Customer Churn Analysis – Key Drivers & Predictive Insights

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Springboard – Capstone 3

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Agenda

Executive Summary

- Subscription churn impacts revenue more than new-acquisition spend
- Analysis on 7,043 Telco customers to pinpoint attrition drivers
- Contract type accounts for ~80% of predictive power
- Logistic Regression model AUC = 0.836
- Actionable levers: contract incentives, auto-pay, service quality

Problem Statement & Business Context

Monthly churn rates erode subscription revenues by millions

Manual retention campaigns miss high-risk segments, waste budget

Need shift from reactive to proactive, data-driven retention

Goal: Identify at-risk customers and root causes of churn

Data Overview & Methodology

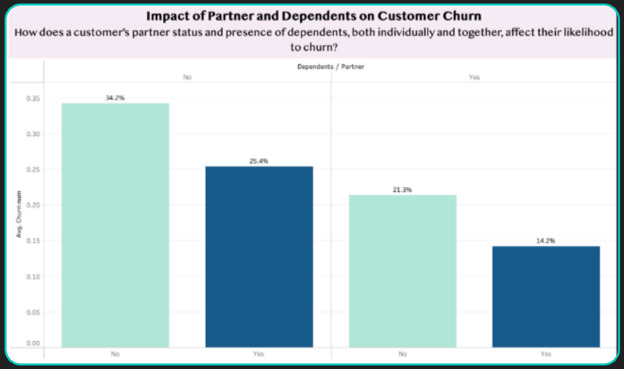
- Telco Customer Churn Dataset (Kaggle): 7,043 records, 21 features - Demographics, service usage, account details, financials
- Workflow: Clean & engineer features (tenure buckets, charges ratios)
- Models: Logistic Regression (interpretability) & Decision Tree (non-linear)
- Tools: Python (Pandas, NumPy, scikit-learn), Tableau, Matplotlib, Seaborn

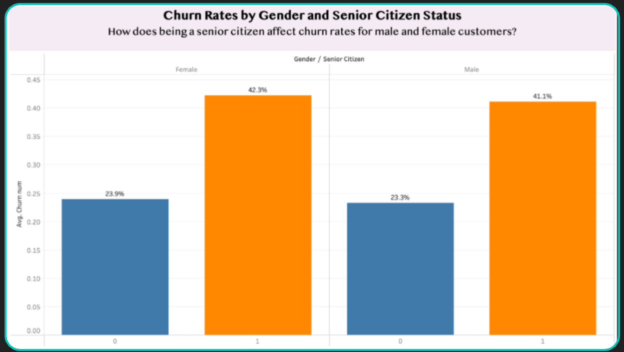
Demographic & Relationship Factors

Customers with no partner/dependents churn at 34.2%; both = 14.2%

Presence of family ties reduces churn by ~20 percentage points

Seniors churn ~42% vs. non-seniors ~24%; gender effect negligible



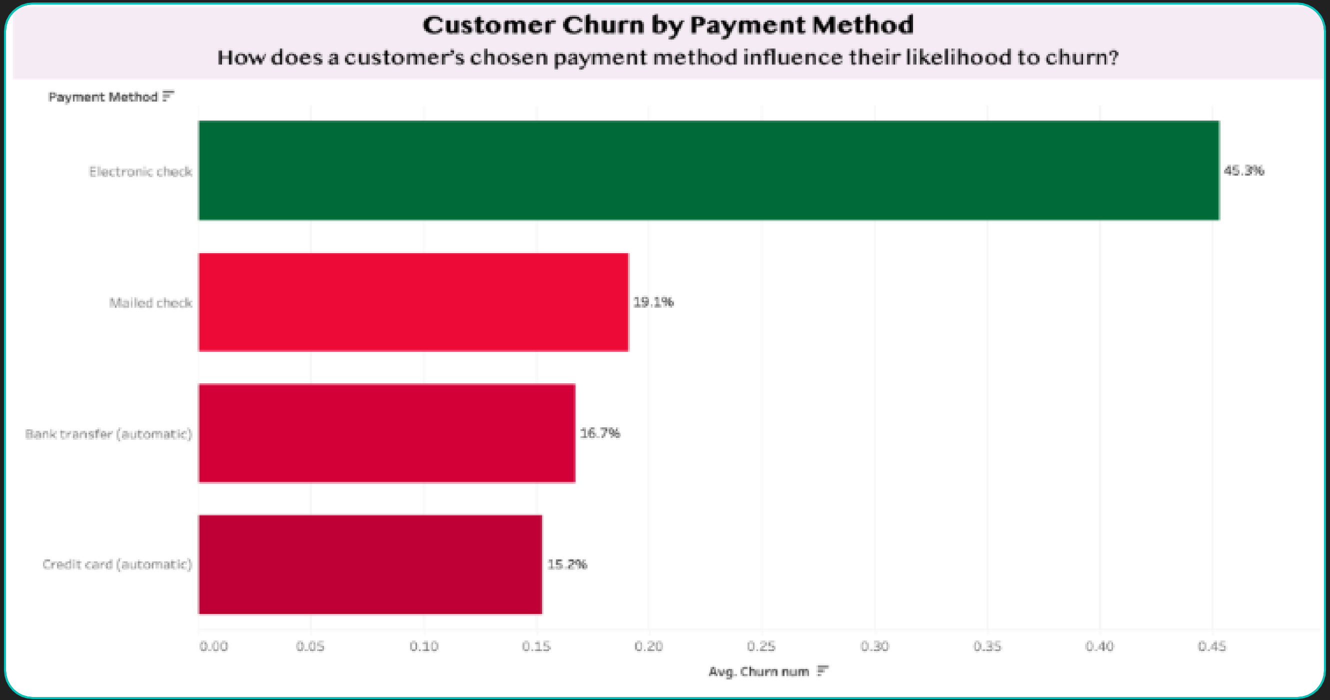


Financial & Payment Behavior

Electronic check users churn 45.3%; auto-pay users churn ~16%

Automatic payments indicate higher commitment and reduce attrition

Suggested levers: migrate to bank-transfer or credit-card auto-pay

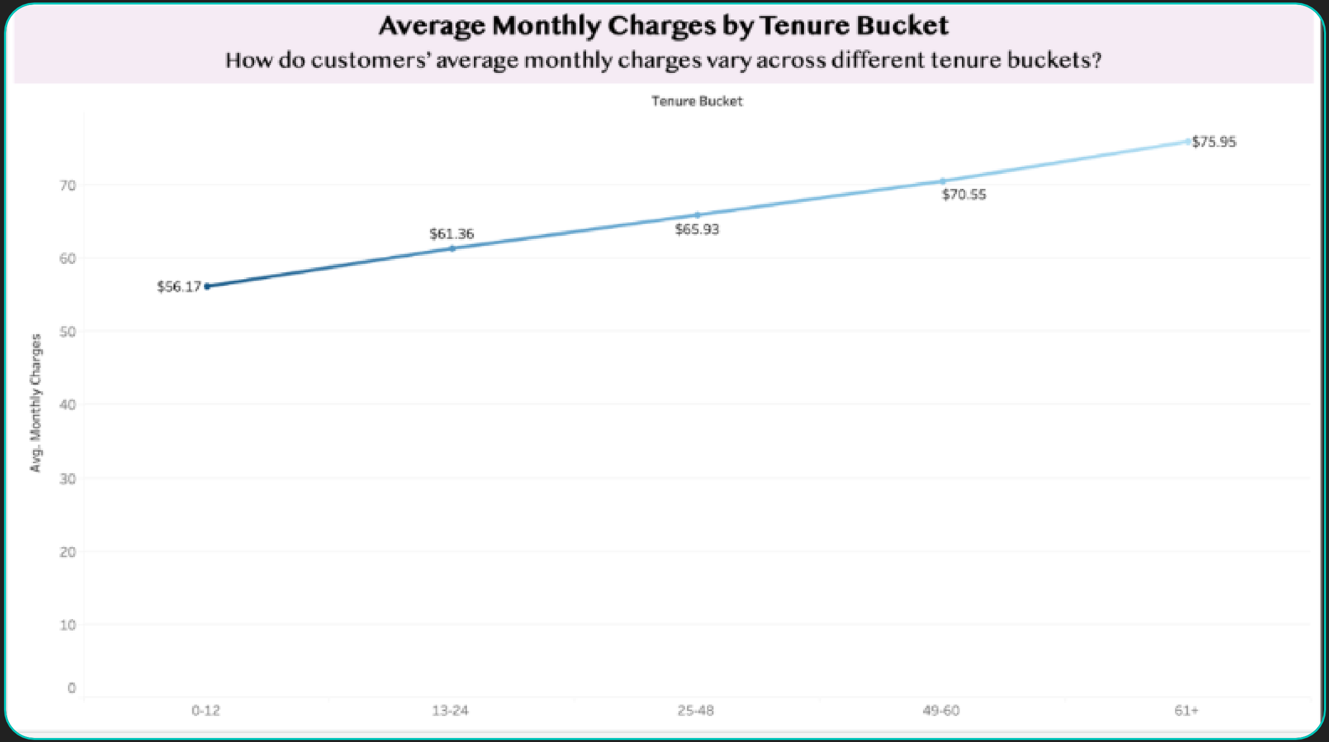


Tenure & Pricing Paradox

Early-tenure customers (0-12 months) pay avg. $56.17; long-tenure (61+ months) pay $75.95

Loyal customers accept higher-rates – possibly due to upgrade or price hikes

Key insight: price isn't sole driver; service expectations matter

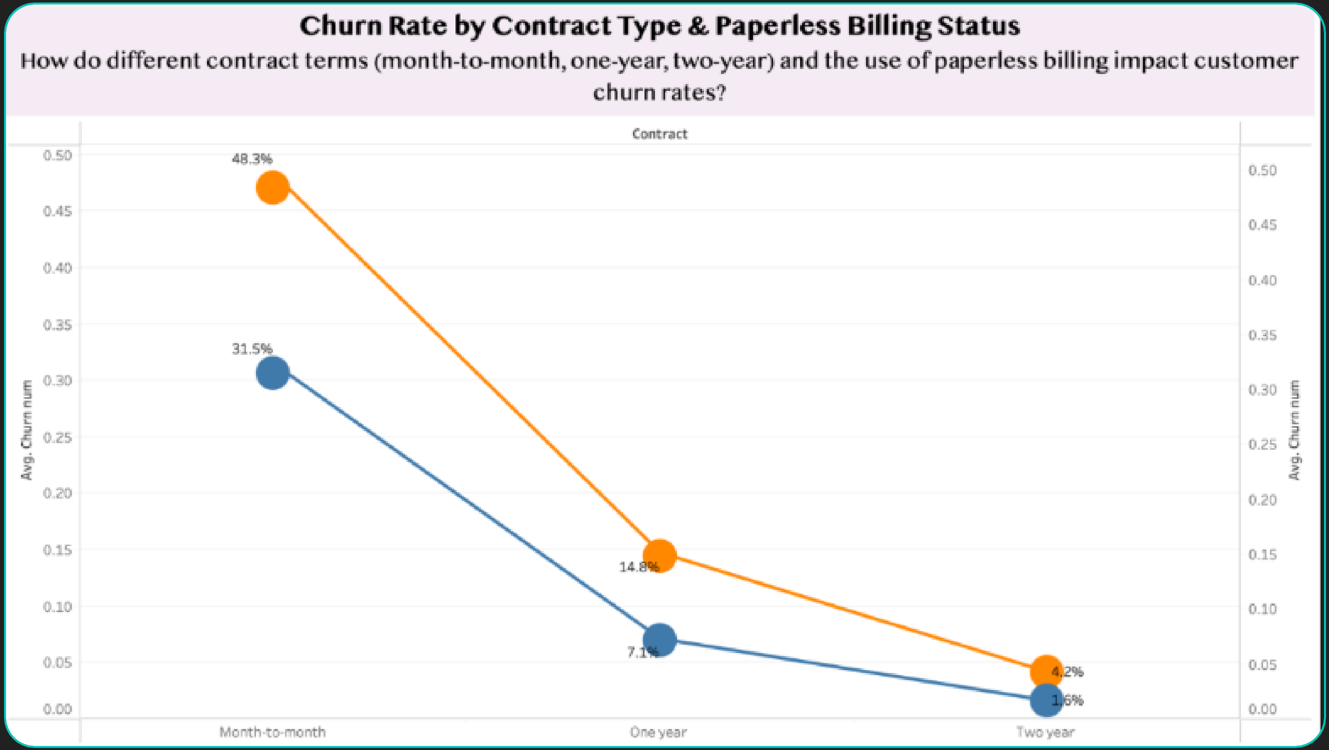


Contract & Service Factors

Months-to-month churn: 31.5-48.3%; one-year: 7.1-14.8%; two-year: 1.6-4.2%

Paperless billing correlates with ~1.5x higher churn across all contracts

Contract incentives are the single biggest retention lever



Predictive Model Development

Why these models?

Logistic Regression: clear coefficients → actionable risk scores

Decision Tree: uncovers non-linear interactions

Feature engineering: one-hot encoding, scaling, tenure brackets, charges ratios

AIM: balance interpretability & predictive power for real-world deployment

Model Performance Comparison

Logistic Regression

- **AUC = 0.836**, recall = 91.0%, precision trade-offs
- Confusion matrix: 739 TN, 301 TP, 296 FP, 73 FN

Decision Tree

- Recall = 92.9%, but 444 FP vs. 45 FN → more false alarms

Model Performance Comparison (cont)

Logistic Regression Confusion Matrix

Actual/LogReg Predicted	0 (No Churn)	1 (Churn)
0 (No Churn)	739	296
1 (Churn)	73	301

Decision Tree Confusion Matrix

Actual/ Tree Predicted	0 (No Churn)	1 (Churn)
0 (No Churn)	591	444
1 (Churn)	45	329

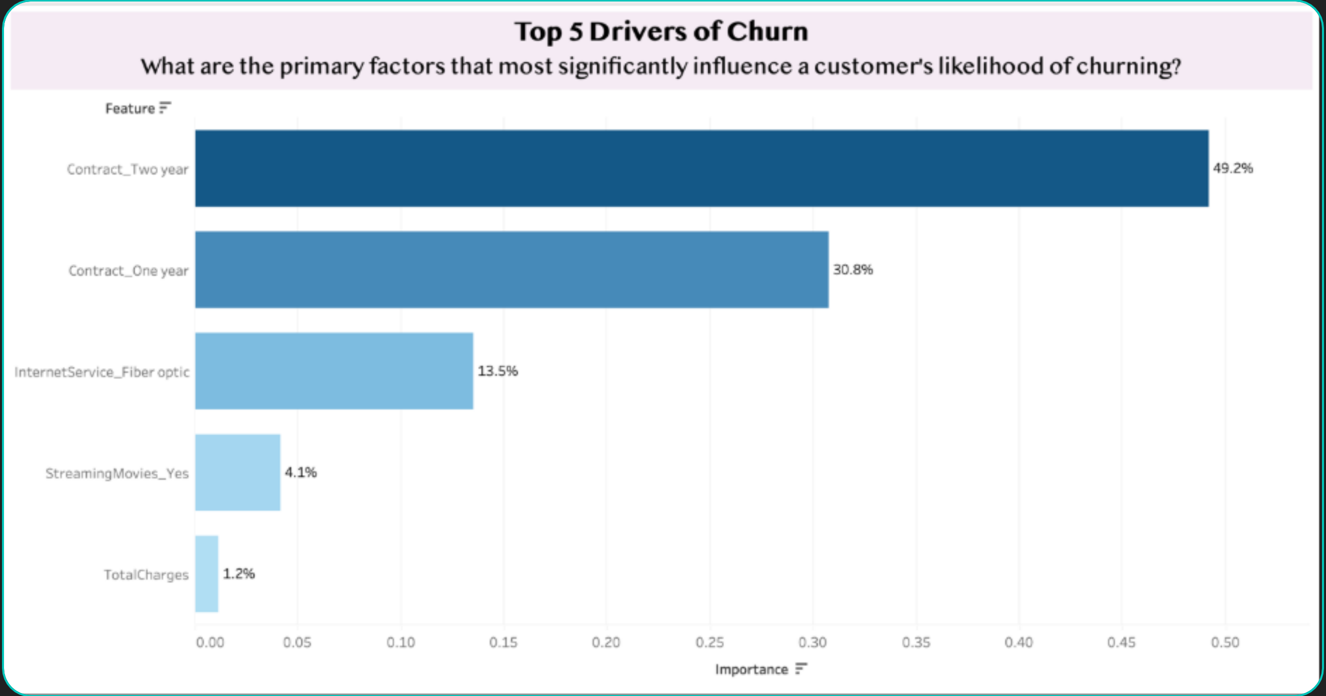
Feature Importance Analysis

Contract_Two year: 49.2% of model power

Contract_One year: 30.8%

InternetService_Fiber optics: 13.5% (signals potential quality issues)

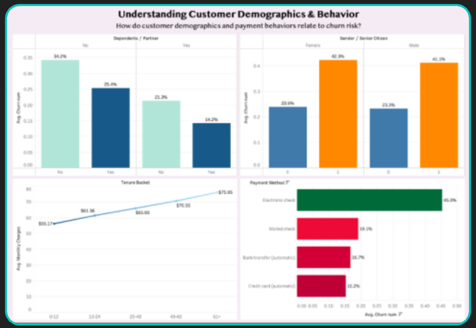
StreamingMovies: 4.1%; TotalCharges: 1.2%

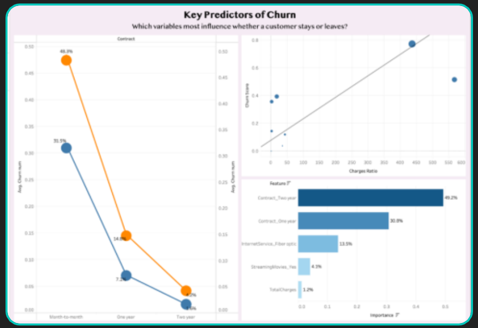


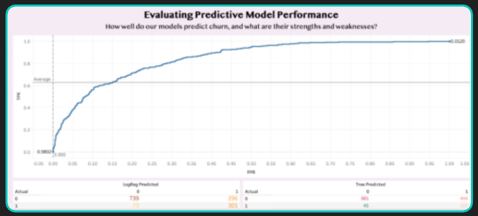
Interactive Dashboard Highlights

Dynamic filters: churn risk score, tenure, contract, payment method

High-risk cohort: month-to-month + fiber + electronic check + tenure <12 mo → 45–50% churn







Limitations

Data Constraints
- Simulated dataset may not mirror real-world complexity
- Excludes external drivers such as seasonality, competitive activity, and macroeconomic trends

Modeling Challenges
- Decision Tree exhibited overfitting (high false positives)
- Narrow feature set — lacking behavioral metrics and customer service interactions

Scope Boundaries
- Focus limited to churn prediction; no analysis of upsell/downgrade patterns
- Assumes customer preferences remain constant over time

Recommendations for Implementation

Immediate Actions:

- Tiered contract incentives (10–20% discounts + perks)
- Auto-payment migration program with $5–10 credits + signup bonus
- Embed churn-risk scoring in CRM for real-time alerts

Strategic Initiative: Fiber service satisfaction program: surveys, ticket analysis, infrastructure upgrades

Business Impact & Strategic Implications

Financial:

- Contract incentives can slash churn from 40% to <15%
- Auto-pay migration could cut churn among check users by 60%

Operational:

- Investigate fiber service quality (high churn despite premium pricing)

Tailor retention for senior demographic & paperless billing users

Future Research Directions

- Ensemble models (Random Forest, GBM), neural networks for deeper patterns
- Time-series analytics to capture seasonality and churn timing
- Integrate Customer Lifetime Value into retention prioritization
- Enrich dataset: support tickets, usage logs, competitive intelligence
- A/B test framework for retention tactics and pricing experiments

Conclusion & Next Steps

Data-driven insights transform churn from reactive pain into strategic advantage

Contract terms dominate churn decisions; payment & service quality follow

Next: pilot recommended interventions, deploy logistic model in CRM

Q&A / Feedback

What resonates most with your current retention challenges?

Any concerns on data assumptions or model deployment?

Suggestions for additional analyses or focus areas?

Thank you—your feedback will refine our next steps!