Improving Customer Retention Through Churn Prediction

A Data-Driven Business Proposal for Company A Telecommunications

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CUSTOMER RETENTION IS A CRITICAL BUSINESS CHALLENGE

5-7x

Cost Multiplier

Acquiring a new customer costs significantly more than retaining an existing loyal one.

Market Realities

- Telecom companies operate in a highly competitive, saturated market landscape.
- Customer churn directly impacts baseline revenue and long-term profitability.
- Leading telecom organizations now leverage predictive analytics to shift from reactive to proactive customer retention.

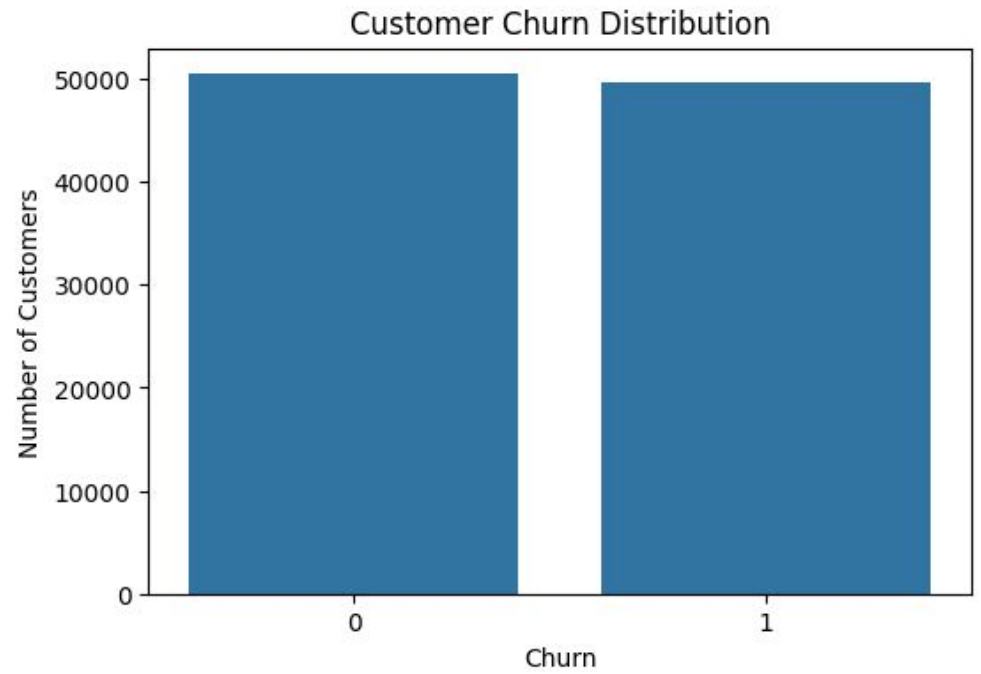
Sources:
Saleh & Saha (2023);
Harvard Business Review (2014)

CUSTOMER CHURN IS A MAJOR REVENUE RISK

Nearly half of the customers left the service, showing the need to identify at-risk customers and encourage them to stay.

50,438
Customers Stayed (Active)

49,562
Customers Churned (Left)



Evidence: Near equal split between retained and churned customers.

AI-BASED CUSTOMER RETENTION SYSTEM

An end-to-end predictive workflow designed to identify at-risk accounts before they terminate service.



DATASET OVERVIEW

Dataset Source: Company A Telecommunications Dataset

100,000
Total Customer Records

100 Features
Analytical Variables

Target Variable
Customer Churn (0 = Stayed, 1 = Left)

Dataset Characteristics

- **Customer demographics:** Age, household size, dwelling type.
- **Device information:** Equipment age, active devices.
- **Mobile usage patterns:** Monthly minutes, data usage, usage changes.
- **Revenue information:** Total revenue, monthly billing.
- **Customer service activity:** Care calls, reported issues.

DATA QUALITY ASSESSMENT

Rigorous Preprocessing Required

Several variables had missing values and were cleaned before building the model to improve accuracy and reliability.

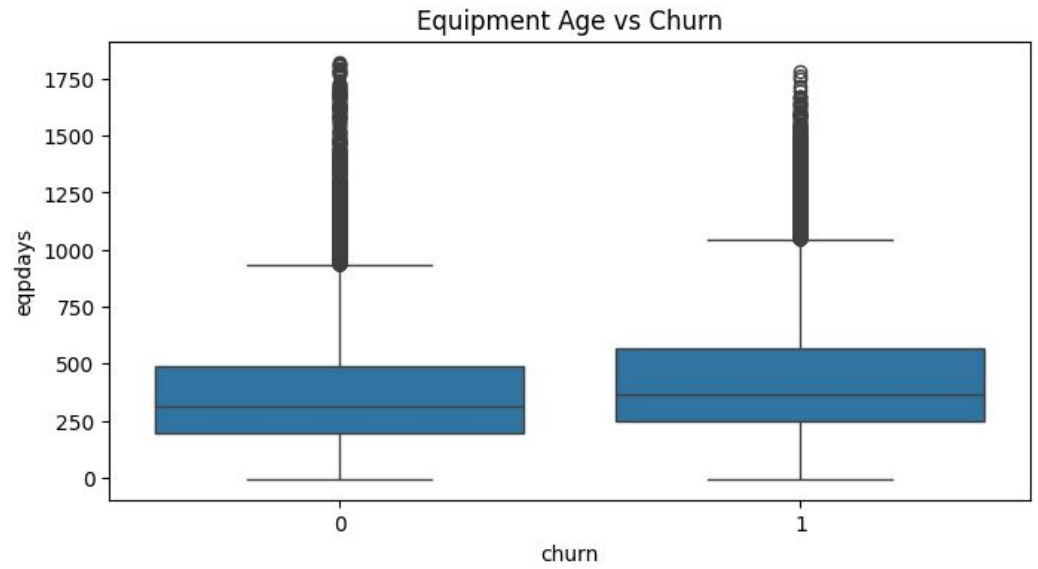
> **Action Taken:** Missing values were filled in, and categorical data was converted into a format that the model could understand.

	0
numbcars	49.366
dwllsize	38.308
HHstatin	37.923
ownrent	33.706
dwlltype	31.909
lor	30.190
income	25.436
adults	23.019
infobase	22.079
hnd_webcap	10.189
prizm_social_one	7.388
avg6rev	2.839
avg6qty	2.839
avg6mou	2.839
ethnic	1.732
forgntvl	1.732
marital	1.732
kid0_2	1.732
rv	1.732
truck	1.732

Evidence: Top variables requiring imputation.

CUSTOMER BEHAVIOR INSIGHTS

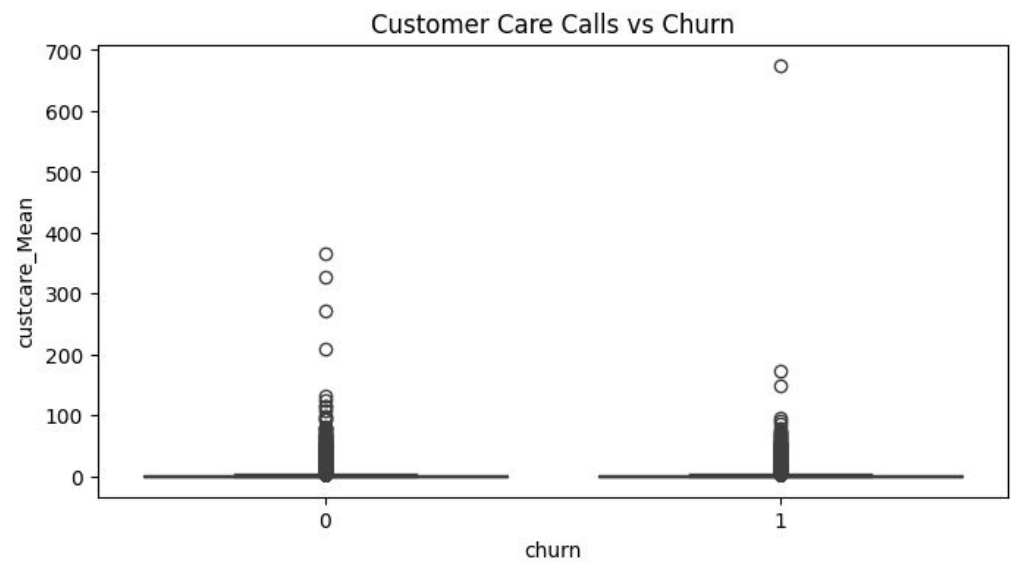
Equipment Age vs Churn



Insight:

Customers with older devices showed a significantly higher tendency to churn.

Customer Care Calls vs Churn

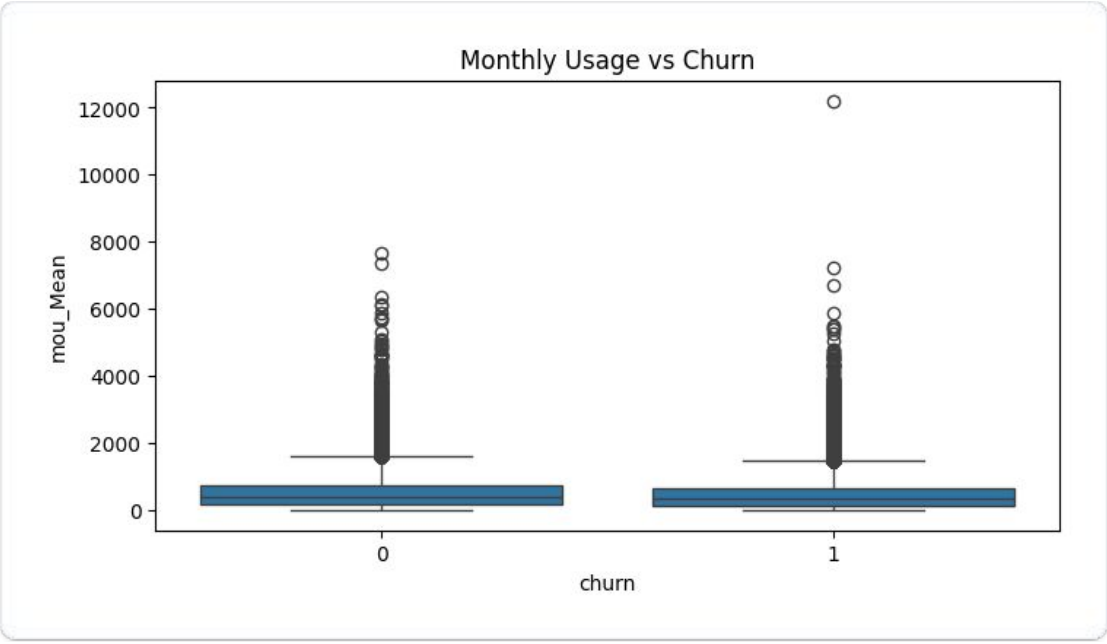


Insight:

Increased service interactions may indicate underlying dissatisfaction and higher risk.

CUSTOMER USAGE PATTERNS

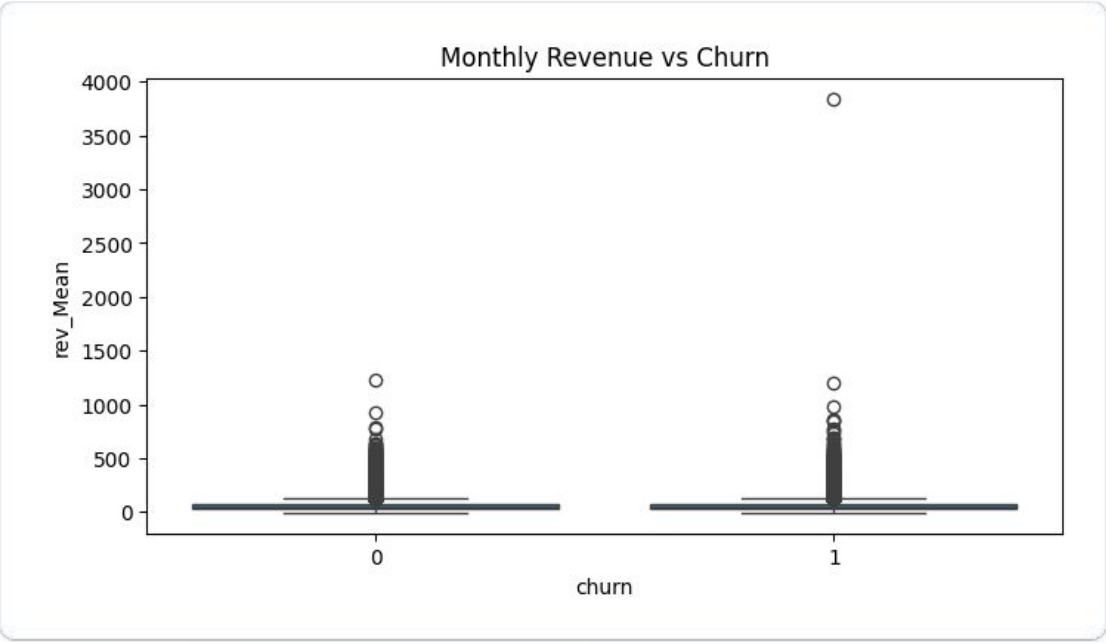
Monthly Usage vs Churn



Insight:

Usage behavior differs between churned and retained customers and may help identify churn risk.

Monthly Revenue vs Churn



Insight:

Revenue and usage behavior combined provide highly valuable retention indicators.

CHURN PREDICTION MODEL

Primary Objective

Chosen because it performs well, handles data effectively, and helps identify the factors that influence customer churn.

Selected Algorithm

Random Forest Classifier

To identify customers who may leave the company so that actions can be taken early to retain them.

Data Preparation Workflow

- **Missing Value Handling:** Ensured data integrity across all features.
- **One-Hot Encoding:** Translated categorical variables into required machine-readable formats.
- **Train/Test Split:** Rigorously partitioned data to validate the model's accuracy on strictly unseen information.

MODEL PERFORMANCE RESULTS

63.0%	62.9%	63.3%
ACCURACY	PRECISION	RECALL

63.1%	68.1%
F1 SCORE	ROC-AUC

Executive Interpretation

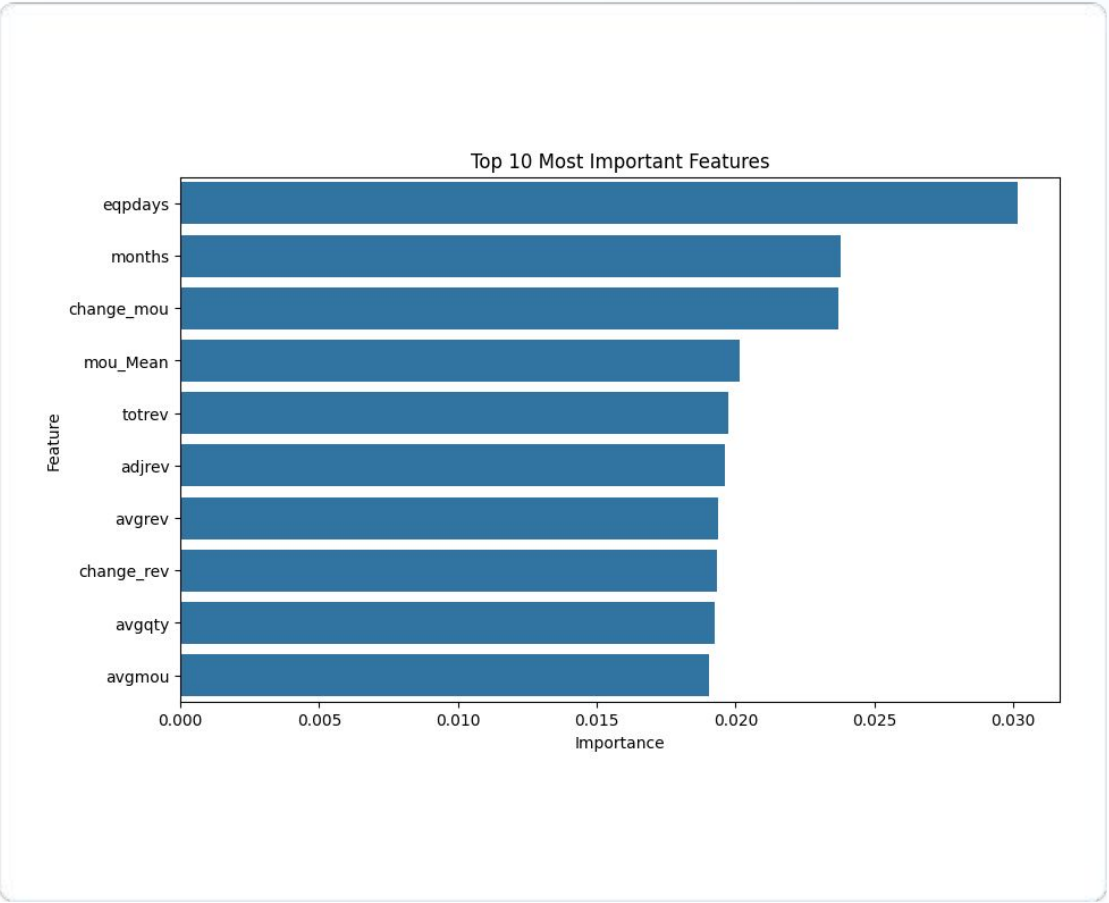
"The model helps predict which customers may leave, allowing the company to take steps to improve customer retention. "

WHAT DRIVES CUSTOMER CHURN?

Key Analytical Findings

- **Device Age (eqpdays):** The strongest predictor of customer churn. Customers with older devices were more likely to leave.
- **Usage Changes (change_mou):** Significant changes in customer usage were strongly associated with churn risk.
- **Customer Tenure (months):** The length of the customer relationship influenced retention behavior.

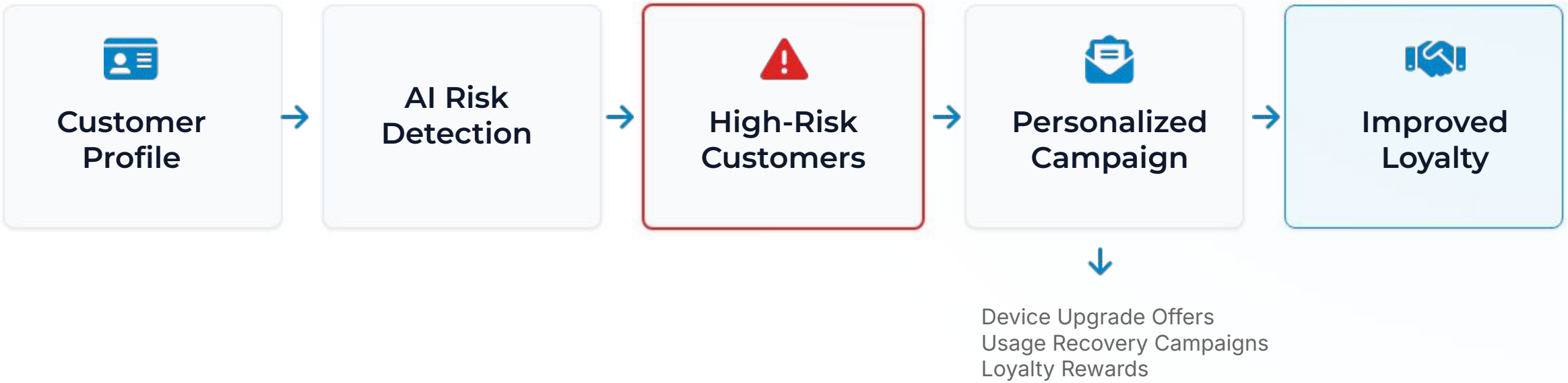
> These variables were identified as the strongest predictors of customer churn and directly informed the proposed retention strategy.



Evidence: Random Forest Feature Importance output.

RECOMMENDED RETENTION STRATEGY

"The retention strategy was designed based on the model's top predictors: device age, usage changes, and customer tenure."



EXPECTED BUSINESS IMPACT

Illustrative Scenario (Assumption-Based)

TOTAL CHURNED CUSTOMERS

49,562

ASSUMED CHURN REDUCTION

5%

POTENTIAL CUSTOMERS RETAINED

2,478

How the model supports this:

- Older-device users receive upgrade offers.
- Customers with declining usage receive retention campaigns.
- Long-term customers receive loyalty rewards.

Business Value Proposition

- **Protect Future Revenue:** Keeping more customers helps the company maintain a steady income.
- **Lower Acquisition Costs:** Bypasses the 5-7x cost premium associated with capturing replacement customers.
- **Strengthen Customer Loyalty:** Reaching out to customers early can make them more satisfied and encourage them to stay.
- **Efficient Marketing:** Focuses budgetary resources strictly on accounts identified as "at-risk" by the model.

IMPLEMENTATION ROADMAP & NEXT STEPS

Month 1

Model Deployment

Integrate predictive algorithms seamlessly into CRM.

Month 2

Pilot Testing

Launch targeted device upgrade campaigns for high-risk tiers.

Month 3

Full Implementation

Automate loyalty rewards and execute early warning systems.

Ongoing

Support & Scaling

Refine service protocols based on continuous AI feedback.

- Device Upgrade Campaigns
- Targeted Loyalty Rewards
- Early Churn Monitoring
- Improved Customer Support

REFERENCES & SOURCES

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