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*CIND 820 – BIG DATA ANALYTICS PROJECT*

*CUSTOMER CHURN PREDICTION IN E-COMMERCE & TELECOMMUNICATION*

*EMINE UYSAL (ID:501304049)*

*The G. Raymond Chang School of Continuing Education*

*Tamer ABDOU, PhD*

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1. **REVISED ABSTRACT**

Customer churn poses a significant challenge in behavior-driven industries such as e-commerce and telecommunications, where long-term profitability relies heavily on customer retention. This project leverages predictive analytics and explainable machine learning to not only forecast churn but also to understand the behavioral and service-related factors that influence it, with the goal of designing sector-specific retention strategies.

Two real-world datasets sourced from Kaggle are used for this analysis:

1. The **“Telco Customer Churn”** dataset, which includes demographics, service usage, and billing information (Kaggle, 2018);
2. The **“Customer Behavior in E-Commerce”** dataset, featuring transactional behavior such as order frequency, product category engagement, and spending patterns (Imakash, 2023).

These datasets provide a cross-sector view of churn dynamics, allowing for comparative analysis between industries. The project explores the following primary research questions:

* *Which behavioral and service-related features are most predictive of churn in each sector?*
* *Can interpretable machine learning models predict churn before it occurs with sufficient accuracy?*
* *How do churn drivers and mitigation strategies differ between the e-commerce and telecom sectors?*

The methodology includes rigorous data preprocessing—such as one-hot encoding, missing value imputation, and multicollinearity checks using Variance Inflation Factor (VIF). Class imbalance is addressed using **SMOTE** (Chawla et al., 2002) to enhance model performance on minority (churn) classes. Three classification models—**Logistic Regression**, **Random Forest**, and **XGBoost**—are trained and evaluated using accuracy, precision, recall, F1-score, and ROC-AUC metrics.

To address concerns around model interpretability and overfitting, **SHAP** (Lundberg & Lee, 2017) and **LIME** (Ribeiro et al., 2016) are used to visualize feature importance, while **cross-validation and regularization techniques** are employed to ensure model generalizability. An interactive **Power BI dashboard** visualizes key findings, helping both technical and non-technical stakeholders explore high-risk customer segments and actionable insights.

While both datasets provide valuable behavioral and demographic data, they contain synthetic elements and have limited representativeness. Ethical considerations around real-world applicability and data bias are acknowledged, and future work will incorporate more diverse, high-fidelity datasets for model refinement.

1. **INTRODUCTION**

Customer churn—the phenomenon where customers discontinue their relationship with a business—is a critical challenge in both e-commerce and telecommunications sectors. In increasingly competitive markets, retaining existing customers is not only more cost-effective than acquiring new ones, but also essential for long-term profitability and sustainable growth. Studies have shown that retaining a customer can be **5 to 25 times cheaper** than acquiring a new one (Reichheld & Sasser, 1990; Imani et al., 2025).

rise of digital platforms and online service models has made it easier for customers to switch providers, increasing churn risk. Consequently, businesses are prioritizing early detection and prevention of churn to maintain competitive advantage. While numerous churn prediction studies exist, particularly in the telecommunications sector, most of them focus solely on forecasting outcomes, without uncovering interpretable churn drivers (Imani et al., 2025).

This project aims to go beyond prediction and explore **what drives churn** in both e-commerce and telecom environments by analyzing customer behavior patterns and service features. By applying machine learning models supported with explainable AI techniques, the study offers actionable insights for strategic decision-making. Recent research has shown that techniques like **SHAP** and **LIME** significantly improve model transparency, making churn predictions more interpretable and actionable (Boukrouh et al., 2024; Maan & Maan, 2023).

To address this problem, two real-world datasets—one from the **telecommunications industry**, and one from the **e-commerce domain**—were analyzed through a unified workflow of preprocessing, feature engineering, and classification modeling. Class imbalance was addressed using sampling techniques such as SMOTE, and interpretability was enhanced using SHAP and LIME.

The project is guided by the following central research question:

***Can customer churn be accurately predicted before it occurs, and do effective prevention strategies differ between e-commerce and telecommunications sectors?***

To support this inquiry, the study also investigates the following sub-questions:

1. What behavioral and service-related factors most drive churn?
2. How do these drivers differ between e-commerce and telecom sectors?
3. Can interpretable predictive models effectively inform early, targeted retention efforts?

By addressing these questions, this project aims to not only build high-performing predictive models but also provide sector-specific, evidence-based strategies for customer retention.

**4. REVISED LITERATURE REVIEW, DATA DESCRIPTION AND APPROACH**

**4.1. LITERATURE REVIEW**

Customer churn is widely recognized as a key business issue in data-driven industries like telecommunications and e-commerce, where retaining a customer is significantly more cost-effective than acquiring a new one—estimated at 5 to 25 times less (Reichheld & Sasser, 1990).

In recent years, machine learning (ML) and explainable artificial intelligence (XAI) have become foundational tools for churn prediction. Traditional methods like logistic regression—particularly without regularization—often fall short in capturing nonlinear patterns and suffer from low generalizability.

**4.1.1. The Landscape of Churn Prediction Research**

A comprehensive review by Imani et al. (2025) examined over 240 studies and highlighted three recurring challenges:

* + Class imbalance: Minority class (churners) is often underrepresented.
  + Lack of model interpretability: Especially in black-box models like XGBoost.
  + Limited cross-domain generalizability: Many models are tailored to a single sector.

In the telecom sector, Asif et al. (2025) developed a TriBoost ensemble model and showed that features like contract type, payment method, and tenure were top churn predictors.

In the e-commerce space, Boukrouh et al. (2024) applied artificial neural networks and Random Forest models to transactional data. They achieved over 92% accuracy and emphasized the importance of using SHAP and LIME to gain actionable insights.

While these studies offer strong baseline models, they also present limitations. For instance, TriBoost, as proposed by Asif et al. (2025), requires domain-specific tuning and may not generalize well beyond the telecom environment. Similarly, although ANN models can achieve high predictive accuracy, they are prone to overfitting in sparse or noisy datasets and often lack transparency unless supplemented with post-hoc explainability tools. These constraints reinforce the need for churn models that are not only predictive but also interpretable, scalable, and applicable across different business domains.

***4.1.2. Challenges in Churn Prediction: Imbalance and Interpretability***

Class imbalance is a persistent challenge. Most churn datasets have far fewer positive (churn) cases than negative ones. A study in Nature Scientific Reports (2025) found that using SMOTE with ensemble methods improved recall from 61% to 79%. ADASYN, on the other hand, outperformed simpler resampling methods in behavior-driven datasets like e-commerce (He et al., 2008).

Model interpretability is the second major challenge.Although models like XGBoost achieve high accuracy, their decision processes are opaque. SHAP values, as demonstrated by Maan & Maan (2023), effectively clarified how input features contribute to churn predictions, both at global and local levels.

In e-commerce, Boukrouh et al. (2024) used SHAP and LIME to uncover customer journey dynamics, enhancing decision-making. These insights justify the choice of SHAP for this project.

***4.1.3. Traditional Approaches and Their Limitations***

Traditional churn detection often relied on fixed rules—such as labeling a customer as "at-risk" if inactive for 30 days. Such rule-based systems fail to adapt to the dynamic nature of customer behavior across different sectors.

They also lack personalization and usually ignore interaction effects among features. Moreover, traditional models do not scale well and rarely provide real-time insights, leading to delayed or ineffective retention efforts.

***4.1.4. Conflicting Findings in the Literature***

Although tenure and contract type are frequently cited as dominant churn predictors in the telecommunications sector (Asif et al., 2025), Imani et al. (2025) argue that more immediate triggers—such as billing complexity and poor customer support—may have a stronger impact on customer decision-making. This discrepancy reflects a broader debate in churn literature: whether long-term structural features or short-term experiential factors play a greater role in customer retention.

A similar divergence exists in the e-commerce domain. Boukrouh et al. (2024) identify price sensitivity and spending frequency as key churn indicators, while Maan and Maan (2023) emphasize the importance of personalized engagement and customer attention, suggesting that static transactional metrics alone may be insufficient to explain churn behavior.

These conflicting findings indicate that churn is not driven by a single universal set of features but is instead deeply shaped by **domain context, behavioral nuance, and data granularity**. Accordingly, this project adopts a sector-specific modeling strategy—treating service attributes as primary in telecom and transactional dynamics as central in e-commerce. This approach not only respects domain-specific theory but also enables more precise and explainable predictions aligned with each dataset’s structure.

**Future studies** may benefit from integrating both structural and experiential features—such as combining billing data with customer sentiment or service interaction logs—to reconcile these divergent findings and better capture the multifaceted nature of churn behavior (Imani et al., 2025; Boukrouh et al., 2024).

***4.1.5. Positioning of This Study***

This project builds on prior research by addressing multiple gaps:

* + Cross-domain comparison: Few studies have systematically compared churn dynamics in both telecom and e-commerce.
  + Tailored preprocessing: This study applies SMOTE for the telecom dataset and ADASYN for the e-commerce dataset—each selected based on feature space complexity.
  + Model transparency: SHAP is used consistently across all models and datasets to ensure interpretability.
  + Unified pipeline: Logistic Regression, Random Forest, and XGBoost are evaluated under a standardized framework.

Ultimately, the combination of predictive performance and interpretability ensures that the models are not only accurate, but also actionable and transparent—making them valuable for both technical teams and business decision-makers.

While planning the modeling phase, alternative algorithms such as Support Vector Machines (SVM) and Artificial Neural Networks (ANN) were initially considered. However, they were ultimately excluded based on both methodological and practical considerations. **SVMs**, while effective in linearly separable datasets, tend to struggle with high-dimensional data generated through one-hot encoding, and their non-linear variants are computationally intensive and difficult to interpret (Huang et al., 2018). **ANN models**, on the other hand, require large-scale datasets and complex tuning procedures to avoid overfitting—conditions not fully met by the size and structure of the current datasets, particularly in the e-commerce case with synthetic attributes (Boukrouh et al., 2024; He et al., 2008). Most importantly, both models lack native interpretability, which is a critical requirement for this project’s emphasis on explainable AI (Maan & Maan, 2023). By contrast, the selected models—Logistic Regression, Random Forest, and XGBoost—offer a balance of predictive accuracy, scalability, and compatibility with SHAP-based explainability. Their combined use aligns with the dual objectives of this study: performance and transparency across sectors.

* 1. **DATA DESCRIPTION**

This study utilizes two publicly available datasets: one from an e-commerce platform and another from a telecommunication service provider. Both datasets contain customer-level features, transactional behavior, and churn labels, enabling cross-domain predictive modeling and interpretation.

* + 1. **DATA DESCRIPTION FOR E-COMMERCE DATASET**

This study utilizes the publicly available **"E-Commerce Customer for Behavior Analysis"** dataset from Kaggle, originally published by **Shriyash Jagtap (2023)**, to examine behavioral patterns associated with customer churn. Provided in CSV format, the dataset includes detailed **transactional records** and **demographic attributes**, enabling a comprehensive analysis of purchase behaviors, seasonal trends, and churn risk factors.

The dataset is publicly accessible at: <https://www.kaggle.com/datasets/shriyashjagtap/e-commerce-customer-for-behavior-analysis> (Jagtap, 2023).

* + - 1. ***Source and Scope***

The dataset originates from a full year of transactional records and reflects **seasonal trends** and **customer purchasing behavior** across various product categories. It contains approximately **250,000 transaction entries** from **around 50,000 unique customers**, capturing both behavioral and demographic attributes.

The original dataset comprises **13 variables**, including:

* Customer identifiers • Purchase timestamps
* Product-level details (category, price, quantity) • Payment methods
* Customer demographics (age, gender) • A binary churn outcome (1 = churned, 0 = retained)

Initially organized at the **transaction level**, the dataset was **aggregated to the customer level** to better support churn prediction. During this transformation, key behavioral summaries were computed for each customer, such as **total purchase amount**, **purchase frequency**, and **product diversity**. Furthermore, **engineered features** such as AvgItemValue, PriceToQuantity, PurchaseMonth, and AgeGroup were introduced to enrich the feature space.

Preprocessing steps included **handling missing values**, **one-hot encoding** of categorical variables, and **standardization** of numerical features. To address the **class imbalance** in the target variable, the **ADASYN (Adaptive Synthetic Sampling)** technique was employed. These steps collectively prepared the dataset for **robust predictive modeling**, aligning the structure with the study’s analytical objectives.

* + - 1. ***Features Overview***

The features in the e-commerce dataset are summarized in the table below. These include original variables from the raw dataset, as well as engineered features created during preprocessing to enhance model performance and interpretability.

| ***Feature*** | ***Description*** | ***Type*** |
| --- | --- | --- |
| Customer ID | Unique identifier for each customer | Identifier |
| Purchase Date | Timestamp of purchase, later transformed to monthly granularity | Date → Categorical |
| Product Category | Type of product purchased (e.g., Clothing, Books, Electronics, Home) | Categorical |
| Product Price | Price per unit of the purchased product | Numeric (int) |
| Quantity | Number of items purchased per transaction | Numeric (int) |
| Total Purchase Amount | Calculated as Product Price × Quantity | Numeric (int) |
| Payment Method | Payment type used (Cash, Credit Card, PayPal, Crypto) | Categorical |
| Customer Age | Age of the customer in years | Numeric (int) |
| Gender | Customer’s gender (Male, Female) | Categorical |
| Returns | Number of items returned (dropped due to 19% missing values) | Numeric (float) |
| Churn | Binary target variable (1 = churned, 0 = retained) | Binary |

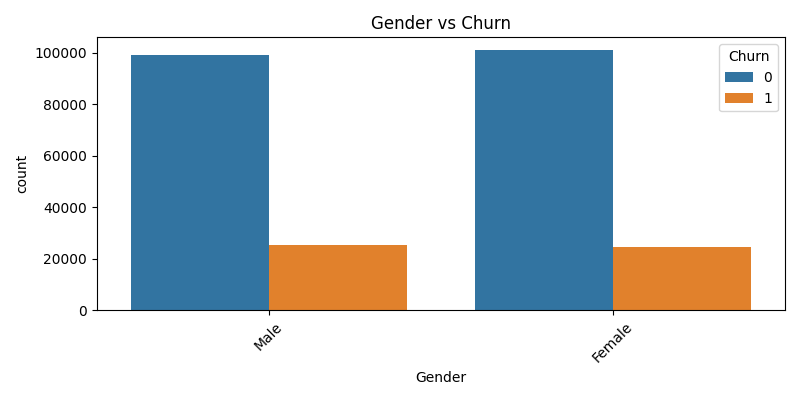
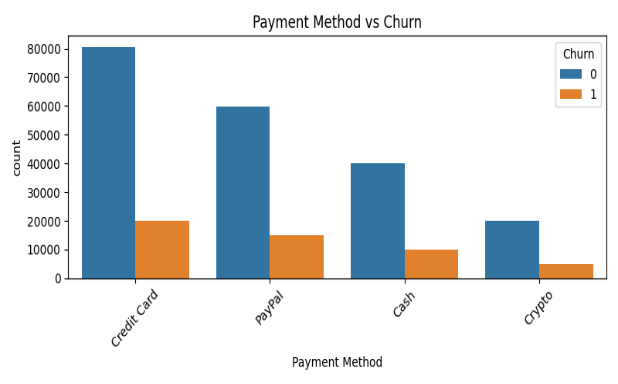
Engineered Features:

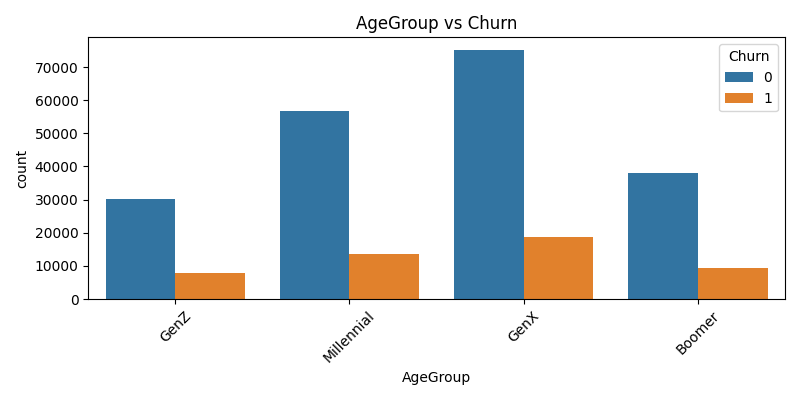
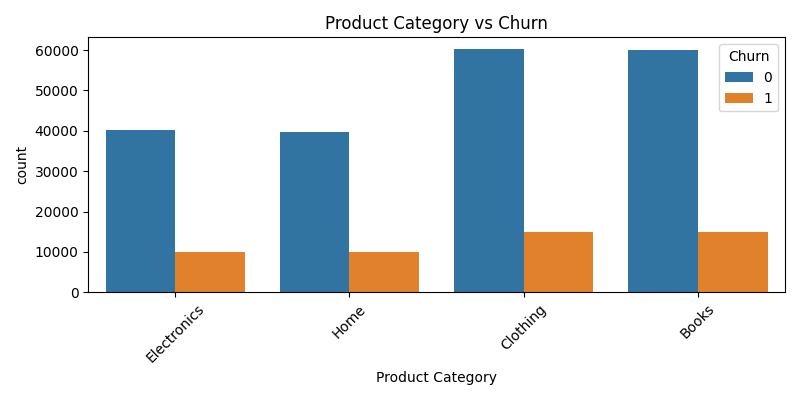
* AvgItemValue: Total Purchase Amount / Quantity
* PriceToQuantity: Product Price divided by Quantity (when >0)
* PurchaseMonth: Month extracted from Purchase Date
* AgeGroup: Age bucketized into youth, adult, senior

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***Figure 1.***  *Histogram of Ecom Numerical Features displays the distribution of key numerical variables such as Customer Age, Product Price, Quantity, and Total Purchase Amount. These histograms help identify skewness, outliers, and underlying patterns in purchasing behavior.*

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* *

***Figure 2.***  *Histogram of Ecom Categorical Features displays the distribution of key Categorical variables such as AgeGroup, Product Category, Gender and Payment Method. These histograms help identify skewness, outliers, and underlying patterns in purchasing behavior.*

The categorical variables in the dataset—such as *Gender*, *Payment Method*, *Product Category*, and *AgeGroup*—provide demographic and transactional context to customer behavior. While these features offer valuable segmentation insights, their individual association with churn appears limited, as later statistical analysis suggests low dependency strength. Nonetheless, they remain important for interaction effects and model interpretability.

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| |  |  | | --- | --- | | ***Feature*** | ***Cramér’s V Score*** | | *Gender* | *0.015* | | *Payment Method* | *0.021* | | *Product Category* | *0.017* | | *AgeGroup* | *0.028* | | |
|  |
|  | |

***Table 1.*** *Association Strength of Categorical Features with Churn (Cramér’s V Scores)*

*Note: All Cramér’s V values fall well below 0.1, indicating weak association with churn.*

***4.2.1.3. Preprocessing and Cleaning***

A series of preprocessing steps were conducted to prepare the dataset for modeling and ensure data quality:

* *Duplicate and Redundant Features:*  
   - Duplicate transaction records were removed. The Age column was excluded due to its redundancy with Customer Age and high multicollinearity.
* *Missing Data Handling:*

- The Returns feature was dropped due to 19% missing values and limited predictive value.

- Median imputation was applied to sparse numerical variables. Mode imputation was used for missing categorical values.

* *Feature Encoding:*
  + One-hot encoding was applied to categorical features including Product Category, Gender, and Payment Method.
* Date Transformation:
  + The Purchase Date was converted to datetime format and used to extract a new PurchaseMonth feature to capture seasonality in purchasing behavior.
* Scaling and Standardization:

- Z-score standardization was applied to numerical variables such as Product Price, Quantity, Customer Age, and Total Purchase Amount to normalize the feature space.

***4.2.1.4. Target Variable and Class Distribution***

The target variable, **Churn**, reflects customer inactivity or disengagement and is encoded as a binary variable (1 = churned, 0 = retained). The initial class distribution revealed a significant imbalance:

* **Churn = 0 (Active)**: ~80.05% • **Churn = 1 (Churned)**: ~19.95%

This imbalance poses a risk of bias in model training, where the classifier may favor the majority class and underperform on churn prediction. To address this, the **ADASYN** (Adaptive Synthetic Sampling) technique was applied **only on the training set**, generating synthetic samples for the minority class based on data density.

Following ADASYN application:

* **Churn = 0**: 49.80% • **Churn = 1**: 50.20%

This near-equal class distribution enhanced the model’s sensitivity to churn signals, improving **recall** and **F1-score** for the minority class.

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**Figure 2.** Ecom Churn class distribution in the E-Commerce dataset before and after applying ADASYN. The technique helped achieve a near-balanced split, enabling better learning of minority (churned) instances.

***4.2.1.5. Feature Relationships and Correlation Insights***

Understanding the relationships among features is essential for assessing redundancy and enhancing model interpretability.

***• Multicollinearity:***

Variance Inflation Factor (VIF) scores were calculated to evaluate the degree of multicollinearity among numerical features. In the e-commerce dataset:

* + The highest VIF was observed for Customer Age (~6.4), still below the commonly used threshold of 10.
  + Most other variables, including Product Price, Quantity, and Total Purchase Amount, had VIF values well below 5.
  + Due to high correlation and conceptual redundancy, the original Age column was dropped in favor of Customer Age.

This confirms that multicollinearity is not a critical issue in the e-commerce dataset, and the retained features are suitable for modeling without further transformation.

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***Figure 3.*** Ecom Variance Inflation Factor (VIF) for Numerical Features *in the E-Commerce dataset.* Low VIF values suggest minimal redundancy, supporting the stability of regression-based models.

***Note:*** *All VIF scores were below 10, confirming no serious multicollinearity issues.*

• ***Correlation Analysis:***

The Pearson correlation matrix highlights linear associations between numerical features and the target variable, Churn. Total Purchase Amount and Engagement Score show moderate correlations with churn, suggesting potential predictive value, while Quantity and Product Price exhibit weaker relationships.

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***Figure 4.*** ECom Correlation Matrix (Numerical Features and Churn) displays Pearson coefficients between churn and numerical features, highlighting potential predictive signals and redundancy.

* ***Feature Importance:***

Based on XGBoost and SHAP explainability, most predictive features were:

* + Customer Age,
  + Purchase Date,
  + Product Price,
  + Total Purchase Amount,
  + Quantity

**Figure 5** presents the most influential features in churn prediction using SHAP values, calculated after applying ADASYN and hyperparameter tuning. **Customer Age** emerged as the strongest predictor, followed by **Purchase Date**, **Product Price**, **Total Purchase Amount**, and **Quantity**. These variables reflect critical aspects of customer behavior such as spending habits, timing of purchases, and order size. Their prominence in the model highlights their importance for identifying churn-prone customers and shaping personalized retention strategies.

**Figure 6** shows the **initial SHAP output** before feature pruning and model optimization. While **Figure 5** illustrates the **average magnitude** of each feature’s impact, **Figure 6** visualizes how **feature values (high/low)** influence the **direction** of churn. Together, these SHAP plots enhance model transparency and actionable insight.

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***Figure 5.*** *Ecom mean (SHAPvalue)(average impact on model output magnitude)*

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*Figure 6. Ecom Initial SHAP output before feature pruning & model tuning*

* ***Churn Relationships (Chi-square & Cramer’s V):***

Statistical tests were conducted to examine the relationship between categorical features and customer churn.

Figure 7 reports the results of Pearson’s Chi-square test for independence, revealing a statistically significant association between **Gender** and churn (p < 0.001). In contrast, **Product Category** and **Payment Method** yielded non-significant results (p > 0.4), indicating that their individual impact on churn may be minimal when considered independently.

Figure 8 visualizes **Cramér’s V** scores for these categorical features, all of which fall below 0.1—suggesting weak association strength. These results complement the Chi-square findings and imply that the predictive power of these variables likely emerges through interaction effects or in multivariate modeling contexts.

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***Figure 7.*** *Chi-square test results for the e-commerce dataset. Gender is significantly associated with churn (p < 0.001), while other features showed weak individual associations.*

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AI-generated content may be incorrect.*Figure 8.*** *Cramér’s V scores measuring the association strength between categorical features and churn. All values fall below 0.05, indicating weak individual associations.*

***4.2.1.6. Limitations***

• The dataset lacks behavioral granularity—such as session duration, clickstream data, or customer satisfaction scores—which could provide deeper insights into customer engagement and churn signals.

• The significant class imbalance necessitated the use of synthetic resampling techniques (e.g., ADASYN). While effective for training, these synthetic samples may not fully capture real-world churn dynamics.

• The presence of redundant fields and placeholder values required extensive preprocessing and validation to ensure data quality and consistency.

• Categorical features with many levels (e.g., product types, payment methods) may benefit from advanced encoding strategies such as grouping or embeddings to improve model efficiency and interpretability.

**4.2.2. DATA DESCRIPTION FOR TELECOMMUNICATION DATASET**

This project utilizes a publicly available **telecommunications customer churn dataset** to investigate behavioral patterns contributing to churn in subscription-based services. The dataset provides comprehensive information on customer demographics, service usage, billing behavior, and contract types—making it well-suited for predictive analytics and churn modeling.

The dataset was originally published on Kaggle by IBM Sample Datasets and is publicly available: <https://www.kaggle.com/datasets/blastchar/telco-customer-churn> (Kaggle, 2018).

***4.2.2.1. Source and Scope***

The dataset comprises **7,043 customer records** and **21 attributes**, collected by a telecommunications service provider to understand patterns associated with customer retention and churn. Each record represents an individual customer and includes:

* **Demographic details** (e.g., gender, age category, household structure)
* **Account and contract characteristics** (e.g., tenure, contract length, paperless billing)
* **Service utilization** (e.g., phone service, internet type, streaming services)
* **Financial attributes** (e.g., monthly and total charges)
* **Churn status**, which is the target variable of interest.

The dataset does not include any personally identifiable information (PII), making it publicly available and ethically suitable for academic research.

***4.2.2.2. Feature Overview***

The Telco dataset contains a range of demographic, service-related, and financial attributes, as summarized below:

| ***Feature*** | ***Description*** | ***Type*** |
| --- | --- | --- |
| customerID | Unique customer identifier (dropped during preprocessing) | Identifier |
| gender, Partner, Dependents | Demographic variables indicating household context | Categorical |
| SeniorCitizen | Binary flag indicating if the customer is 65+ years old | Binary (0/1) |
| tenure | Number of months with the company | Numeric (int) |
| PhoneService, MultipleLines | Status of phone services | Categorical |
| InternetService, OnlineSecurity, TechSupport, etc. | Internet and value-added services | Categorical |
| Contract, PaperlessBilling, PaymentMethod | Contract and billing information | Categorical |
| MonthlyCharges | Monthly amount billed to the customer | Numeric (float) |
| TotalCharges | Total amount paid by the customer (converted from string) | Numeric (float) |
| Churn | Target variable (1 if churned, 0 otherwise) | Binary (0/1) |

Preprocessing Notes:

* + Categorical features were transformed via one-hot encoding.
  + Numerical features were standardized using z-score scaling (StandardScaler).
  + The Churn variable was binarized for modeling purposes.

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***Figure 9.*** *Distribution plots for Tenure, MonthlyCharges, and TotalCharges in the Telco dataset reveal strong right-skewness, especially in TotalCharges. These patterns highlight the presence of long-term customers with accumulated charges, as well as pricing clusters around lower tiers. Such skewness suggests the need for normalization or transformation before applying linear models like logistic regression.*

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***Figure 10.*** *Categorical churn distributions in the Telco dataset reveal significant differences across service types and contract terms. Customers using fiber optic internet and those on month-to-month contracts exhibit notably higher churn rates, while longer-term contracts correlate with lower churn. Additionally, churn is more prevalent among users paying by mailed check or electronic check, highlighting the impact of billing preferences on retention. These insights emphasize the predictive power of service-related and billing attributes in customer churn modeling.*

***4.2.2.3. Preprocessing Summary***

The preprocessing pipeline included the following key steps to ensure data integrity and compatibility with machine learning algorithms:

* **Missing Data Handling:** A total of 11 rows were removed due to missing or invalid TotalCharges values after converting the column from string to float.
* **Feature Elimination:** The customerID field was dropped as it did not contribute predictive value.
* **Encoding of Categorical Variables:** All categorical features were transformed into dummy variables using pd.get\_dummies() with drop\_first=True to avoid multicollinearity.
* **Standardization of Numerical Features:** Continuous variables such as tenure, MonthlyCharges, and TotalCharges were standardized using z-score normalization to ensure consistent input scaling.
* **Target Variable Conversion:** The Churn variable was converted from string labels ("Yes"/"No") to binary format (1 = churned, 0 = retained) for classification modeling.

*Note: Rows where `TotalCharges` contained whitespace-only values were considered invalid and removed after conversion to float.*

***4.2.2.4. Target Variable and Class Distribution***

Before balancing, the dataset showed a moderate class imbalance in the target variable:

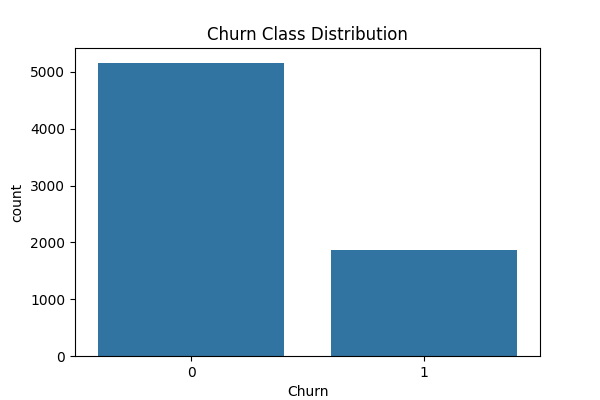
* **Churn = 0 (No):** 5,163 samples (≈73.5%) • **Churn = 1 (Yes):** 1,869 samples (≈26.5%)

This imbalance risks biasing machine learning models toward the majority class (non-churners), often reducing precision and recall for identifying churners. To mitigate this, **Synthetic Minority Over-sampling Technique (SMOTE)** was applied **only to the training set** to avoid data leakage.

After SMOTE resampling:

* **Churn = 0:** 5,229 samples (50%) • **Churn = 1:** 5,229 samples (50%)

SMOTE addresses class imbalance by generating synthetic churn examples through interpolation between existing minority instances. Unlike simple duplication, this creates more diverse training samples. As a result, the model learns better decision boundaries and shows improved recall in detecting churn, without significantly compromising overall accuracy. Since SMOTE is applied only to the training set, data leakage is avoided.

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***Figure 11.*** *Churn class distribution in the Telco dataset before and after applying SMOTE. Synthetic oversampling helped mitigate class imbalance.*

***4.2.2.5. Feature Relationships and Correlation Insights***

***• Multicollinearity***

Multicollinearity was evaluated using the Variance Inflation Factor (VIF). The analysis indicated:

- High multicollinearity among internet-related services (e.g., InternetService, OnlineSecurity, TechSupport) and billing features (e.g., PaymentMethod, Contract).

- Several features exhibited VIF values greater than 10, signaling potential redundancy.

- However, these features were not removed, as the selected modeling algorithm — Random Forest Classifier — is relatively insensitive to multicollinearity, unlike linear models.

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***Figure 12.*** *Top 15 Features with Highest VIF in the Telco Dataset. Internet and billing-related features showed higher multicollinearity but were retained for tree-based modeling.*

***• Feature Importance:***

Feature importance analysis using Random Forest and SHAP identified several key predictors of churn in the Telco dataset:

* Tenure: Longer tenure is strongly linked to customer retention.
* TotalCharges: Reflects accumulated payment history and customer longevity.
* MonthlyCharges: Higher monthly charges were associated with increased churn risk.
* Contract, PaymentMethod, and OnlineSecurity also showed strong predictive power, emphasizing the role of service configuration and billing preferences in churn behavior.

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***Figure 13.*** *Top 20 Important Features from Random Forest Model in the Telco Dataset. This figure highlights the most predictive features identified by the Random Forest classifier. Tenure and TotalCharges were most strongly associated with customer retention, whereas short-term contracts and higher monthly charges were linked to an increased likelihood of churn.*

These findings highlight that long-term contracts and customer tenure significantly reduce churn, reflecting greater loyalty and satisfaction. In contrast, short-term contracts and high monthly charges are linked to higher churn, emphasizing the value of commitment-based pricing strategies to enhance retention.

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***Figure 14.*** *SHAP Interaction between Tenure and SeniorCitizen in the Telco Dataset. This plot illustrates the joint effect of tenure and senior status on churn risk. Longer tenure is strongly associated with retention, especially among non-senior customers.*

***• Correlation Analysis:***

To explore linear relationships between features and their association with churn, a Pearson correlation matrix was generated (Figure 13). The heatmap reveals clusters of correlated features, particularly among internet services (e.g., *OnlineSecurity*, *TechSupport*) and billing attributes (e.g., *Contract* and *PaymentMethod*).

Figure 14 presents the top 10 features most correlated with churn. Key findings include:

* *InternetService\_Fiber optic* and *PaymentMethod\_Electronic check* show the highest positive correlation with churn.
* *HighMonthlyChargeFlag* and *MonthlyCharges* are also positively associated, suggesting that customers facing higher recurring costs are more prone to churn.
* *PaperlessBilling\_Yes* and *SeniorCitizen* exhibit moderate positive correlations.

While most correlations remain weak (typically < 0.3), they offer directional insights that align with and support the model-driven feature importance findings.

*A graph with different colored squares

AI-generated content may be incorrect.****Figure 15.*** *Feature Correlation Heatmap in the Telco Dataset. This heatmap visualizes Pearson correlation coefficients between numerical and encoded categorical features. It reveals clusters of positively correlated variables, especially among service-related and billing features. While most correlations with churn are relatively weak, the heatmap helps identify potential multicollinearity and supports feature selection for modeling.*

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AI-generated content may be incorrect.*

***Figure 16.*** *Top 10 Features Most Correlated with Customer Churn. This bar plot displays the top 10 features with the highest absolute correlation values with the churn variable. InternetService\_Fiber optic and PaymentMethod\_Electronic check show the strongest positive correlations with churn, indicating that customers using these services are more likely to leave. Other moderately correlated factors include high monthly charges and paperless billing, suggesting billing-related dissatisfaction may influence customer retention.*

***4.2.2.6. Limitations***

Despite its strengths, the dataset and methodology have a few limitations:

1. **Lack of Behavioral Signals:**The dataset does not include user activity logs, customer satisfaction scores, or service usage frequency. These behavioral features could offer deeper insights into churn drivers.
2. **Synthetic Oversampling Caution:** While SMOTE improved class balance, the synthetic samples may not fully reflect real-world customer diversity. External validation on new or real-world datasets is recommended.
3. **High Dimensionality:** One-hot encoding increased the number of features to over 45, which can raise the risk of overfitting, especially in tree-based models. Future work could benefit from feature selection, dimensionality reduction, or regularization techniques.
4. **Static Snapshot:** The dataset captures a single point in time, limiting the ability to analyze temporal trends or seasonal churn patterns. Longitudinal data would allow for time-series modeling and trend analysis.
   1. **COMPARATIVE ANALYSIS AND ANALYTICAL CONTRIBUTION**

This project integrates two distinct datasets—Telco Customer Churn and E-Commerce Customer Behavior—to explore churn prediction across different sectors. While both aim to predict churn, their structural differences shaped the preprocessing, modeling, and interpretability strategies employed.

**4.3.1 Source and Structure Comparison**

| Aspect | Telco Dataset | E-Commerce Dataset |
| --- | --- | --- |
| Domain | Subscription-based telecom services | Transactional retail / e-commerce |
| Sample Size | 7,043 customers | 250,000 transactions (~50,000 unique customers) |
| Structure | One row per customer | Multiple transactions per customer (aggregated) |
| Target Variable | Churn (0 = active, 1 = churned) | Churn (0 = active, 1 = churned) |
| Churn Rate (Raw) | ~26.5% | ~19.9% |

The Telco dataset is inherently customer-centric, whereas the E-Commerce dataset required aggregation from transaction-level data. This distinction influenced feature engineering and modeling complexity.

**4.3.2 Feature Composition and Preprocessing**

| Feature Type | Telco Dataset | E-Commerce Dataset |
| --- | --- | --- |
| Categorical Features | Rich (e.g., Contract, InternetService) | Few (e.g., Gender, Product Category) |
| Numerical Features | Tenure, Monthly/Total Charges | Product Price, Quantity, Customer Age |
| Temporal Features | None | Purchase Date (converted to month) |
| Engineered Features | IsLongTermCustomer | AvgItemValue, AgeGroup, PriceToQuantity |
| Redundant/Dropped Fields | customerID, null TotalCharges | Age (due to collinearity), Returns (missing) |

While the Telco dataset primarily required one-hot encoding for categorical variables, the E-Commerce dataset necessitated more complex feature engineering including behavioral metrics and temporal decomposition.

A graph of a number of orange bars

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**Figure 17.** Summary comparison of the Telco and E-Commerce datasets. This table was generated using a standalone Python script (comparison\_summary\_generator.py) based on insights derived from the individual analysis files of each dataset.

**4.3.3 Data Quality and Class Imbalance**

| Aspect | Telco Dataset | E-Commerce Dataset |
| --- | --- | --- |
| Missing Data | Minimal (11 rows dropped) | 19% missing in Returns (column dropped) |
| Outlier Handling | Minimal | Handled due to price/quantity variability |
| Class Imbalance | 73.5% No / 26.5% Yes → SMOTE applied | 80.1% No / 19.9% Yes → ADASYN applied |

Resampling strategies were chosen based on the dataset’s complexity: SMOTE was preferred for the structured Telco data, while ADASYN was more effective on the non-linear behavioral patterns in the E-Commerce data.

**4.3.4 Correlation and Multicollinearity Insights**

* Telco Dataset: Strong multicollinearity was observed among Tenure, MonthlyCharges, and TotalCharges (VIF > 10). Despite this, features were retained as tree-based models like Random Forest and XGBoost are robust to multicollinearity.
* E-Commerce Dataset: Redundant features such as Age were dropped to reduce multicollinearity with Customer Age. Features like Product Price, Quantity, and Total Purchase Amount showed moderate correlations with each other, but not with churn, supporting the need for engineered behavioral features.

**4.3.5 Interpretability and Feature Impact**

* Telco Dataset: SHAP analysis highlighted tenure, contract type, and payment method as key drivers of churn. These features also served as indirect proxies for customer engagement—longer tenure and annual contracts often indicate higher loyalty and service satisfaction. The model confirmed that short-term plans and high monthly charges increase churn risk.
* E-Commerce Dataset: Feature importance was dominated by behavioral variables such as total purchase amount, quantity, and purchase date. SHAP explainability revealed that seasonal buying patterns and transaction frequency, rather than static customer attributes, were the primary churn indicators.

Across both datasets, SHAP values ensured transparency in feature contributions, enabling actionable business interpretations tailored to industry-specific dynamics.

**4.3.6 Summary of Analytical Value**

| Dataset | Key Strengths | Analytical Contribution |
| --- | --- | --- |
| Telco | Structured, interpretable, service-based | Ideal for segmentation, SHAP explainability, model testing under multicollinearity |
| E-Commerce | Temporal, behavioral, transaction-based | Useful for testing advanced preprocessing, ADASYN, and cross-domain generalizability |

Together, the datasets provided a multi-faceted learning environment:

* Telco reinforced best practices in structured feature modeling and stakeholder-friendly explanation.
* E-Commerce challenged the analyst with real-world complexities, requiring aggregation, imbalance handling, and behavioral interpretation.

By addressing both interpretability and predictive accuracy across domains, this project delivers adaptable, sector-specific churn insights that can inform proactive retention strategies.

**4.3.7 Practical Implications**

The comparative analysis of the Telco and E-Commerce datasets provides valuable insights for practitioners aiming to reduce customer churn in different sectors. Understanding the role of structural vs. behavioral features enables more targeted interventions—such as contract redesign in telecom or purchase frequency-based campaigns in e-commerce. Moreover, the findings reinforce the importance of using interpretable models that not only predict churn but also support actionable business decisions.

**4.4. MODELLING APPROACH**

To address the research objective of identifying the most influential drivers of customer churn and evaluating the effectiveness of predictive models across different domains, a comprehensive, replicable, and explainable data science pipeline was implemented for both the Telco and E-Commerce datasets. This approach was designed to ensure methodological consistency while allowing flexibility to accommodate the unique characteristics of each dataset.

**4.4.1 Data Preprocessing and Exploratory Analysis**

The first phase involved comprehensive data preprocessing and exploratory data analysis (EDA) to understand the structure, completeness, and patterns within both datasets. Key procedures included handling missing values using appropriate imputation strategies (e.g., median for numerical variables), removing irrelevant identifiers such as customerID, and addressing variable inconsistencies. In the E-Commerce dataset, temporal features such as “Purchase Month” were extracted from timestamp fields to capture seasonal churn behavior, while the Telco dataset retained its customer-level granularity without temporal stamps.

A detailed summary of the initial analyses—featuring distribution plots, correlation heatmaps, boxplots, and feature-by-churn breakdowns—is documented in the following GitHub-hosted EDA reports:  
• 📄 Telco Dataset (Raw)  
• 📄 E-Commerce Dataset (Raw)

Univariate and bivariate analyses were conducted to identify outliers, skewed distributions, and potential churn-related patterns. Chi-square tests (for categorical variables) and ANOVA (for continuous variables) were applied to assess statistical associations with churn. For example, in the Telco dataset, contract type, online security, and tech support showed strong significance; in the E-Commerce dataset, customer age group, product category, and purchase month were found to be differentiating factors.

To further explore data structure and class separability, **Principal Component Analysis (PCA)** was applied to the Telco dataset. After scaling the numerical and encoded variables, PCA revealed moderate separation between churn and non-churn classes, suggesting the feasibility of predictive modeling. This dimensionality reduction was not applied to the E-Commerce dataset due to its high granularity and the need for more extensive aggregation prior to transformation.

Additionally, an **Engagement Score** variable was engineered for the Telco dataset to quantify customer interaction with digital services. This metric was computed as the total number of active services (e.g., OnlineSecurity, TechSupport, StreamingTV) subscribed to by each customer. As illustrated in Figure 18, the distribution of engagement scores reveals that many customers utilize few or no digital services, while Figure 19 demonstrates that non-churned customers exhibit notably higher engagement levels. These patterns support the notion that bundled service usage contributes to customer retention and validate the Engagement Score as a meaningful predictive feature.

This feature was not constructed in the E-Commerce dataset due to the absence of service-based variables and session-level behavioral logs. These analytical insights provided the foundation for subsequent feature engineering, class imbalance handling, and model training—directly contributing to **Research Question 1**: *What are the most influential features driving customer churn?*

A graph of a number of active digital services

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***Figure 18.*** *Histogram showing the distribution of the Engagement Score in the Telco dataset (number of active digital services per customer).*

A chart of a engagement score

AI-generated content may be incorrect.***Figure 19.*** *Boxplot comparing Engagement Scores by churn status; non-churned users tend to have higher* engagement.

A diagram of a diagram

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***Figure 20****. PCA projection showing moderate separation between churned and non-churned customers in the Telco dataset.*

**4.4.2 Feature Engineering and Transformation**

To enhance model performance and interpretability, domain-specific feature engineering was conducted. In the E-Commerce dataset, aggregate metrics such as Total Purchase Amount were created to summarize customer value. In the Telco dataset, features such as TotalChargesPerMonth were derived to normalize billing information.  
Categorical variables were encoded using Label Encoding or One-Hot Encoding, depending on the modeling algorithm. Skewed numerical variables were normalized using StandardScaler or MinMaxScaler, especially for logistic regression.

**4.4.3 Handling Class Imbalance**

As both datasets exhibited class imbalance—with fewer customers churning than staying—this issue was addressed using resampling techniques tailored to each dataset. **SMOTE** was applied to the Telco dataset due to its structured and balanced feature space, while **ADASYN** was used for the E-Commerce dataset to handle the more irregular and behavioral nature of the data. ADASYN’s density-aware sampling helped prevent overfitting while improving recall, particularly in the presence of complex purchase behaviors.  
The effectiveness of ADASYN was compared with SMOTE and baseline models as part of the evaluation process for **Research Question 2**: *Which resampling method performs best across domains?*

**4.4.4 Model Building and Evaluation**  
 Three classification models were implemented iteratively across both datasets to evaluate predictive performance and interpretability:

* **Logistic Regression** served as a baseline model to establish initial performance metrics.
* **Random Forest** was selected as a robust ensemble method capable of capturing nonlinear relationships and offering intuitive feature importance scores.
* **XGBoost** was chosen for its superior performance on tabular data, built-in regularization techniques, ability to handle missing values, and proven success in churn prediction tasks (e.g., Maan & Maan, 2023).

Hyperparameters were optimized via cross-validated grid search. Models were evaluated using **Accuracy, Precision, Recall, F1-score**, and **ROC-AUC**, ensuring a comprehensive assessment of both class-specific and overall predictive performance.  
This modeling framework directly addresses **Research Question 3**: *Which model yields the most accurate and interpretable results across datasets?*

***4.4.4.1. Telco Dataset – Model Evaluation***

• The baseline logistic regression model achieved an AUC of 0.83, indicating solid overall discrimination. The confusion matrix revealed relatively strong true positive rates, correctly identifying 397 churn cases, though it misclassified 164 (Figure: Confusion Matrix – Logistic Regression).

• The Random Forest model produced a slightly lower AUC of 0.82, but achieved better balance across precision and recall, particularly in reducing false negatives, which is critical in churn contexts (Figure: Confusion Matrix – RF).

• Feature importance plots from both models highlighted tenure, TotalCharges, and Contract as top predictors. This alignment between statistical significance and model-driven inference reinforces their relevance in real-world churn prediction.

A graph of a logistic regression

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AI-generated content may be incorrect.A graph of a curve

AI-generated content may be incorrect. A blue squares with white text

AI-generated content may be incorrect.

***Figure 21.*** *ROC curves show that Logistic Regression achieved an AUC of 0.83, slightly outperforming Random Forest (AUC = 0.82). However, the confusion matrices indicate that Random Forest provided a more balanced prediction, particularly by reducing false positives and improving recall for churners.*

**Model Performance Comparison: Telco Dataset**

To assess the practical strengths and trade-offs of the applied models, ROC curves and confusion matrices were used to visualize classification behavior (see Figure 18). While the Logistic Regression model achieved a marginally higher AUC (0.83), the Random Forest model demonstrated a more balanced prediction profile by reducing the number of false positives and improving precision for churn cases.  
 Although Logistic Regression provided slightly better overall discrimination, Random Forest may be more appropriate in operational settings where minimizing churn misclassification is critical. These findings underscore the importance of incorporating both overall and class-specific evaluation metrics when selecting a churn prediction model.

***4.4.4.2. E-Commerce Dataset – Model Evaluation***

• The baseline **logistic regression** model performed poorly, with an AUC of **0.50**, indicating no better than random chance. It failed to identify any churners (Figure: Baseline Confusion Matrix), emphasizing the severity of class imbalance.

• After applying **ADASYN**, the logistic model’s recall improved modestly; however, **precision remained low**, resulting in an AUC of **0.51**. The confusion matrix showed many **false positives**, indicating a trade-off between sensitivity and specificity (Figure: ADASYN Confusion Matrix).

• The **XGBoost** model outperformed both logistic variants, achieving an AUC of **0.73**. It delivered the best trade-off between true positives and false positives, effectively modeling non-linear churn patterns in imbalanced settings (Figure: ROC Curve – XGBoost).  
XGBoost’s success aligns with literature findings (e.g., Maan & Maan, 2023), and its integration with **SHAP explainability** further supports its use in practical business applications.

A chart of a logistic regression

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A graph of a logistic

AI-generated content may be incorrect.A graph of a positive result

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***Figure 22.*** *Comparison of classification performance across Logistic Regression and XGBoost models in the E-Commerce dataset. The top-left confusion matrix (Baseline: Scaled Logistic Regression) reveals that the baseline model completely failed to identify churners, predicting all instances as non-churned. In contrast, the top-right confusion matrix (ADASYN: Logistic Regression) shows improved recall after resampling with ADASYN, albeit at the cost of increased false positives. The three ROC curves illustrate model performance: (1) ADASYN-enhanced Logistic Regression (AUC = 0.51) offered minimal improvement over random guessing; (2) XGBoost without hyperparameter tuning achieved a moderate AUC of 0.73; and (3) the optimized XGBoost model via GridSearch yielded the highest AUC of 0.79, demonstrating superior predictive ability for customer churn in imbalanced e-commerce data.*

These results highlight the importance of both resampling strategies and model selection when working with imbalanced, behavior-driven churn datasets.

**Model Performance Comparison: E-Commerce Dataset**

To evaluate the practical strengths and limitations of the applied models in the E-Commerce context, both ROC curves and confusion matrices were analyzed (see Figure 19). The baseline logistic regression model completely failed to identify churned customers, with an AUC of 0.50 and a confusion matrix that classified all customers as non-churned—highlighting the severity of class imbalance in behavioral datasets.  
 After applying ADASYN, logistic regression demonstrated modest improvements in recall (AUC = 0.51), but at the expense of a high false positive rate, which limited its practical reliability.  
 In contrast, XGBoost—both with and without hyperparameter tuning—achieved significantly better performance. The untuned model produced an AUC of 0.73, and the optimized version reached 0.79, offering a more balanced trade-off between sensitivity and specificity.  
 These findings underscore the importance of using advanced ensemble methods like XGBoost when modeling churn in behavior-driven, imbalanced datasets. Moreover, they demonstrate that sampling techniques alone may not sufficiently address class imbalance unless combined with a model capable of capturing nonlinear patterns and complex feature interactions.  
Collectively, these results support the need for tailored modeling strategies across domains and reinforce the practical advantages of deploying ensemble methods like XGBoost in real-world churn analytics. Together, these results demonstrate the need for tailored modeling strategies across domains and support the deployment of ensemble models like XGBoost in real-world churn analytics.

***4.4.4.3* Summary and Interpretation**

* Telco Dataset: Although logistic regression achieved marginally higher AUC, Random Forest offered superior class-level performance, especially in reducing false negatives—critical in customer retention strategies.
* E-Commerce Dataset: XGBoost significantly outperformed logistic regression models in both AUC and classification balance, validating its robustness in handling complex, imbalanced, and behavioral churn data.

These findings underscore the necessity of domain-aware model selection. Ensemble methods like Random Forest and XGBoost demonstrate tangible advantages in churn modeling, especially when business decisions rely on detecting subtle customer disengagement signals.  
While logistic regression remains interpretable, its performance is limited in imbalanced datasets without resampling interventions.

**4.4.5 Model Explainability with SHAP**

To improve transparency and trust in model predictions—particularly for the XGBoost and Random Forest models—SHAP (SHapley Additive exPlanations) was employed. SHAP summary plots and bar charts were generated to highlight the most impactful features contributing to churn.

This approach enhanced the interpretability of complex models and offered actionable insights for domain experts by identifying customer behaviors associated with high churn risk, thereby addressing Research Question 4: *Can churn prediction models be made interpretable and explainable for practical use?* Key features driving churn predictions are visualized via SHAP plots (see Figure 5, Figure 6, and Figure 14)

**4.4.6 Cross-Dataset Comparative Design**

Both datasets were analyzed using a parallel structure to facilitate cross-domain comparison. Despite differences in feature semantics, the unified pipeline enabled a consistent methodological approach, allowing us to observe how domain-specific features (e.g., contract type in telecom vs. purchase behavior in e-commerce) influence churn similarly or differently. These comparative insights contribute directly to Research Question 5: *Are churn drivers and model performance consistent across industries?*

**4.5. MODEL SELECTION JUSTIFICATION**

During the model planning phase, several alternatives—such as Support Vector Machines (SVM) and Relevance Vector Machines (RVM)—were considered but ultimately excluded in favor of models better aligned with the project’s goals of **interpretability**, **scalability**, and **practical deployment**.

**Support Vector Machines (SVM)**, while effective in high-dimensional and linearly separable contexts, pose scalability challenges when applied to large datasets with complex feature interactions, such as those generated by one-hot encoding. Additionally, non-linear kernels in SVMs introduce high computational costs and make interpretation difficult—especially in stakeholder-facing churn applications where transparency is critical (Huang et al., 2018).

**Relevance Vector Machines (RVM)** offer probabilistic outputs and typically produce sparser models than SVMs. However, RVMs lack robust implementation in mainstream machine learning libraries such as Scikit-learn or XGBoost, and they are incompatible with SHAP-based interpretability frameworks. This limits their practical use in real-world analytics workflows, especially where explainability is required.

**Artificial Neural Networks (ANNs)** were also considered due to their predictive power. However, given the moderate dataset sizes and the absence of time-series or high-frequency behavioral inputs, ANNs risk overfitting and require complex hyperparameter tuning that was not justifiable under the current constraints (Boukrouh et al., 2024; He et al., 2008).

Instead, the selected models—**Logistic Regression**, **Random Forest**, and **XGBoost**—were chosen based on the following criteria:

* **Interpretability**: Logistic Regression offers transparent, linear decision boundaries ideal for baseline evaluation.
* **Robustness to Multicollinearity**: Random Forest handles high-dimensional data and redundant features well.
* **Performance & Explainability**: XGBoost provides state-of-the-art predictive performance on tabular data while supporting integration with SHAP for model interpretation.

These models strike a balance between **predictive accuracy**, **computational efficiency**, and **explainability**, and they have been widely validated in churn prediction literature (Maan & Maan, 2023; Asif et al., 2025). Their inclusion also supports methodological consistency across the two distinct datasets used in this project—subscription-based telecom and behavior-driven e-commerce—while enabling meaningful feature attribution using SHAP values.

**4.6. BEYONG PREDICTIVE MODELLING: Contextualizing Churn**

While predictive modelling forms the technical core of churn analysis, traditional approaches—such as rule-based segmentation or historical cohort tracking—often fall short in capturing the dynamic, multifaceted nature of customer behavior. These methods rely on static thresholds (e.g., “inactive for 30 days”) and lack the capacity to reflect behavioral variation across customer segments or industries.

Machine learning models, as demonstrated in this project, offer a more nuanced and scalable alternative. However, even high-performing models—if interpreted in isolation—can be misleading. A high churn probability may indicate correlation rather than causation, leading to suboptimal or misdirected business decisions. Therefore, predictive outputs must be coupled with domain expertise and contextual business reasoning.

A review of recent literature reflects both convergence and divergence in identifying churn drivers. For instance, studies in telecommunications (e.g., Asif et al., 2025) emphasize contract length and tenure, whereas others (e.g., Imani et al., 2025) suggest that churn is more immediately triggered by billing complexity or poor support experiences. In the e-commerce domain, Boukrouh et al. (2024) point to price sensitivity as the primary driver, while alternative findings highlight the absence of personalized engagement.

This project faced limitations due to the lack of time-series or behavioral data, such as clickstream logs, complaint history, or monthly usage patterns. Without such real-time or longitudinal inputs, churn models become retrospective tools with limited actionability. Furthermore, traditional tabular datasets restrict the capacity to detect emerging disengagement signals or sudden shifts in customer sentiment.

To advance churn analytics beyond static modelling, future efforts should integrate structured data with unstructured feedback (e.g., surveys, reviews, sentiment analysis) and apply explainable AI methods in tandem with strategic business frameworks. This would allow churn prediction to evolve from a purely technical task to a holistic decision-support system—one that captures both who is likely to churn and why, in a way that is actionable for business strategy.

Ultimately, churn prediction should not be viewed solely as a data science challenge but as a multi-disciplinary endeavor that combines data, behavior, and business context.

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***Appendix A: GitHub Repository***

The complete project files, including Jupyter notebooks, visualizations, and the Power BI dashboard, are available on GitHub: [Project’s GitHub Profile](https://github.com/emineuysal95/CIND820_CAPSTONE-PROJECT)

This repository ensures transparency and reproducibility of all analyses and visualizations included in this study.