlights contract type and tenure as the dominant within-group contributors, with MonthlyCharges and TotalCharges playing secondary but still meaningful roles. This pattern is consistent with the centrality of relationship duration and contractual commitment in explaining churn risk in the dataset.

For digital communication and billing, a bar chart is used because this construct contains only two variables. PaymentMethod emerges as the most salient contributor, while PaperlessBilling plays a comparatively smaller role, indicating that billing channel configuration is unevenly distributed in its influence on churn predictions.

For support and value-added services, the radar chart shows that InternetService is the most influential variable, followed by OnlineSecurity and TechSupport, whereas StreamingTV, OnlineBackup, and MultipleLines contribute less within the construct. This suggests that core connectivity and security-related services play a more prominent role than supplementary service features.

Finally, within demographic and household controls, the radar chart indicates that SeniorCitizen is the most prominent driver, with partner status, dependents, and gender contributing more modestly. Taken together, these visualizations provide a construct-consistent representation of how importance is distributed across variables within each construct, reinforcing the conclusion that churn predictions are primarily shaped by relationship structure and service configuration, with billing practices and demographic characteristics playing supporting roles.

3.6 Summary of Key Findings

The results can be summarized in three main points. First, the descriptive analyses indicate that churn is concentrated among customers with short tenure, month-to-month contracts, and less stable billing arrangements. This pattern suggests that early stages of the customer relationship are comparatively fragile and that contract commitment is a central correlate of churn risk in the dataset. Second, the predictive modeling results show that the evaluated supervised learning models provide solid discrimination between churners and non-churners. The random forest model is used as the benchmark for the explainability analyses. Class-imbalance handling is incorporated to mitigate skewed outcome distributions and to support sensitivity to churners, which is important for retention-oriented decision making. Third, SHAP-based explainability indicates that relationship and contract attributes account for the largest share of model importance, followed by support and value-added services and digital communication and billing channels, while demographic and household controls contribute comparatively less. Aggregating SHAP values to the construct level and examining within-construct patterns through radar charts offers a communication-oriented lens for interpreting churn risk, supporting the development of more targeted retention strategies, particularly for higher-risk customers in early relationship stages.

4. Discussion

4.1 Interpretation of Key Findings

The empirical findings provide convergent evidence across descriptive statistics, predictive performance, and SHAP-based explanations that customer churn in the analyzed telecom context is primarily structured by relationship depth and contractual commitment rather than by demographic heterogeneity. This convergence is important because it demonstrates internal consistency between statistical patterns and model-based explanations, thereby strengthening the study's evidentiary basis. Importantly, the conclusions drawn in this study are directly supported by multiple layers of empirical evidence. At the descriptive level, observable patterns indicate that churn is concentrated among customers with shorter tenure*s* and more flexible contract arrangements. At the model level, predictive performance confirms that these attributes consistently contribute to accurate discrimination between churners and non-churners. Most critically, SHAP-based explanations provide convergent evidence by quantifying the contribution of these variables at both the feature and construct levels, with relationship and contract attributes emerging as dominant predictors across all analytical representations. This alignment between descriptive patterns, predictive modeling, and explainable outputs strengthens the validity of the conclusions and reduces the risk of interpretation driven solely by model artifacts. Taken together, these results provide a coherent empirical basis for the study’s theoretical and managerial conclusions.

At the feature level, short tenure and month-to-month contracts systematically produce positive SHAP contributions to churn probability, while longer tenure and fixed-term contracts contribute negatively. This pattern is not merely correlational but also theoretically consistent with switching-cost theory and relationship-marketing perspectives, which posit that weaker contractual and relational ties reduce exit barriers and increase sensitivity to alternative offers (Ribeiro et al., 2024). The model evidence therefore supports the interpretation that early-stage relationships are structurally more vulnerable to disruption.

In addition, monetary variables such as MonthlyCharges and TotalCharges function as proxies for perceived value and accumulated investment in the relationship. The joint effect observed in the SHAP analysis indicates that customers with high recurring costs, but low accumulated value are particularly prone to churn. This interaction reinforces the interpretation that churn is driven by a mismatch between perceived cost and realized value, rather than by price alone.

At the construct level, the dominance of relationship and contract attributes (43 percent of total SHAP importance) and support and value-added services (40 percent) further supports the view that churn is shaped by both structural commitment and experiential reinforcement. This dual structure aligns with prior literature that distinguishes between contractual lock-in mechanisms and ongoing service experience as complementary drivers of retention (Wu et al., 2021; Zhou et al., 2023)

4.2 Stage-Contingent Mechanisms of Churn

A key contribution of the analysis is demonstrating that churn drivers are not uniform across the customer lifecycle but exhibit stage-contingent patterns. The segmentation results indicate that, in early relationship stages, churn risk is predominantly explained by contractual flexibility and limited relationship duration. In contrast, for longer-tenure customers, the relative importance of support and value-added services increases.

This transition suggests a shift from structural to experiential determinants of retention. In the early stages, customers evaluate whether to remain based on commitment mechanisms and initial value perception. As the relationship matures, the decision to stay becomes increasingly dependent on ongoing service quality and interaction experiences. This finding extends existing churn literature by empirically linking lifecycle stages to distinct explanatory mechanisms, rather than treating churn as a homogeneous outcome.

Importantly, this stage-based interpretation is supported directly by the SHAP decomposition, which shows systematic variation in construct importance across segments. Therefore, the conclusion regarding lifecycle dynamics is grounded in model-based evidence rather than speculative reasoning.

4.3 Communication-Oriented Interpretation of Explainability

The study further demonstrates that explainable machine learning outputs can be transformed into communication-relevant insights when features are aggregated into theoretically grounded constructs. Rather than interpreting SHAP values as isolated technical indicators, the construct-based aggregation provides a higher-level representation of customer relationships that aligns with managerial decision frameworks.

This transformation is consistent with the argument that explanations in organizational contexts must be selective, contrastive, and aligned with decision needs (Miller, 2019). By grouping predictors into relationship, billing, service, and demographic constructs, the analysis reduces cognitive complexity and enables actionable interpretation. For example, identifying that churn risk is primarily driven by relationship and contract factors suggests communication strategies focused on onboarding and commitment reinforcement, whereas service-driven risk implies the need for support-oriented interventions.

Thus, the study provides empirical support for the proposition that explainable AI becomes strategically valuable only when its outputs are translated into domain-relevant constructs. This addresses a critical gap in prior research, where explainability often remains at the level of feature importance without clear implications for communication strategy (Rai, 2020).

4.4 Theoretical Contributions

This study contributes to the literature in three main ways.

First, it integrates churn prediction with communication theory by demonstrating that predictive drivers can be interpreted as communication touchpoints within the customer relationship. This shifts the analytical focus from purely algorithmic performance to communication-oriented meaning.

Second, it introduces a construct-based SHAP aggregation approach that bridges the gap between technical explainability and managerial interpretability. This approach extends prior work on explainable AI by embedding explanations within theoretically grounded categories rather than treating them as isolated variables.

Third, it provides empirical evidence for stage-contingent churn mechanisms, showing that the relative importance of structural and experiential factors evolves across the customer lifecycle. This dynamic perspective adds nuance to existing churn models, which often assume static relationships between predictors and outcomes.

4.5 Managerial and Governance Implications

From a managerial perspective, the findings indicate that churn management should be reframed as a communication design problem rather than a purely predictive task. The construct-level results suggest that different communication strategies are required for different relationship stages.

For early-stage customers, communication should emphasize clarifying value and building commitment. For later-stage customers, the focus should shift toward service quality and support interactions. This segmentation is directly supported by the observed variation in SHAP importance across constructs.

From a governance perspective, the study emphasizes the importance of transparency and interpretability in deploying predictive models. The relatively low influence of demographic variables indicates limited direct bias in this dataset. However, the concentration of importance in economic and contractual variables raises concerns about fairness in targeting strategies, especially if retention efforts focus *on* high-value customers.

Therefore, explainable analytics should be integrated into larger governance frameworks that ensure accountability, transparency, and alignment with long-term relationship goals.

5. Conclusion

This study examined customer churn in a telecommunications setting by combining predictive modeling with explainable artificial intelligence and a communication-focused interpretive framework. Using a secondary dataset of 7,032 subscribers, the analysis merged supervised learning models with SHAP-based explanations to identify the main drivers of churn and translate them into theoretically meaningful concepts.

The findings indicate that churn is primarily influenced by relationship depth and contractual structure, with service-related factors playing a secondary role. Demographic characteristics have a relatively minor impact. Short tenure and flexible contract arrangements are strongly linked to higher churn risk, whereas longer relationships and firm contractual commitments reduce the risk of churn. Additionally, the significance of support and value-added services increases during later stages of the customer lifecycle, suggesting that retention strategies shift from structural to experiential factors over time.

Importantly, the results provide evidence that explainable machine learning can provide actionable insights when technical predictors are organized into communication-related constructs. This construct-based method allows managers to understand churn risk in terms of relationship dynamics, billing communication, and service interactions, rather than as separate variables.

From a theoretical perspective, the study advances the literature by connecting churn analytics with communication theory, introducing a construct-based explainability framework, and providing empirical evidence for stage-dependent churn mechanisms. From a practical standpoint, the findings indicate that retention strategies should be customized to relationship stages and should combine predictive insights with communication design.

Overall, the study emphasizes that effective churn management requires not only accurate prediction but also meaningful explanation and strategic interpretation. Future research should expand this framework by incorporating richer behavioral and communication data, testing its applicability across diverse contexts, and incorporating formal governance mechanisms to promote responsible and transparent use of predictive analytics in customer relationship management.

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Author contributions

N.J. and W.N. were responsible for the study design, methodology, and formal analysis. Both authors contributed equally to data curation, investigation, and manuscript preparation. N.J. and W.N. drafted the manuscript, and both authors contributed to its review and revision. W.N. supervised the overall research process. All authors contributed equally to this work and have read and approved the final manuscript.

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