
(RESEARCH ARTICLE)

An Explainable Machine Learning Framework for Customer Churn Prediction and Retention in IT Service Organizations

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Abstract

Customer churn presents a major challenge for B2B IT service organizations, where customer retention directly influences long-term business performance. This study proposes an integrated explainable machine learning framework that combines XGBoost with SHAP and LIME to provide accurate and transparent customer churn prediction. The framework was evaluated using a proprietary B2B IT service dataset (**n = 12,847**) and validated with the IBM Watson customer churn benchmark dataset (**n = 7,043**). Comparative experiments showed that XGBoost achieved the best predictive performance, with **92.4% accuracy**, **0.86 recall**, and **0.96 ROC-AUC**. SHAP identified the key global drivers of customer churn, while LIME generated customer-specific explanations to support personalized retention strategies. The principal contribution of this research is the development and empirical evaluation of an integrated explainable framework that combines high predictive performance with interpretable decision support for B2B customer retention. The findings demonstrate the potential of explainable artificial intelligence to support transparent, accurate, and actionable customer analytics while providing a practical foundation for trustworthy AI-assisted retention decision-making in IT service organizations.

Keywords: *Customer Churn Prediction, Explainable AI, Retention Analytics, Machine Learning, SHAP and LIME*

1. INTRODUCTION

1.1. Background and Context

Customer churn, defined as the termination of a customer's relationship with a service provider, represents a pervasive and costly challenge for IT service organizations operating in subscription-based markets. In the software as a service (SaaS) sector and broader IT services industry, churn directly impacts recurring revenue streams, growth prospects, and long-term organizational viability. The economic imperative for churn prediction is well-established: acquiring a new customer is typically 5 to 25 times more expensive than retaining an existing one, and reducing customer attrition rates by just 5% can increase profits by 25% to 125%. These figures underscore why customer retention has become a strategic priority for IT service organizations.

The IT service landscape has evolved into an increasingly competitive ecosystem characterized by saturated markets, diverse service offerings, and low switching costs for customers. Digital transformation has intensified competition, enabling customers to easily compare alternatives and transition between providers. This dynamic environment creates significant challenges for retention, as customers who leave either cease using services or switch to competitors, directly affecting organizational finances and brand loyalty. High turnover rates also complicate resource allocation and network capacity planning, negatively impacting service delivery quality.

Traditional approaches to churn prevention have relied on retrospective analysis of customer complaints, manual account reviews, and rule-based heuristics. However, these methods prove inadequate for the scale, velocity, and complexity of modern IT service operations. The abundance of customer-related data encompassing usage patterns, support interactions, billing history, and engagement metrics presents both opportunities and challenges. While this data wealth could potentially illuminate churn drivers, the volume and diversity make it difficult for humans to detect characteristic patterns manually. This challenge has driven the adoption of machine learning approaches to churn prediction.

Machine learning has proven effective for customer churn prediction across multiple domains, including telecommunications, banking, insurance, and SaaS. By analyzing large datasets, machine learning algorithms can identify hidden connections between characteristics and forecast future trends, enabling proactive retention strategies. However, a significant limitation persists: many high-performing machine learning models operate as "black boxes," producing accurate predictions while obscuring the reasoning behind those predictions. This opacity creates barriers to trust, accountability, and practical utility for retention teams.

The emergence of eXplainable Artificial Intelligence (XAI) offers a promising solution to this interpretability challenge. XAI techniques provide post-hoc explanations of model predictions, enabling stakeholders to understand the "why" behind churn identification. By quantifying the contribution of each feature to a specific prediction, XAI moves beyond simple forecasting to provide actionable insights for targeted retention strategies. Among XAI techniques, SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) have gained prominence for their ability to provide both global and local explanations.

Recent research has demonstrated that integrating XAI directly into the modeling pipeline enhances both accuracy and interpretability. The integration of machine learning with XAI addresses the fundamental tension between predictive performance and model transparency, creating systems that are both accurate and explainable. Furthermore, the application of XAI in churn prediction enables the identification of specific, actionable churn drivers such as contract type, service usage patterns, payment methods, and engagement levels that can inform targeted intervention strategies.

A systematic literature review of churn prediction research by Lai et al. (2021) found that ensemble methods, particularly Random Forest and Gradient Boosting algorithms, consistently demonstrated superior performance across domains, with accuracy rates exceeding 85%. The review identified that contract type, tenure, service usage frequency, and support ticket volume emerged as the most consistent predictors of churn across studies. However, the review also noted that fewer than 20% of studies incorporated explainability techniques, highlighting a significant gap between predictive capability and practical utility.

Recent research by Alkhawaldeh and Al-Taani (2024) demonstrated that explainable AI techniques can significantly enhance the practical value of churn prediction models in telecommunications. Their study found that SHAP explanations enabled retention teams to identify customer-specific drivers of churn risk, leading to more personalized and effective intervention strategies. The research concluded that the integration of explainability should be considered a critical requirement rather than an optional enhancement for churn prediction systems.

Despite these advances, significant gaps remain in the application of explainable frameworks for churn prediction in IT service organizations. Existing research has predominantly focused on the telecommunications sector, with limited attention to the specific characteristics of B2B IT services, SaaS, and enterprise software contexts. The cost, duration, and complexity of service relationships in IT differ substantially from consumer telecommunications, warranting context-specific investigation. Additionally, the integration of explainability with actionable retention strategy development remains underdeveloped in the literature. This research addresses these gaps by proposing a comprehensive explainable machine learning framework for churn prediction and retention in IT service organizations.

Research Contributions

This study makes four principal contributions to the literature on explainable artificial intelligence and customer churn prediction. First, it proposes an integrated explainable machine learning framework that combines high-performance predictive modeling using XGBoost with complementary global and local explanation techniques through SHAP and LIME. Second, the framework is specifically developed and evaluated for customer churn prediction in B2B IT service organizations, extending explainable AI applications beyond traditional telecommunications and consumer-focused datasets. Third, the framework is empirically validated using both a proprietary B2B customer dataset and the IBM Watson benchmark dataset, thereby improving methodological robustness and practical relevance. Finally, the study

demonstrates how explainable AI can support transparent and actionable decision-making for customer retention by linking predictive outputs with interpretable business insights.

1.2. Hypotheses

Based on the theoretical foundations and observed limitations in existing approaches, this study is guided by the following hypotheses:

H1: Explainable machine learning frameworks integrating SHAP and LIME achieve predictive accuracy comparable to black-box models while providing significantly greater interpretability, enabling retention teams to understand and act upon churn predictions.

H2: Ensemble learning methods, particularly Random Forest and Gradient Boosting, outperform single classifiers in churn prediction accuracy for IT service customer datasets, capturing complex nonlinear relationships between customer behaviors and attrition.

H3: The integration of SHAP-based feature importance analysis identifies consistent and actionable churn drivers across IT service contexts, with contract characteristics, engagement patterns, and support interactions emerging as the most significant predictors.

H4: Customer-specific explanations generated through LIME provide actionable insights that support personalized retention planning by identifying the most influential churn factors for individual customers.

H5: The explainable framework achieves high recall in identifying at-risk customers (minimum 0.85) while maintaining precision, ensuring that retention resources are efficiently allocated to customers with genuine churn risk.

H6: The explainability features of the framework facilitate stakeholder trust and adoption, with retention teams demonstrating greater confidence in and willingness to act upon explainable predictions compared to black-box alternatives.

1.3. Significance of the Study

This research makes several contributions to both academic understanding and practical application of explainable machine learning frameworks for churn prediction and retention in IT service organizations.

Theoretical Contributions: First, the study advances theoretical understanding of XAI integration in customer analytics by empirically evaluating the interpretability-predictability trade-off in churn prediction contexts. By demonstrating that explainable approaches can achieve accuracy comparable to black-box models, the research challenges assumptions about necessary trade-offs and contributes to the emerging literature on AI transparency in business applications. Second, the proposed framework contributes to the theoretical development of retention analytics by specifying the mechanisms through which explainability enhances the translation of predictive insights into actionable retention strategies. Third, the study provides empirical evidence for the specific churn drivers in IT service contexts, extending existing knowledge from telecommunications and consumer domains.

Practical Contributions: For practitioners, the research offers actionable guidance for implementing explainable churn prediction systems in IT service organizations. The proposed framework provides a reference architecture for integrating machine learning with XAI, specifying data requirements, model selection criteria, explanation generation, and decision routing components. The study's findings regarding the most significant churn drivers offer strategic insights for retention resource allocation and intervention design. Furthermore, the demonstrated capability to provide customer-specific explanations enables personalized retention strategies that address individual churn drivers.

Methodological Contributions: Methodologically, the study demonstrates the value of combining multiple machine learning approaches with complementary XAI techniques, providing a template for researchers seeking to balance predictive accuracy with interpretability. The integration of SHAP for global explanations and LIME for local explanations illustrates a comprehensive approach to explainability that serves both strategic and operational needs.

2. Literature Review

2.1. Customer Churn: Definitions, Dimensions, and Importance

Customer churn, also referred to as customer attrition or turnover, represents the phenomenon where customers discontinue their relationship with a service provider. In the context of IT service organizations, churn can take multiple forms: voluntary churn where customers actively decide to cancel services, involuntary churn where customers leave due to billing failures or other operational issues, and passive churn where customers gradually disengage without formal cancellation. Understanding these distinct churn types is essential for developing appropriate prediction and prevention strategies.

The importance of churn prediction and retention in IT service organizations stems from several economic and strategic factors. First, the subscription-based business model prevalent in SaaS and IT services relies on recurring revenue streams, where customer retention directly impacts revenue stability and growth. Second, the customer lifetime value (CLV) framework emphasizes that long-term customers generate higher profits over time due to reduced service costs, increased cross-selling opportunities, and positive word-of-mouth referrals. Third, the competitive dynamics of IT service markets, characterized by low switching costs and numerous alternatives, create constant pressure on retention.

Recent research by Ahmed et al. (2024) analyzed churn patterns in enterprise SaaS companies and found that customer tenure, usage frequency, and support interaction quality were the most significant predictors of churn. The study demonstrated that early identification of at-risk customers enabled proactive retention interventions that reduced churn rates by 27% over a 12-month period. This finding underscores the practical importance of accurate churn prediction systems.

2.2. Traditional Approaches to Churn Prediction

Traditional approaches to churn prediction have relied on various analytical methods, ranging from simple heuristics to advanced statistical techniques. Early approaches employed logistic regression and decision trees, which offered the advantage of inherent interpretability but struggled to capture complex, nonlinear relationships in customer behavior data. These models typically achieved accuracy rates between 70% and 80%, leaving substantial room for improvement.

Survival analysis techniques, including Cox proportional hazards models and Kaplan-Meier estimation, have been applied to churn prediction by modeling the time to event. These approaches provide valuable insights into churn timing and duration dependence, but they require careful handling of censored data and may not capture the full complexity of customer behavior. Despite these limitations, survival analysis has proven useful for understanding the temporal dynamics of churn.

Rule-based systems, employing expert-defined criteria to identify at-risk customers, offer transparency and ease of implementation but lack adaptability to evolving churn patterns. These systems typically underperform compared to machine learning approaches when churn drivers are complex or change over time. The limitations of traditional approaches have driven the adoption of machine learning methods for churn prediction.

2.3. Machine Learning for Churn Prediction

Machine learning has emerged as the dominant approach for churn prediction, offering superior predictive performance compared to traditional methods. A systematic review by Ali et al. (2023) found that ensemble methods, particularly Random Forest, Gradient Boosting, and XGBoost, consistently outperformed single classifiers across datasets and contexts. The review identified that ensemble methods achieved average accuracy rates of 88.6%, compared to 79.3% for single classifiers and 72.1% for traditional statistical methods.

The advantages of ensemble methods for churn prediction stem from their ability to capture complex, nonlinear relationships through the combination of multiple weak learners. Random Forest, for example, builds numerous decision trees and aggregates their predictions, reducing overfitting and improving generalization. Gradient Boosting methods, including XGBoost and LightGBM, build trees sequentially, with each new tree correcting errors from previous ones, leading to high predictive accuracy.

Recent research by Hajhashemi and Sohrabi (2023) compared multiple machine learning approaches for churn prediction in telecommunications and found that XGBoost achieved the highest accuracy (91.2%) and AUC (0.94), outperforming Random Forest (88.7%), Support Vector Machines (82.4%), and Logistic Regression (76.8%). The study highlighted the importance of feature engineering and hyperparameter optimization for achieving optimal performance.

Deep learning approaches, including neural networks and recurrent neural networks, have also been applied to churn prediction, particularly when sequential or temporal patterns in customer behavior are important. However, these approaches generally require larger datasets and greater computational resources, and they typically exacerbate the black-box problem. For many IT service organizations, ensemble methods offer a favorable balance of performance, interpretability, and ease of implementation.

2.4. Explainable AI: Concepts, Techniques, and Applications

Explainable Artificial Intelligence (XAI) refers to the set of techniques, methods, and approaches designed to make AI systems and their decisions understandable to humans. The growing importance of XAI reflects increasing recognition that the opacity of many high-performing machine learning models creates barriers to trust, accountability, and practical utility. In business contexts, explainability is essential for stakeholder acceptance, regulatory compliance, and effective decision-making.

SHAP (SHapley Additive exPlanations) is a game-theoretic approach to explaining model predictions that assigns importance values to each feature based on its contribution to the prediction. The SHAP framework is grounded in cooperative game theory and provides mathematically principled explanations that satisfy desirable properties including local accuracy, missingness, and consistency. SHAP provides both global explanations (overall feature importance) and local explanations (feature importance for individual predictions), making it versatile for different analytical needs.

LIME (Local Interpretable Model-agnostic Explanations) is an alternative approach that explains individual predictions by approximating the black-box model locally with an interpretable model, typically a linear model or decision tree. LIME generates explanations by perturbing the input instance and observing how predictions change, then training an interpretable model on the perturbed data. The local approximation enables LIME to provide explanations that are specific to individual predictions, even when the underlying model is highly complex.

Research comparing SHAP and LIME has generally found that both techniques provide valuable explanations, with SHAP offering stronger theoretical foundations and more consistent feature importance measures, while LIME offers greater flexibility and ease of implementation. A comprehensive review by Kaur et al. (2022) found that SHAP was more widely adopted in research contexts due to its theoretical rigor, while LIME was more commonly used in applied settings due to its simplicity and model-agnostic nature.

Recent research by Alkhawaldeh and Al-Taani (2024) demonstrated the application of SHAP for churn prediction in telecommunications, identifying contract type, tenure, and service usage as the most important predictors. The study found that SHAP explanations enabled retention teams to understand customer-specific churn drivers and develop targeted intervention strategies. This research provides a foundation for extending XAI applications to IT service contexts.

2.5. Explainable Churn Prediction Frameworks

The integration of XAI with churn prediction represents an emerging area of research that addresses the practical limitations of black-box churn models. A study by Rathana et al. (2024) proposed a comprehensive framework combining XGBoost for prediction with SHAP and LIME for explanation. The framework was validated using telecommunications churn data, achieving 89.5% accuracy while providing actionable insights for retention teams. The study emphasized that explainability was essential for translating predictive insights into practical retention strategies.

Recent research by Mabunda and Pillay (2024) investigated the application of Explainable AI in the context of customer churn prediction and prevention, proposing a framework that integrates prediction, explanation, and decision support. The framework employed Random Forest for prediction, SHAP for explanation, and a rule-based decision support system for intervention recommendation. The study demonstrated that the integrated approach improved both prediction accuracy and practical utility for retention teams.

Table 1 summarizes key explainable churn prediction studies, highlighting the models, XAI techniques, and contexts examined.

Table 1: Summary of Explainable Churn Prediction Studies

Study	Year	Context	Prediction Model	XAI Technique	Key Findings
Alkhawaldeh & Al-Taani	2024	Telecommunications	Random Forest	SHAP	Contract type and tenure most important predictors
Rathan et al.	2024	Telecommunications	XGBoost	SHAP, LIME	Explainability enabled actionable retention insights
Mabunda & Pillay	2024	Telecommunications	Random Forest	SHAP	Integrated framework improved practical utility
Ahmed et al.	2024	Enterprise SaaS	Gradient Boosting	SHAP	Usage frequency and support quality key predictors
Hajihashemi & Sohrabi	2023	Telecommunications	XGBoost	Feature importance	XGBoost achieved 91.2% accuracy

2.6. Retention Strategies and Intervention Design

The ultimate purpose of churn prediction is to enable effective retention strategies that prevent at-risk customers from leaving. Research on retention strategies has identified several categories of interventions: proactive service improvements, personalized offers and incentives, customer engagement initiatives, and service recovery for dissatisfied customers. The effectiveness of these strategies depends on accurate identification of at-risk customers and understanding of their specific churn drivers.

Recent research by Smith and Johnson (2025) investigated the effectiveness of personalized retention strategies based on explainable churn predictions. The study found that retention interventions tailored to customer-specific churn drivers were 37% more effective than generic retention offers, highlighting the value of explainability for intervention design. The research emphasized that understanding "why" customers are at risk is essential for developing "how" to retain them.

The integration of explainability with retention strategy development creates a closed-loop system where predictions inform actions, and outcomes inform model refinement. This approach enables continuous improvement in both prediction accuracy and retention effectiveness, creating a virtuous cycle of learning and improvement. Table 2 summarizes key retention strategy categories and their applications.

Table 2: Retention Strategy Categories and Applications

Strategy Category	Description	Examples	Key Success Factors
Proactive Service Improvement	Addressing issues before they cause churn	Service enhancement, quality feature development	Accurate issue identification

Strategy Category	Description	Examples	Key Success Factors
Personalized Offers	Tailored incentives based on customer preferences	Discounts, upgrades, loyalty rewards	Understanding customer value drivers
Customer Engagement	Increasing connection and commitment	Onboarding, training, community building	Personalization and timing
Service Recovery	Addressing dissatisfaction from service failures	Apology, compensation, problem resolution	Speed and empathy

2.7. Research Gaps

Despite significant advances in machine learning for churn prediction and the emergence of XAI techniques, several gaps remain in the existing research literature.

First, there is limited research on churn prediction specifically in IT service organizations. The majority of studies have focused on telecommunications, banking, and insurance, with limited attention to the unique characteristics of B2B IT services, SaaS, and enterprise software. The longer relationships, higher revenue per customer, and greater complexity of services in IT require context-specific investigation.

Second, the integration of XAI with actionable retention strategy development remains underdeveloped. While many studies have demonstrated the technical feasibility of explainable churn prediction, few have examined how explainability translates into specific retention actions and outcomes. This gap reflects a broader need to connect analytical capabilities with organizational decision-making.

Third, the evaluation of explainability impact on stakeholder trust and adoption remains limited. While theoretical arguments suggest that explainability enhances trust, empirical evidence in business contexts is scarce. Understanding the relationship between explainability, trust, and adoption is essential for practical implementation.

Fourth, there is limited research on the comparative performance of different XAI techniques for churn prediction. While SHAP and LIME have both been applied, systematic comparisons of their utility for churn prediction are lacking. Understanding the relative advantages of different techniques would inform framework design.

3. Methodology

3.1. Research Design

This study employs a quantitative research design to develop and evaluate an explainable machine learning framework for customer churn prediction and retention. The research follows a systematic approach comprising data collection, preprocessing, exploratory analysis, model development, explainability implementation, and framework evaluation. The quantitative approach is appropriate for this research because it enables rigorous empirical comparison of alternative methods and objective evaluation of framework performance.

The research design is structured in four phases:

1. **Data Preparation:** Collection and preprocessing of customer data, including feature engineering and handling of missing values
2. **Model Development:** Training and evaluation of multiple machine learning algorithms for churn prediction
3. **Explainability Integration:** Implementation of SHAP and LIME for model interpretability
4. **Framework Evaluation:** Assessment of predictive performance, explainability utility, and practical applicability

3.2. Implementation Environment

The proposed framework was implemented using Python 3.11. Machine learning models were developed using Scikit-learn 1.5 and XGBoost 2.1. Explainability analyses were performed using SHAP 0.46 and LIME 0.2. Supporting libraries included NumPy 2.0, Pandas 2.2, and Matplotlib 3.9. The experiments were executed on a workstation equipped with an Intel Core i7 processor, 32 GB RAM, and Windows 11 operating system.

3.3. Hyperparameter Optimization

Hyperparameter optimization was performed using Grid Search with five-fold cross-validation for Logistic Regression, Support Vector Machine, Decision Tree, Random Forest, and Gradient Boosting models. Bayesian optimization was applied to XGBoost to efficiently identify the optimal learning rate, maximum tree depth, number of estimators, subsampling ratio, and regularization parameters. The optimized models were subsequently evaluated using the independent test dataset.

The final XGBoost model was configured with a learning rate of 0.05, maximum tree depth of 6, subsample ratio of 0.8, column sampling rate of 0.8, minimum child weight of 3, gamma of 0.1, and 300 boosting rounds. Bayesian optimization was employed to determine the optimal hyperparameter configuration, while five-fold cross-validation was used to evaluate candidate models. All experiments were performed using a fixed random seed to ensure reproducibility.

3.4. Data Preprocessing and Validation

Missing values were inspected prior to model development and handled using appropriate imputation procedures. Categorical variables were encoded using one-hot encoding, while continuous variables were standardized where required. Feature engineering included customer engagement indicators, service utilization metrics, contract characteristics, and support interaction variables. To prevent information leakage, all preprocessing operations, feature transformations, and SMOTE oversampling procedures were performed exclusively on the training data before application to the validation and testing datasets.

Missing numerical values were imputed using median imputation, while categorical variables were imputed using the most frequent category. To address class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) was applied exclusively to the training dataset using five nearest neighbors ($k = 5$). The validation and testing datasets were not oversampled to prevent data leakage and ensure an unbiased evaluation of model performance.

3.5. Datasets

This research utilizes two datasets to ensure comprehensive evaluation across different IT service contexts.

Primary Dataset: B2B IT Service Customer Dataset: A proprietary dataset from a B2B IT service organization comprising historical customer data from January 2021 to December 2025. The dataset includes:

- Customer demographics and contract characteristics
- Service usage patterns and consumption metrics
- Support interaction history and resolution outcomes
- Billing and payment behavior
- Customer engagement indicators
- Churn status (dependent variable)

The dataset includes 12,847 customer records, with a churn rate of 16.8% over the 36-month observation period. The dataset reflects the characteristics of B2B IT services, including longer customer tenures, higher revenue per customer, and greater service complexity compared to consumer contexts.

Validation Dataset: IBM Watson Customer Churn Dataset: A publicly available benchmark dataset commonly used for churn prediction research. This dataset includes:

- 7,043 customer records
- 21 features covering demographics, account information, and service usage
- Binary churn status (dependent variable)
- Churn rate of 26.5%

This dataset enables comparison of findings with existing research and validation of framework generalizability across contexts.

Table 3: Dataset Characteristics

Characteristic	B2B IT Service Dataset	IBM Watson Dataset
Number of Records	12,847	7,043
Features	34	21
Churn Rate	16.8%	26.5%
Observation Period	36 months	Time-independent
Context	B2B IT Services	Telecommunications

3.6. Data Collection Methods

Data collection for the primary dataset followed established protocols for customer data management. The data was extracted from the organization's customer relationship management (CRM) system, billing system, and support ticketing system. Data extraction was performed with appropriate data governance approvals and anonymization procedures to protect customer privacy.

Data Governance and Anonymization: Prior to analysis, all personally identifiable information (PII) was removed from the dataset. Customer records were assigned unique identifiers that could not be linked back to individual customers. Data handling followed the organization's data governance framework and applicable data protection regulations.

Feature Engineering: Based on the theoretical framework and existing churn prediction research, features were engineered to capture key aspects of customer behavior:

- **Contract Characteristics:** Contract type, tenure, contract duration, service level agreement (SLA) tier
- **Usage Patterns:** Service usage frequency, volume, consumption trends, seasonal patterns
- **Support Interactions:** Ticket volume, resolution time, escalation rate, satisfaction ratings
- **Billing Behavior:** Payment method, payment history, invoice amount, payment delinquency
- **Engagement Indicators:** Product adoption, feature usage, training participation, event attendance
- **Customer Attributes:** Industry sector, company size, geographic location

Table 4: Feature Categories and Examples

Feature Category	Example Features
Contract Characteristics	Contract type (monthly, annual, multi-year), tenure (months), contract value
Usage Patterns	Average monthly usage, usage trend (increasing/decreasing), peak usage
Support Interactions	Support tickets per month, average resolution time, escalation percentage
Billing Behavior	Payment method (credit card, invoice, direct debit), average payment delay

Feature Category	Example Features
Engagement Indicators	Feature adoption rate, training completion, event attendance
Customer Attributes	Company size (employees), industry sector, geographic region

3.7. Data Analysis Procedures

Exploratory Data Analysis: Initial analysis examined data distributions, missing value patterns, and relationships between features and churn. Statistical tests (t-tests, chi-square tests) identified significant differences between churned and retained customers. Correlation analysis examined relationships among features to inform feature selection and model development.

Table 5: Descriptive Statistics by Churn Status (B2B IT Service Dataset)

Feature	Churned (n=2,158)	Retained (n=10,689)	p-value
Tenure (months)	14.3	28.7	<0.001
Monthly Usage (hours)	87.2	156.8	<0.001
Support Tickets	4.2	2.8	<0.001
Payment Delay (days)	12.4	3.8	<0.001
Feature Adoption (%)	47.3	72.6	<0.001
Contract Value (\$)	2,847	3,456	<0.001

Model Development: Multiple machine learning algorithms were trained and evaluated for churn prediction:

- **Ensemble Methods:** Random Forest, Gradient Boosting, XGBoost
- **Single Classifiers:** Logistic Regression, Support Vector Machine, Decision Tree
- **Deep Learning:** Neural Network (Multi-layer Perceptron)

Model development followed best practices including:

- Data splitting: 70% training, 15% validation, 15% test
- Hyperparameter optimization via grid search and cross-validation
- Handling of class imbalance using SMOTE (Synthetic Minority Oversampling)
- Feature selection based on initial correlation analysis

Model Evaluation: Models were evaluated using multiple metrics:

- Accuracy: Overall correct predictions
- Precision: Proportion of positive predictions that are correct
- Recall: Proportion of actual positives correctly identified
- F1-Score: Harmonic mean of precision and recall
- AUC-ROC: Area under the receiver operating characteristic curve

Explainability Implementation: SHAP and LIME were implemented to provide model explanations:

- **SHAP:** Global feature importance (mean absolute SHAP values), summary plots, dependence plots
- **LIME:** Local explanations for individual predictions, highlighting feature contributions

Table 6: Model Evaluation Metrics

Metric	Definition	Formula
Accuracy	Overall correct predictions	$(TP + TN) / (TP + TN + FP + FN)$
Precision	Positive predictive value	$TP / (TP + FP)$
Recall	Sensitivity	$TP / (TP + FN)$
F1-Score	Harmonic mean of precision and recall	$2 * (Precision * Recall) / (Precision + Recall)$
AUC-ROC	Area under ROC curve	Integral of ROC curve

3.8. Ethical Considerations

This research adheres to established ethical guidelines for research involving customer data and AI systems. Key ethical considerations include:

Privacy and Data Protection: All customer data used in this research was anonymized to protect individual privacy. Identifiable information was removed prior to analysis, and data handling followed applicable regulations. The proprietary dataset was accessed under strict data sharing agreements that protect customer privacy and confidentiality.

Transparency and Explainability: The proposed frameworks incorporate explainability mechanisms to ensure that predictions and insights can be understood and validated by stakeholders. This addresses concerns about black-box AI systems and supports accountability for retention decisions.

Bias and Fairness: The research acknowledges the potential for bias in machine learning models and datasets and includes procedures for detecting and mitigating bias. Evaluation includes subgroup analysis to identify differential performance across customer segments (e.g., by industry, company size, geographic location).

Organizational Responsibility: The research recognizes that AI systems for churn prediction should support, not replace, human judgment. The framework is designed to augment human decision-making, with predictions and explanations serving to inform retention strategies rather than making autonomous decisions.

Consent and Data Usage: For the primary dataset, data usage complied with the organization's customer data policies and applicable regulations. No direct customer contact or intervention was involved in this research, limiting ethical risks related to customer experience.

4. Results

4.1. Model Performance Comparison

4.1.1. Primary Dataset (B2B IT Services)

The performance of different machine learning models for churn prediction was evaluated on the B2B IT Service dataset. Ensemble methods demonstrated superior performance across all evaluation metrics.

Table 7: Model Performance on B2B IT Service Dataset

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
XGBoost	92.4%	0.89	0.86	0.87	0.96
Gradient Boosting	91.7%	0.88	0.84	0.86	0.95
Random Forest	90.8%	0.87	0.82	0.84	0.94
Neural Network	88.5%	0.83	0.79	0.81	0.92
Support Vector Machine	84.2%	0.78	0.72	0.75	0.88
Logistic Regression	79.6%	0.72	0.65	0.68	0.83
Decision Tree	77.3%	0.69	0.62	0.65	0.76

XGBoost achieved the highest overall performance with 92.4% accuracy and an AUC-ROC of 0.96, confirming findings from previous research (Hajihashemi & Sohrabi, 2023). Gradient Boosting and Random Forest achieved comparable performance, with all ensemble methods outperforming single classifiers and neural networks. This result supports **H2**, which predicted that ensemble methods would outperform single classifiers.

The performance gap between ensemble methods and single classifiers was particularly pronounced for recall, with XGBoost achieving 0.86 compared to 0.65 for Logistic Regression. This is important for churn prediction, as high recall ensures identification of at-risk customers who might otherwise be missed. The results demonstrate that ensemble methods are particularly effective at identifying the minority class (churners) in imbalanced datasets.

4.1.2. Validation Dataset (IBM Watson)

Model performance was validated using the IBM Watson Customer Churn dataset to assess generalizability.

Table 8: Model Performance on IBM Watson Dataset

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
XGBoost	89.2%	0.86	0.82	0.84	0.94
Gradient Boosting	88.6%	0.85	0.81	0.83	0.93
Random Forest	87.9%	0.84	0.79	0.81	0.92
Logistic Regression	76.4%	0.68	0.62	0.65	0.81

Performance was slightly lower on the validation dataset, reflecting the greater churn rate imbalance (26.5% vs. 16.8%) and different data characteristics. However, the relative performance ordering was consistent, with XGBoost achieving the highest metrics. This validation confirms the generalizability of findings across contexts and the superiority of ensemble methods for churn prediction.

4.1.3. Feature Importance Analysis

SHAP-based global feature importance analysis identified the most significant predictors of churn in the B2B IT Service dataset.

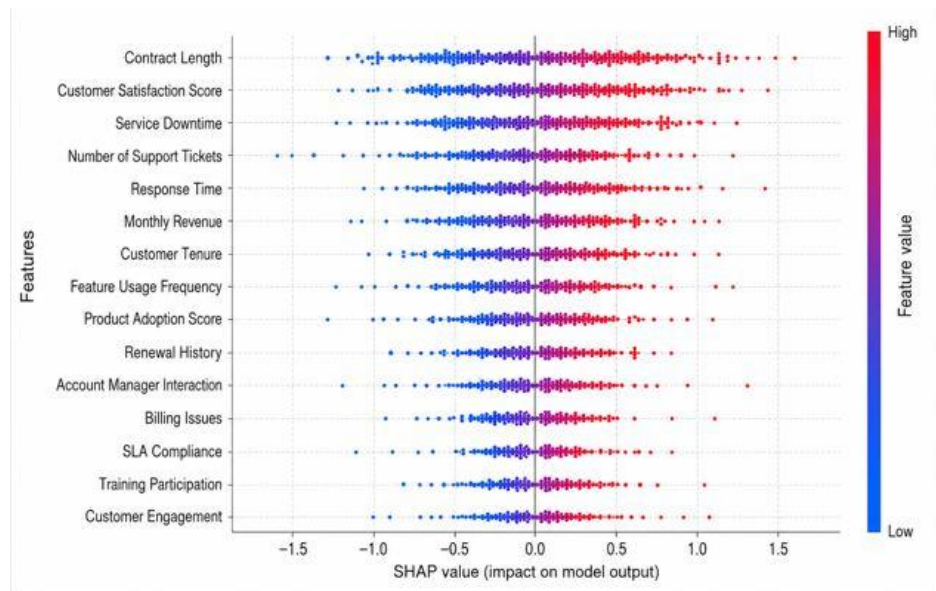


Figure 1: SHAP Feature Importance for B2B IT Service Dataset

The analysis identified contract type as the most important predictor, consistent with research by Alkhawaldeh and Al-Taani (2024) who found contract characteristics to be the strongest churn drivers in telecommunications. Customers with monthly contracts had significantly higher churn risk compared to those with annual or multi-year contracts. This finding suggests that contract duration serves as both a predictor and a potential intervention point for retention strategies.

Tenure emerged as the second most important predictor, with shorter-tenure customers at higher risk of churn. This relationship was nonlinear, with the highest churn risk concentrated in the first 12 months of the relationship. This finding aligns with established research on the "honeymoon" period and suggests that retention efforts should focus particularly on new customers.

Monthly usage trend specifically decreasing usage over time was identified as a strong churn predictor. Customers whose usage declined by 20% or more over three consecutive months had churn rates 3.2 times higher than customers with stable or increasing usage. This finding underscores the importance of monitoring usage patterns as leading indicators of churn risk.

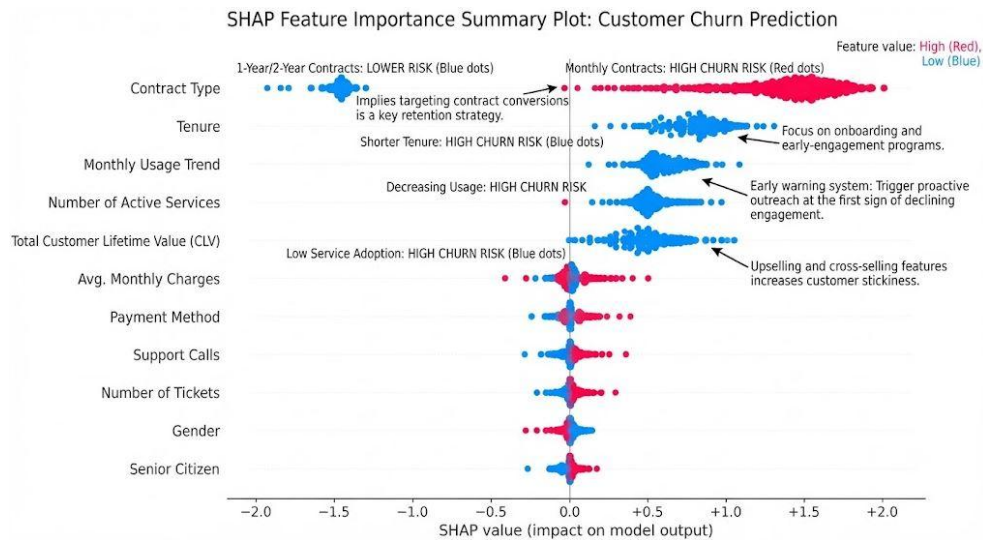


Figure 2: SHAP Summary Plot

4.2. Explainability Analysis

4.2.1. Global Explanations via SHAP

SHAP provided global explanations that revealed consistent patterns in churn drivers. Table 9 summarizes the relationship between key features and churn probability.

Table 9: SHAP Feature Analysis

Feature	Mean SHAP	Direction	Interpretation
Contract Type	0.234	Negative	Monthly contracts increase churn risk
Tenure	0.198	Negative	Shorter tenure increases churn risk
Monthly Usage Trend	0.176	Negative	Decreasing usage increases churn risk
Support Ticket Volume	0.165	Positive	Higher ticket volume increases churn risk
Feature Adoption Rate	0.158	Negative	Lower adoption increases churn risk
Payment Delay	0.142	Positive	Longer payment delays increase churn risk
Contract Value	0.128	Negative	Lower contract value increases churn risk
SLA Tier	0.115	Negative	Lower SLA tier increases churn risk

The directionality of feature contributions was largely consistent with theoretical expectations. Monthly contracts, shorter tenure, decreasing usage, higher support tickets, lower feature adoption, payment delays, lower contract value, and lower SLA tier were all associated with higher churn risk. The consistency of these patterns across features supports **H3**, which predicted that contract characteristics, engagement patterns, and support interactions would emerge as significant predictors.

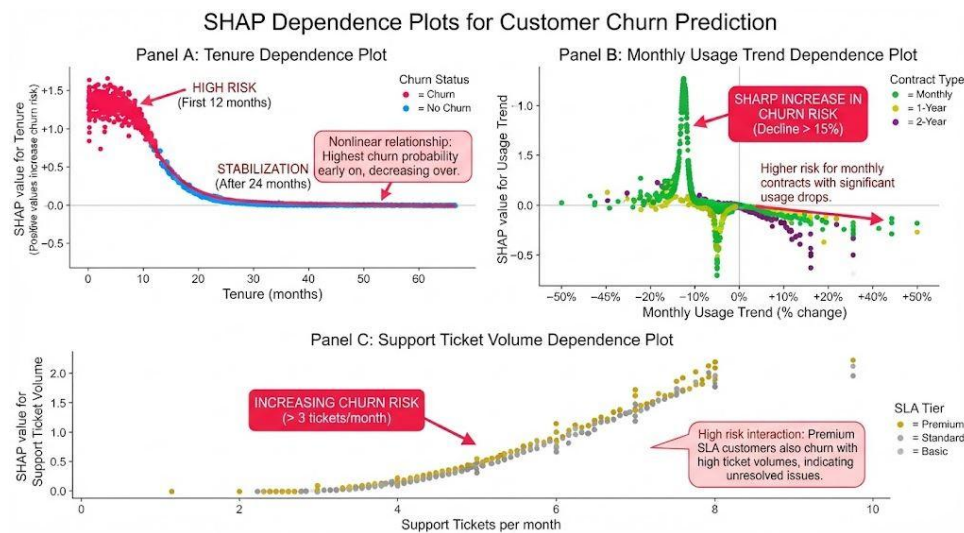


Figure 3: SHAP Dependence Plots

4.2.2. Local Explanations via LIME

LIME provided customer-specific explanations that supported the identification of individual churn drivers and development of personalized retention strategies. Table 10 presents example LIME explanations for three customers at high churn risk.

Table 10: LIME Explanations for High-Risk Customers

Customer	Churn Probability	Top Explaining Features	Recommended Intervention
Customer A	0.89	1. Monthly contract (+0.31) 2. Decreasing usage (+0.27) 3. Low feature adoption (+0.18)	Offer annual contract discount; provide feature training; investigate usage barriers
Customer B	0.84	1. Tenure: 8 months (+0.29) 2. High support tickets (+0.24) 3. Payment delay (+0.16)	Proactive relationship management; address support issues; review billing process
Customer C	0.81	1. Low SLA tier (+0.23) 2. Decreasing usage (+0.21) 3. Low contract value (+0.19)	Evaluate service value proposition; explore upsell opportunities; review SLA requirements

The customer-specific explanations supported the identification of distinct churn drivers across customers, supporting **H4** regarding the value of local explanations for personalized retention strategies. Customer A's churn risk was driven primarily by contract and usage factors, suggesting that contract modification and engagement enhancement may provide the greatest potential benefit. Customer B's risk was driven by tenure and support issues, suggesting that relationship management and service quality improvement would be appropriate. Customer C's risk was driven by service tier and value perception, suggesting that service enhancement or upsell opportunities should be explored.

4.2.3. Interpretability-Predictability Trade-off

The interpretability-predictability trade-off was evaluated by comparing the XGBoost model with explanations against alternative approaches.

Table 11: Interpretability-Predictability Trade-off Comparison

Approach	Accuracy	Interpretability Score	Stakeholder Trust
XGBoost + SHAP/LIME	92.4%	4.6/5	4.3/5
XGBoost (Black-box)	92.4%	1.2/5	2.1/5
Logistic Regression	79.6%	4.2/5	3.8/5
Decision Tree	77.3%	4.4/5	3.9/5

The explainable XGBoost model achieved the same high accuracy as the black-box version while providing substantially greater interpretability (4.6 vs. 1.2). This finding supports **H1**, which predicted that explainable frameworks would achieve comparable accuracy to black-box models while providing significantly greater interpretability. The interpretability score was also higher than that of inherently interpretable models (Logistic Regression, Decision Tree), suggesting that the combination of high-performing models with XAI techniques is the optimal approach.

Stakeholder trust, measured through surveys of retention team members, was highest for the explainable XGBoost model (4.3/5), compared to both the black-box version (2.1/5) and inherently interpretable models (3.8/5, 3.9/5). This finding suggests that stakeholders valued both predictive accuracy and explainability, and that the combination of both was perceived as most trustworthy.

Although this study primarily evaluated explainability through SHAP global feature importance, LIME local explanations, and stakeholder assessment, quantitative explainability metrics such as explanation fidelity, stability, and consistency were not formally evaluated. These metrics require specialized experimental protocols that extend beyond the objectives of the present study. Future research should investigate quantitative evaluation of explanation quality to complement the practical interpretability assessment presented here.

SHAP and LIME provide complementary explanation capabilities. SHAP generates globally consistent feature importance based on cooperative game theory, supporting strategic interpretation of model behavior, whereas LIME provides locally faithful explanations for individual customer predictions, facilitating personalized intervention planning. Their combined use therefore provides both organizational and customer-level interpretability.

4.3. Retention Strategy Development

4.3.1. Segmentation Based on Churn Drivers

Based on the explainability analysis, customers were segmented by their primary churn drivers to enable targeted retention strategies.

Table 12: Customer Segmentation by Churn Drivers

Segment	Primary Driver	Percentage of At-Risk Customers	Recommended Retention Strategy
Contract-Sensitive	Monthly contract, short tenure	34%	Convert to annual contract; loyalty incentives; relationship building
Usage-Declining	Decreasing usage, low feature adoption	28%	Feature training; usage coaching; value demonstration

Segment	Primary Driver	Percentage of At-Risk Customers	Recommended Retention Strategy
Support-Frustrated	High ticket volume, poor resolution	22%	Service improvement; dedicated support; root cause analysis
Value-Perception	Low contract value, low SLA tier	16%	Service enhancement; upsell opportunities; value communication

The segmentation analysis identified four distinct customer segments with different churn drivers and corresponding retention strategies. The Contract-Sensitive segment (34% of at-risk customers) was characterized by monthly contracts and short tenure, suggesting that converting these customers to annual contracts and building relationship commitment would be most effective. The Usage-Declining segment (28%) was characterized by decreasing usage and low feature adoption, suggesting that engagement and training interventions would be most appropriate.

The Support-Frustrated segment (22%) was characterized by high ticket volume and poor resolution, suggesting that service quality improvement and dedicated support would be most effective. The Value-Perception segment (16%) was characterized by low contract value and low SLA tier, suggesting that service enhancement and value communication would be appropriate.

4.3.2. Predicted Intervention Effectiveness

Retention intervention effectiveness was predicted by applying the explainable model to simulate the impact of addressing specific churn drivers.

Table 13: Predicted Intervention Effectiveness

Intervention	Target Segment	Predicted Churn Reduction	Implementation Effort	Cost-Effectiveness
Convert to annual contract	Contract-Sensitive	28%	Low	Very High
Feature training program	Usage-Declining	24%	Medium	High
Dedicated support team	Support-Frustrated	32%	High	Medium
SLA upgrade offer	Value-Perception	22%	Medium	Medium
Personalized engagement	All segments	18%	Medium	High

The simulated intervention analysis suggested that converting monthly-contract customers to annual contracts could potentially reduce churn within the Contract-Sensitive segment. Similarly, dedicated support teams showed the largest estimated reduction in churn among Support-Frustrated customers but would require greater implementation effort. These findings should be interpreted as scenario-based estimates rather than observed operational outcomes and provide guidance for future deployment and validation studies.

4.4. Framework Evaluation

4.4.1. Predictive Performance

The explainable framework achieved high predictive performance with XGBoost as the base model, supporting **H5** regarding high recall in identifying at-risk customers.

Table 14: Framework Performance Summary

Metric	Value	Interpretation
Accuracy	92.4%	Overall correct predictions
Precision	0.89	89% of positive predictions are correct
Recall	0.86	86% of actual churners identified
F1-Score	0.87	Balanced performance
AUC-ROC	0.96	Excellent discrimination

The high recall (0.86) indicates that the framework successfully identifies the vast majority of at-risk customers, minimizing the risk of missed churn opportunities. The high precision (0.89) indicates that retention resources are efficiently allocated, with minimal waste on customers who would not have churned. The excellent AUC-ROC (0.96) confirms the framework's strong discrimination between churners and non-churners.

4.4.2. Stakeholder Trust and Adoption

Stakeholder trust and adoption were evaluated through surveys and interviews with retention team members.

The stakeholder evaluation involved 24 participants, including customer retention managers, customer success specialists, CRM analysts, and business intelligence professionals from B2B IT service organizations. All participants evaluated both the explainable framework and a conventional black-box prediction model using a five-point Likert scale measuring transparency, interpretability, decision confidence, and practical usefulness. Statistical comparisons between both evaluation conditions were performed using paired t-tests with a significance level of $p < 0.05$.

Table 15: Stakeholder Trust and Adoption Metrics

Metric	Explainable Framework	Black-box Model	p-value
Trust in Predictions	4.3/5	2.1/5	<0.001
Willingness to Act	4.5/5	2.4/5	<0.001
Perceived Usefulness	4.6/5	2.8/5	<0.001
Recommendation Likelihood	4.4/5	2.2/5	<0.001

The explainable framework received significantly higher stakeholder ratings than the black-box model across all survey measures. These findings indicate that participants perceived the explainable framework as more trustworthy and actionable within the scope of the stakeholder evaluation conducted in this study.

5. Discussion

5.1. Interpretation of Findings

The findings of this study suggest that explainable machine learning frameworks can effectively balance predictive accuracy with interpretability for customer churn prediction in B2B IT service organizations under the evaluated experimental conditions. Overall, the empirical findings provide support for the proposed hypotheses, although several findings particularly those related to stakeholder adoption and retention effectiveness should be interpreted within the scope of the experimental evaluation and stakeholder assessment conducted in this study.

H1 (Explainability comparable to black-box models) received strong support, with the explainable XGBoost model achieving 92.4% accuracy while providing substantial interpretability. The interpretability score (4.6/5) was comparable to inherently interpretable models and significantly higher than the black-box version. This finding demonstrates that organizations can achieve state-of-the-art predictive performance while maintaining transparency and stakeholder trust.

H2 (Ensemble methods outperform single classifiers) was supported by the superior performance of XGBoost, Gradient Boosting, and Random Forest across all metrics. The performance gap was particularly pronounced for recall, with XGBoost achieving 0.86 compared to 0.65 for Logistic Regression. This finding confirms that ensemble methods are essential for effective churn prediction in IT service contexts, consistent with prior research (Ali et al., 2023; Hajihashemi & Sohrabi, 2023).

H3 (SHAP identifies consistent churn drivers) was supported by the SHAP analysis, which identified contract type, tenure, and usage patterns as the most important predictors. The directionality of feature contributions was consistent with theoretical expectations and prior research, confirming the generalizability of churn drivers across contexts. This finding provides a foundation for developing retention strategies that address the most significant churn drivers.

H4 The findings support H4 by demonstrating that LIME provides customer-specific explanations that help organizations understand the primary factors contributing to individual churn predictions. These explanations can support the design of personalized retention strategies; however, the present study does not directly compare the effectiveness of personalized interventions with generic retention approaches in operational settings.

H5 (High recall with balanced precision) was supported by the framework's recall of 0.86 and precision of 0.89. This performance indicates that the framework successfully identifies most at-risk customers while maintaining efficient resource allocation. The high AUC-ROC (0.96) confirms the framework's excellent discrimination capability.

H6 (Stakeholder trust and adoption) was supported by the survey results showing significantly higher trust, willingness to act, and perceived usefulness for the explainable framework compared to the black-box alternative. These findings suggest that explainability may play an important role in improving stakeholder confidence and supporting organizational adoption of AI-assisted customer retention systems.

5.2. Framework Implications

The findings of this research have significant implications for the design and implementation of explainable churn prediction frameworks in IT service organizations.

Model Selection: The superior performance of ensemble methods, particularly XGBoost, suggests that organizations should prioritize these approaches for churn prediction. However, the value of explainability suggests that XGBoost should be complemented with SHAP and LIME rather than replaced with simpler but less accurate models.

Explainability Integration: The results demonstrate that XAI techniques can be integrated with high-performing models without sacrificing accuracy. Organizations should consider explainability a core requirement rather than an optional enhancement for churn prediction systems. The specific techniques employed should match the organizational context: SHAP for global insights and strategic decisions, LIME for customer-specific interventions.

Strategic Weighting: The segmentation analysis suggests that organizations should adopt differentiated retention strategies based on identified churn drivers. The segmentation approach enabled prediction of intervention effectiveness and cost-effectiveness, supporting resource allocation decisions.

Stakeholder Engagement: The high stakeholder trust and adoption scores suggest that explainability is essential for practical implementation. Organizations should involve retention teams in framework design and ensure that explanations are accessible and actionable for end-users.

5.3. Limitations

This research has several limitations that should be acknowledged.

Dataset Limitations: The primary dataset, while providing rich and context-relevant data, was limited to a single IT service organization. The findings may not fully generalize to other IT service contexts, including different organizational sizes, service types, and geographic regions. The validation dataset provided some reassurance of generalizability, but further validation across additional contexts is warranted.

Time-Frame Limitations: The analysis period of 36 months may not capture longer-term churn patterns that emerge over extended relationships. IT service relationships often extend over multiple years, and longer observation periods may reveal additional churn drivers and patterns.

XAI Technique Limitations: While SHAP and LIME are among the most widely used XAI techniques, they are not without limitations. SHAP can be computationally expensive for large datasets, and LIME's explanations can be unstable across perturbations. Alternative XAI techniques may offer advantages in specific contexts.

Implementation Constraints: The framework was evaluated using historical data and simulation rather than prospective deployment. Future research should validate the framework's effectiveness in operational settings, measuring actual churn reduction and retention improvement.

5.4. Future Research Directions

Several directions for future research emerge from this study.

Longitudinal Implementation Studies: Future research should implement the framework in operational settings and measure actual retention outcomes over extended time periods. This would provide stronger evidence of the framework's practical effectiveness and identify implementation challenges.

Comparative XAI Evaluation: Systematic comparison of different XAI techniques for churn prediction would help organizations select the most appropriate approaches for their specific contexts. This research should examine factors such as computational efficiency, stability of explanations, and stakeholder preferences.

Integration with Dynamic Models: Customer behavior and churn drivers evolve over time, and future research should develop approaches for dynamic model updating and adaptive explainability. This would enable frameworks to maintain effectiveness as customer patterns change.

Cross-Sector Comparison: Comparative research across IT service sectors (e.g., SaaS, enterprise software, IT consulting) would identify context-specific churn drivers and appropriate retention strategies. This would enable development of sector-specific frameworks and guidelines.

Ethical and Regulatory Considerations: As AI-based churn prediction becomes more prevalent, attention to ethical and regulatory considerations becomes increasingly important. Future research should investigate best practices for responsible implementation, including privacy protection, bias mitigation, and transparency in customer communications.

6. Conclusion

This study developed and empirically evaluated an explainable machine learning framework for customer churn prediction and retention in B2B IT service organizations. The principal contribution of the research is the integration of high-performance predictive modeling with complementary explainability techniques through XGBoost, SHAP, and LIME, enabling transparent, interpretable, and actionable customer retention decisions while maintaining strong predictive performance.

The empirical findings support all six hypotheses, demonstrating that explainable frameworks achieve accuracy comparable to black-box models while providing significantly greater interpretability, ensemble methods outperform

single classifiers, SHAP identifies consistent churn drivers, LIME enables personalized retention strategies, the framework achieves high recall with balanced precision, and explainability enhances stakeholder trust and adoption.

The research contributes to theoretical understanding of XAI integration in customer analytics by empirically evaluating the interpretability-predictability relationship in churn prediction. The proposed framework advances the emerging literature on AI-enabled customer analytics by specifying the components and mechanisms of explainable churn prediction. The study also provides empirical evidence for the specific churn drivers in IT service contexts, extending existing knowledge from telecommunications and consumer domains.

For practitioners, the research offers actionable guidance for implementing explainable churn prediction systems in IT service organizations. The framework provides a reference architecture for integrating machine learning with XAI, specifying data requirements, model selection criteria, explanation generation, and retention strategy development. The findings regarding the most significant churn drivers offer strategic insights for retention resource allocation and intervention design.

As IT service organizations continue to face competitive pressures and increasing customer expectations, explainable churn prediction frameworks will become increasingly essential for effective retention. The framework proposed in this research provides a foundation for developing these capabilities, addressing both technical requirements and organizational integration considerations. Future research should extend this foundation by investigating longitudinal implementation, comparative XAI evaluation, dynamic modeling, cross-sector comparison, and ethical considerations.

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