Churn Analysis

Approach

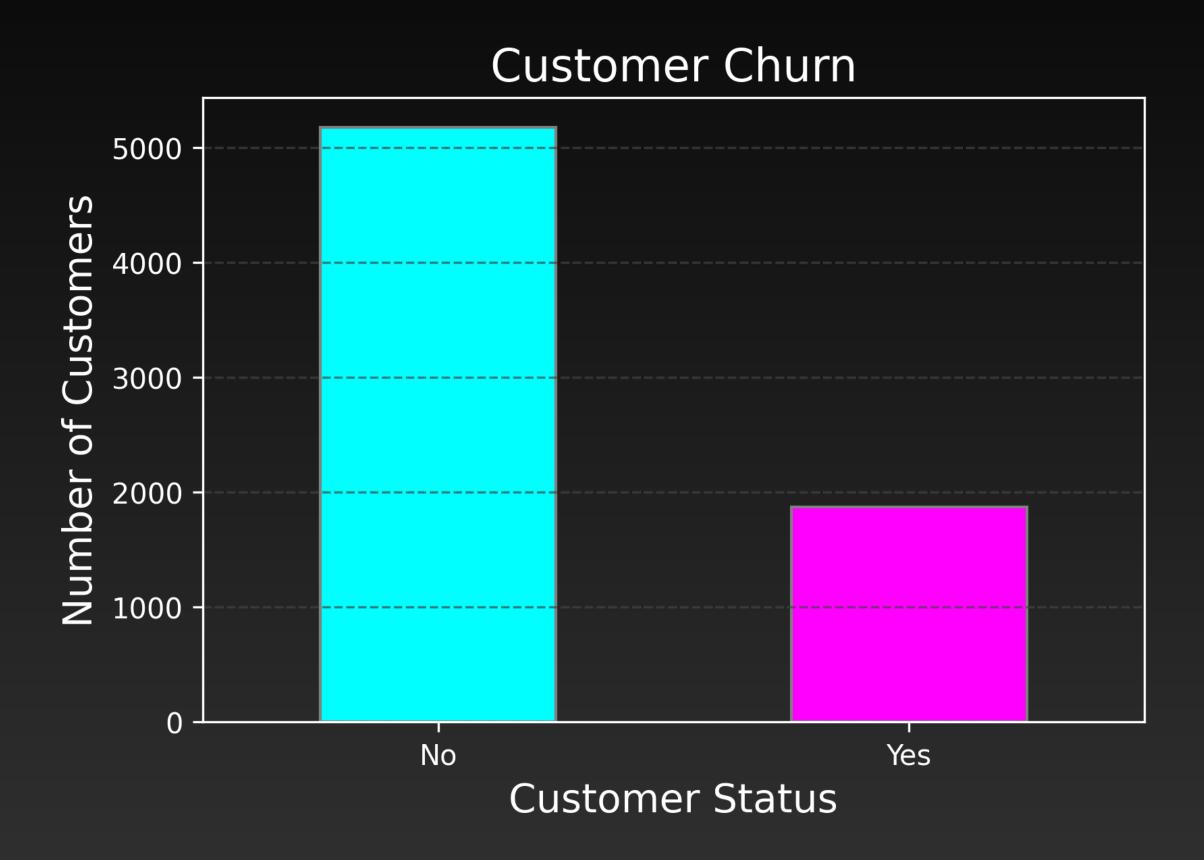
- Data Preparation → Collected 7,043 telecom customer records; cleaned missing values, encoded categorical variables, and engineered features (e.g., tenure groups, contract type).
- Exploratory Analysis → Used summary statistics and visualizations to uncover churn patterns across demographics, payment methods, and contract types.
- Modeling & Evaluation → Built and tuned machine learning models (Random Forest, Logistic Regression) to predict churn, achieving 80% accuracy and 0.84 AUC.
- Insights & Strategy → Identified high-risk segments (e.g., month-to-month, electronic check users, senior citizens) and quantified potential revenue loss to guide retention strategies.

Data Overview

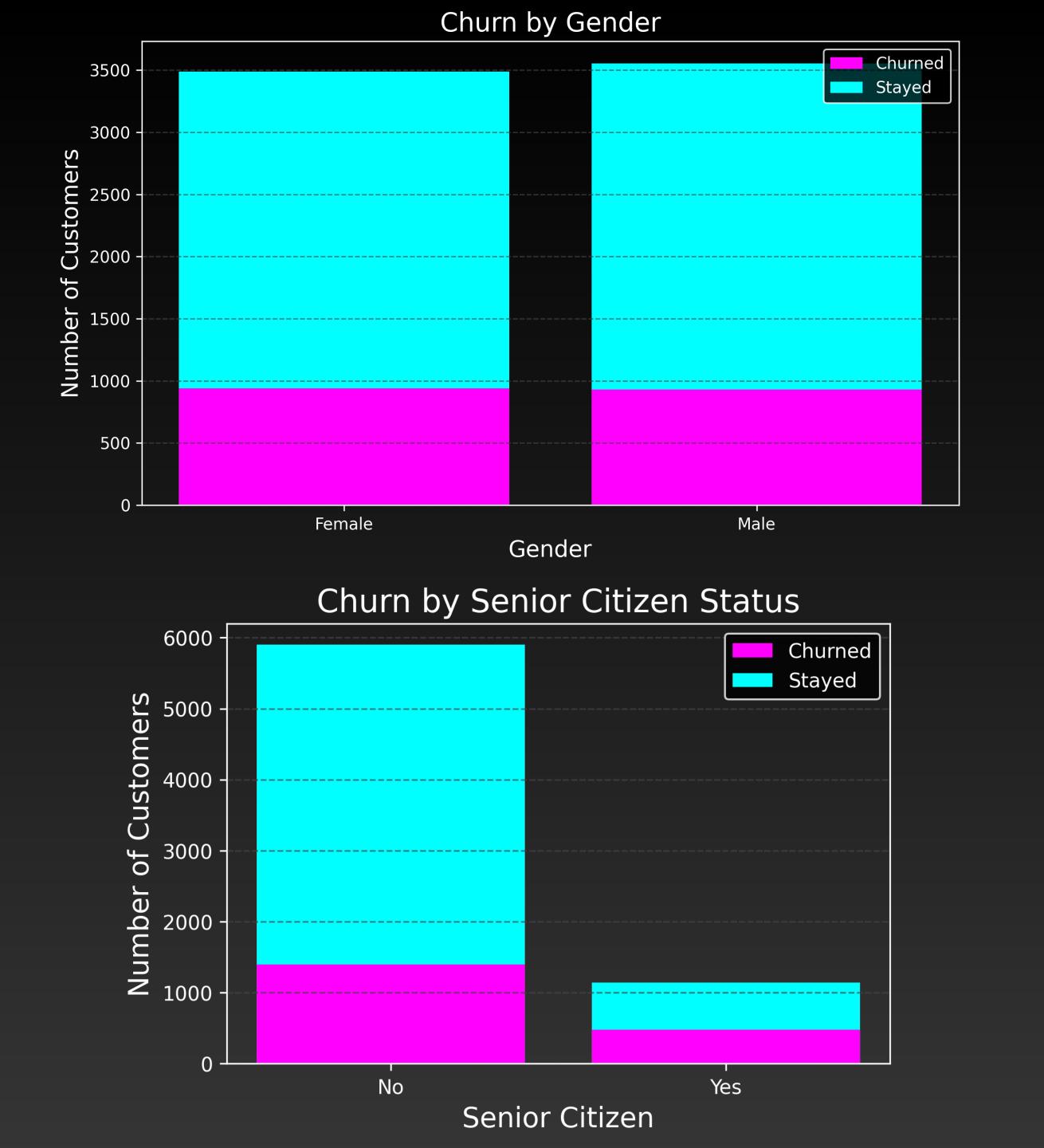
- Dataset size: 7,043 telecom customer records
- Variables:
 - Demographics → gender, age, senior citizen status
 - Services → internet, phone, streaming, add-ons
 - Account details → tenure, contract type, payment method
 - Billing → monthly charges, total charges
- Target variable: Churn (Yes/No)

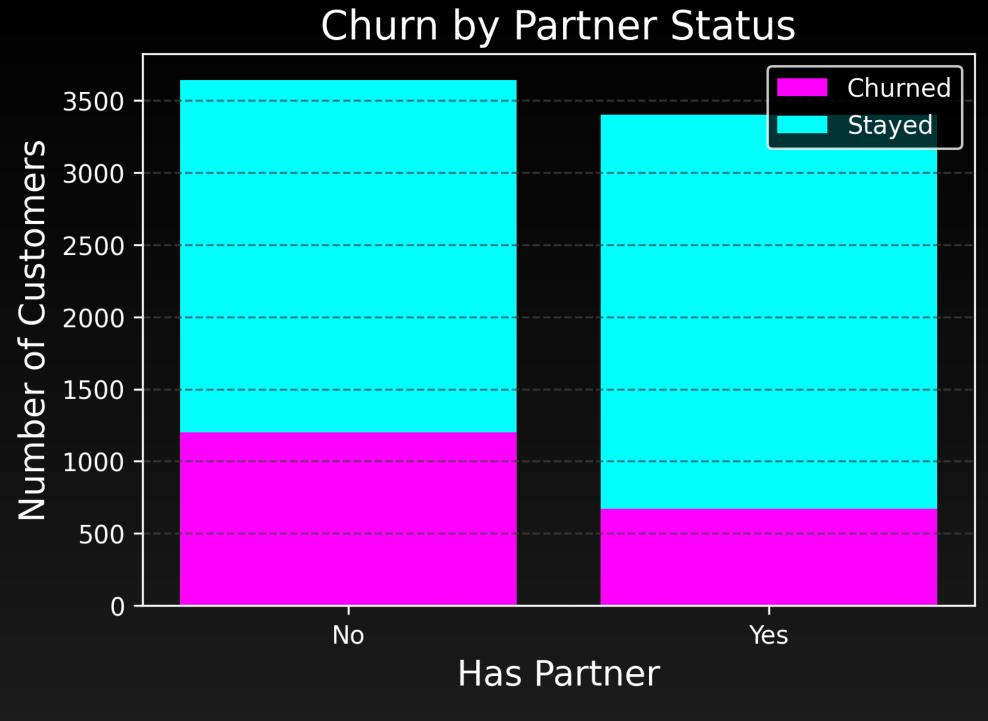
Overall Churners

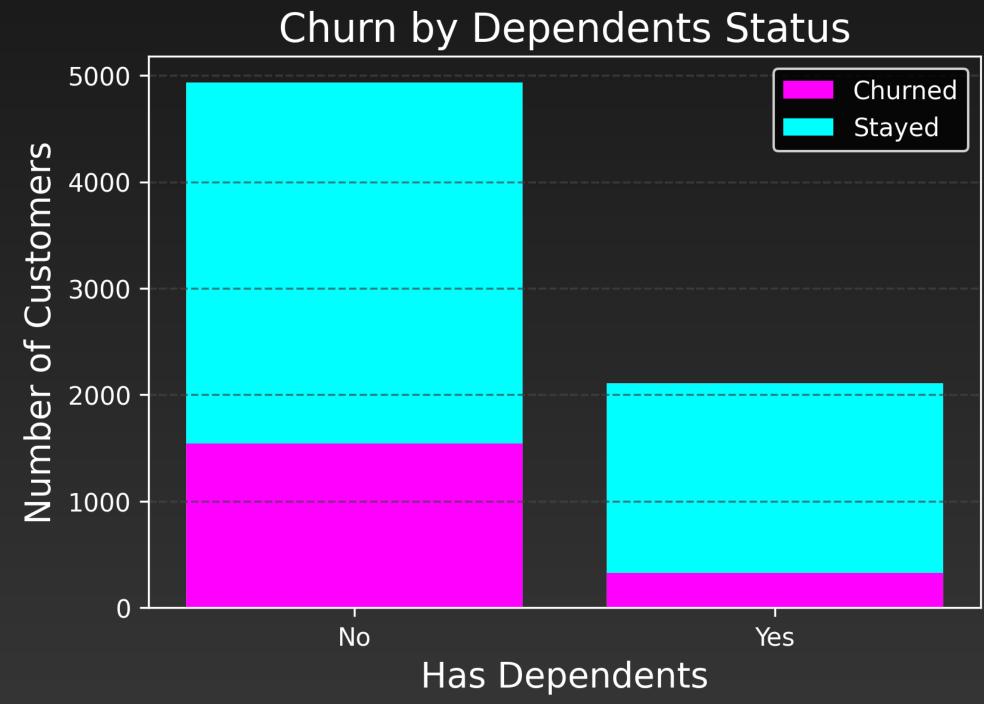
Out of **7,043** customers, **1,869 (26.54%)** left the service.



Demographics

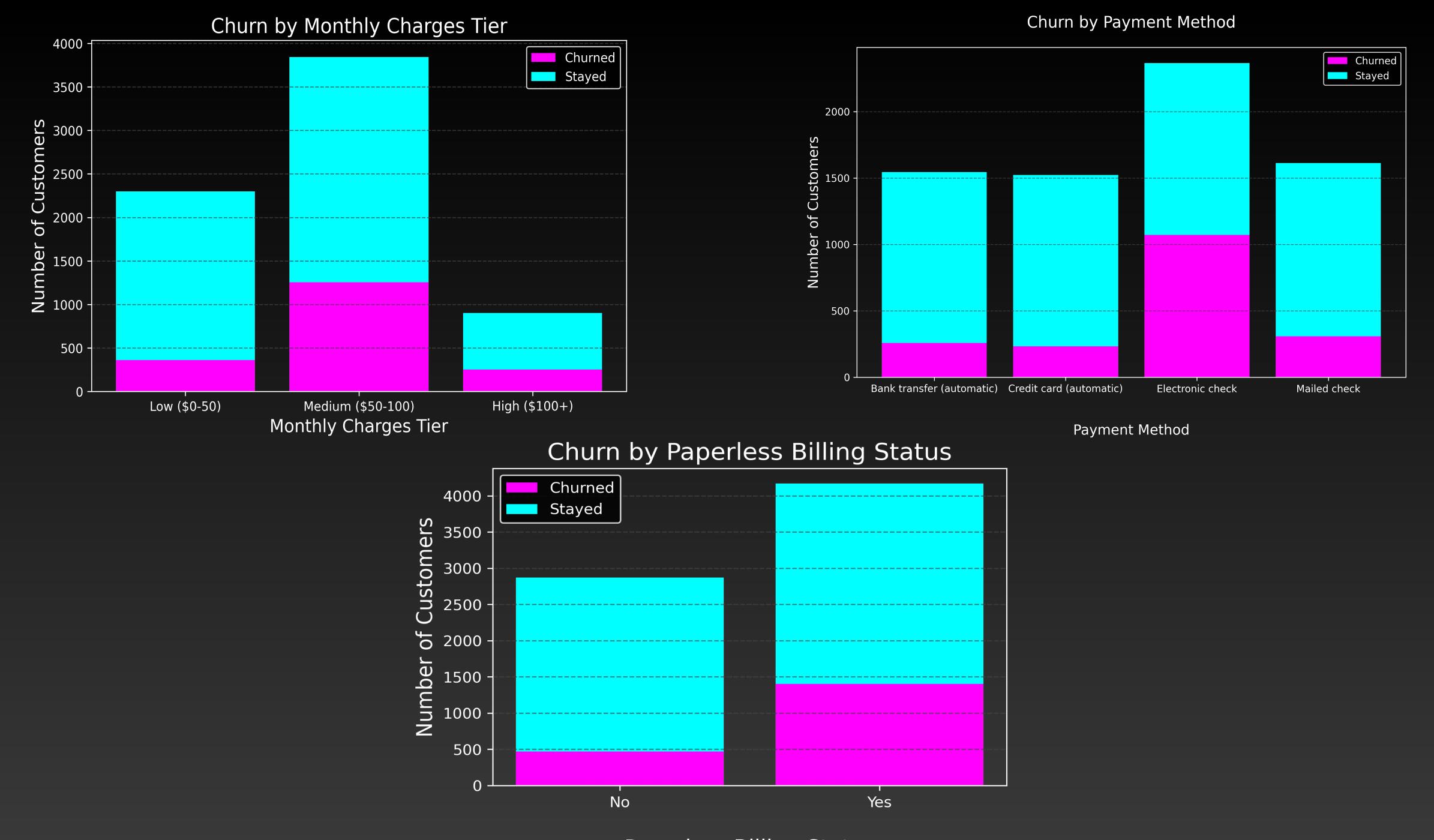






- **Gender:** Male and female customers show similar churn behaviour, with **26.92% of females** and **26.16% of males** churning.
- Senior Citizens: Senior citizens are far more likely to churn, with a rate of 41.68%, compared to only 21.61% of non-seniors.
- Partner Status: Customers with a partner are more likely to stay, with a churn rate of just 19.66%, compared to 32.96% for those without a partner.
- **Dependents:** Customers **with dependents** churn at a much lower rate of **15.45%**, versus **31.28%** for those **without dependents**.

Pricing and Payment



Paperless Billing Status

Monthly Charges:

- Customers paying \$50-\$100 churn the most at 32.67%.
- Customers paying over \$100 churn at 28.05%.
- Customers paying \$50 or less churn the least at 15.7%.

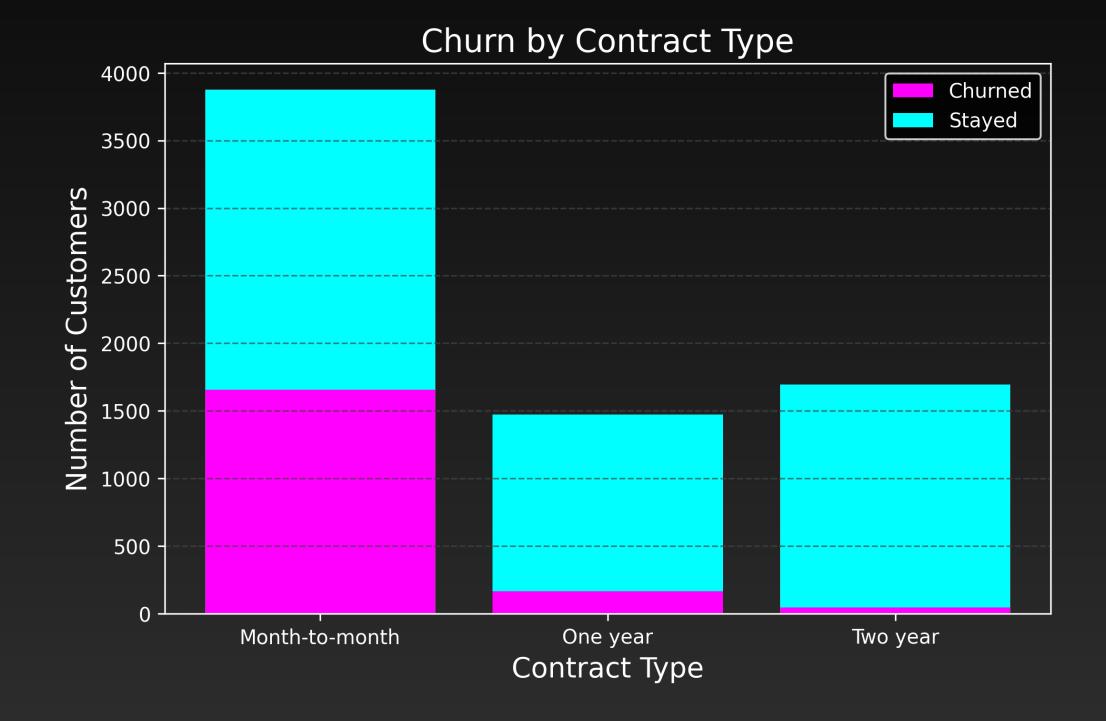
Payment Method:

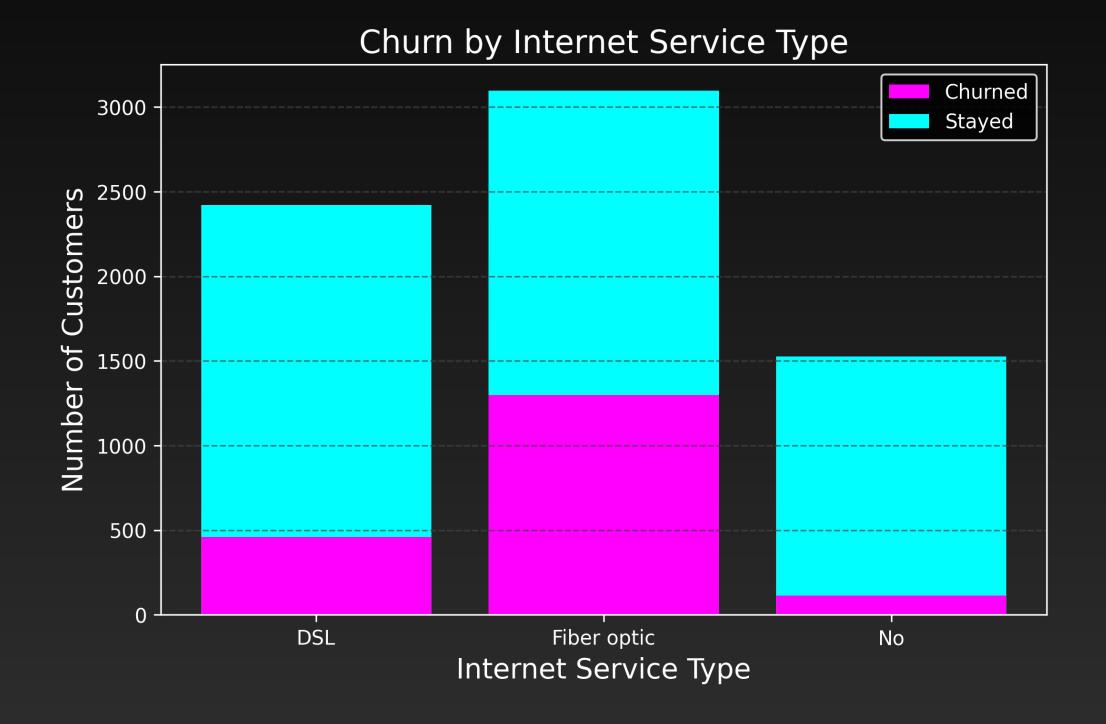
- Automatic payments (Bank transfer: 16.71%, Credit card: 15.24%) have the lowest churn.
- Manual payments churn more (Electronic check: 45.29%, Mailed check: 19.11%).

Paperless Billing:

- Customers with paperless billing churn at 33.57%.
- Customers without paperless billing churn at only 16.57%.

Contracts and Services





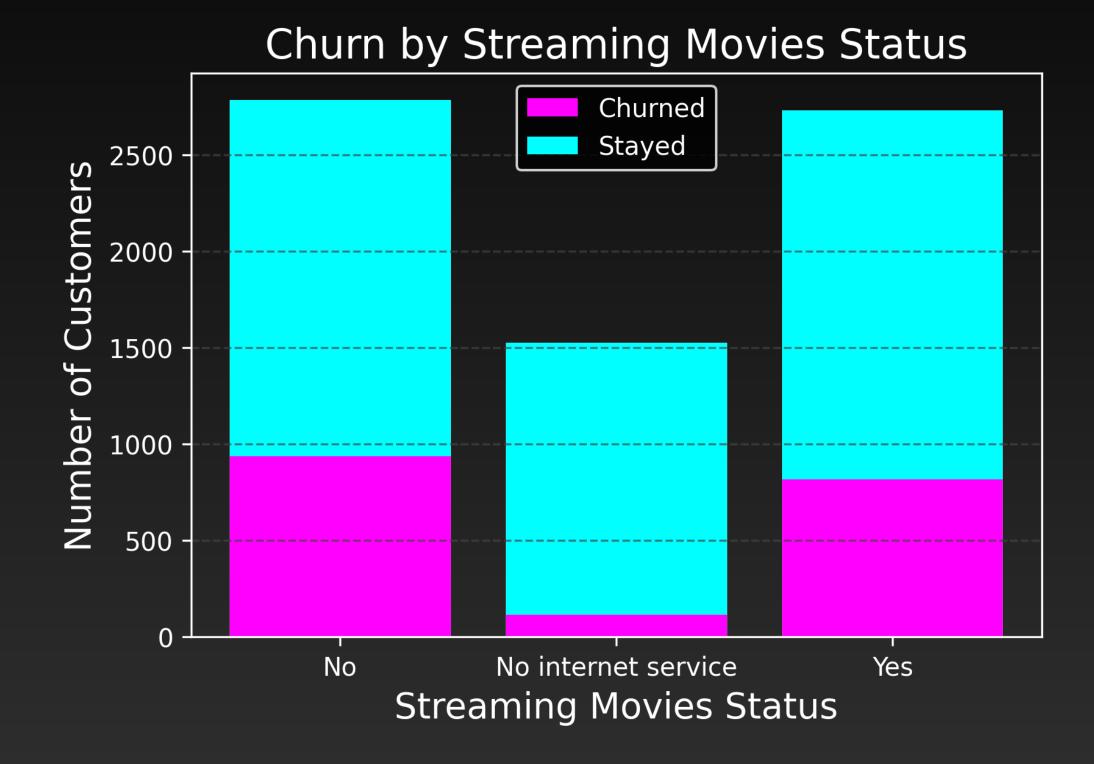
• Contract Type:

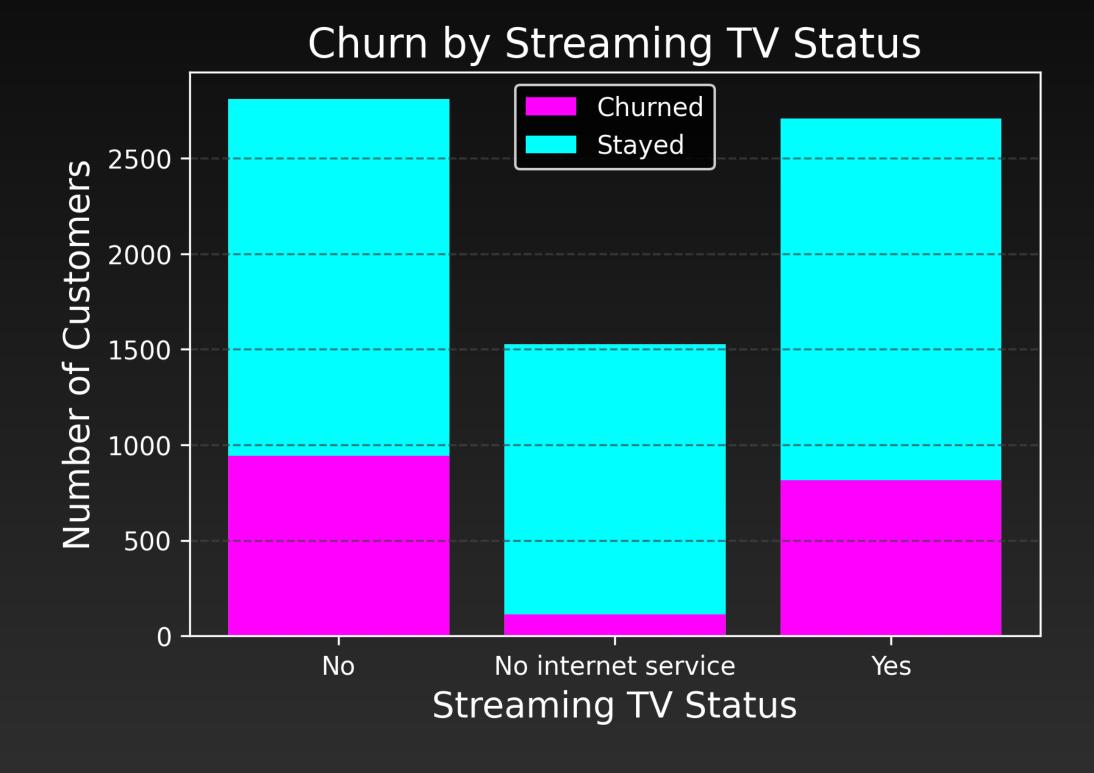
- Month-to-month contracts have by far the highest churn at 42.71%.
- •One-year contracts churn much less at 11.27%.
- Two-year contracts have the lowest churn at just 2.83%.

• Internet Service:

- Fibre optic users churn the most at 41.89%.
- DSL users churn at 18.96%.
- Customers with no internet service churn the least at 7.4%.

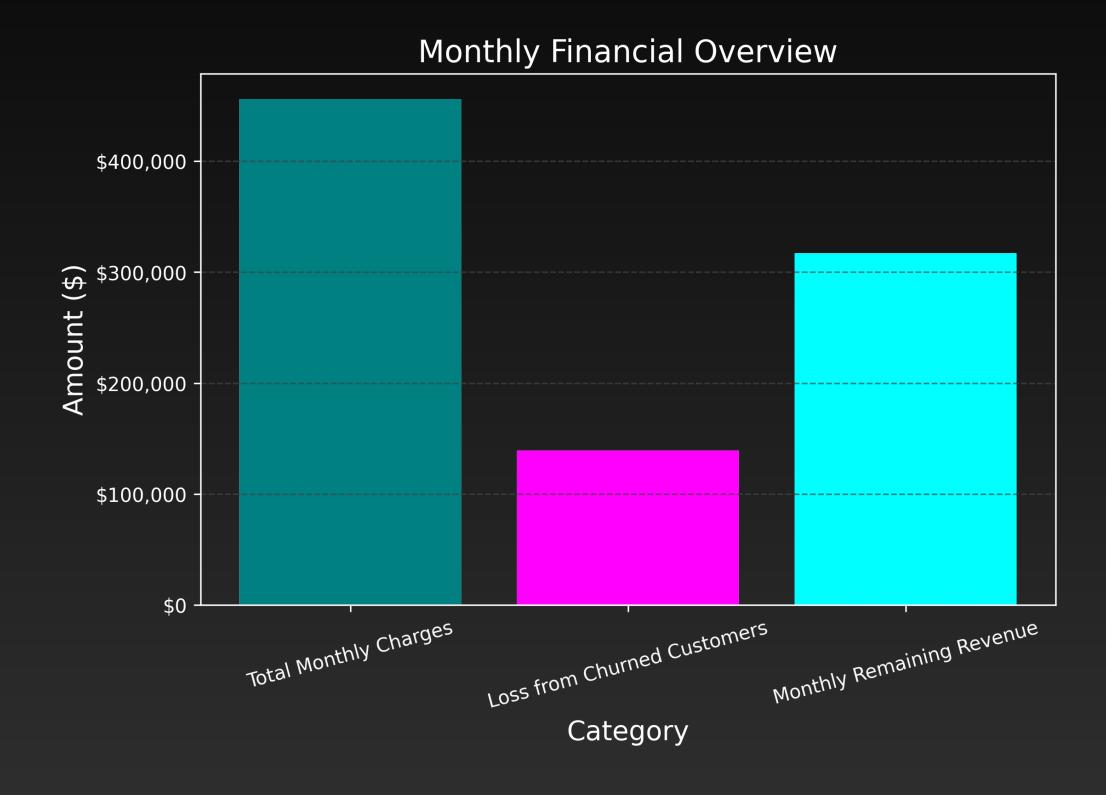
Entertainment Services

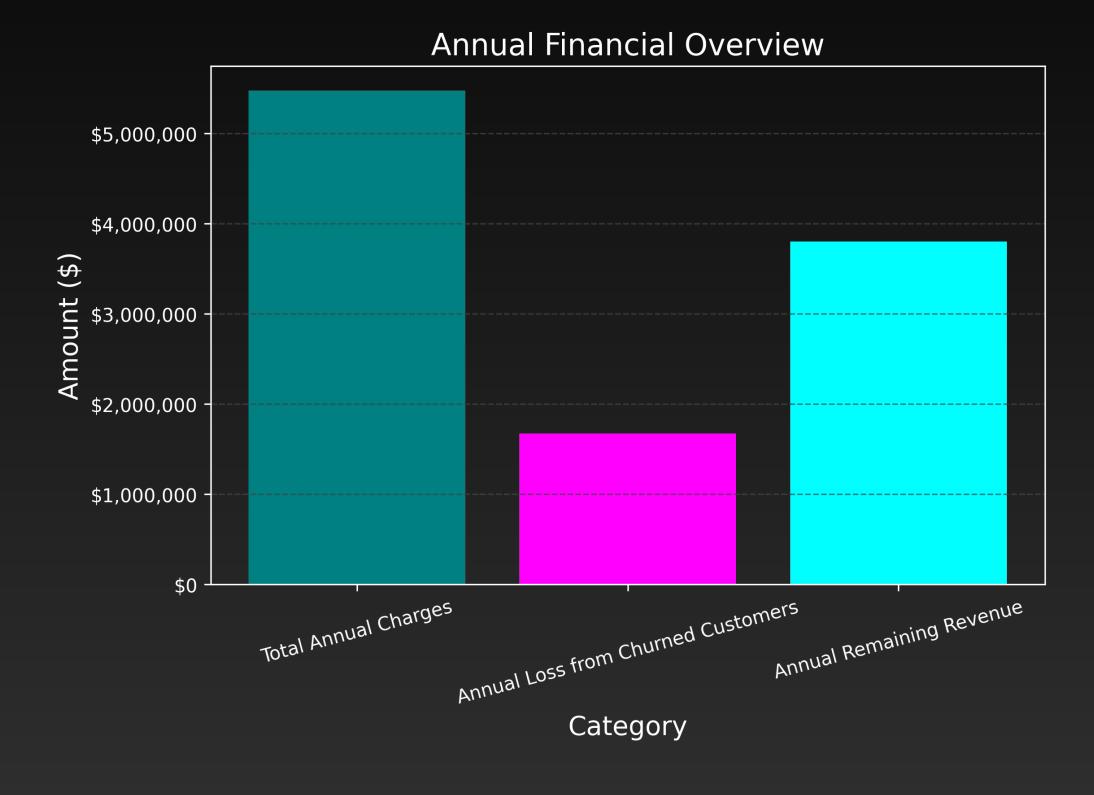




- Customers without TV or movie streaming have the highest churn at 33.5%.
- Customers without internet service churn the least at 7.4%, showing a clear divide between connected vs. unconnected users.
- •Customers with TV, movie, or both subscriptions churn slightly less than those without any subscriptions(30%), indicating similar behavior across these subscription types.
- •Overall, churn rates for TV and movie services are **nearly identical**, suggesting these categories behave almost interchangeably in the dataset.

Financial Impact





Monthly Revenue:

- Without churn: \$456K
- •Lost to churn: \$139K
- •Remaining after churn: \$316K

Yearly Revenue:

- Without churn: \$5.4M
- •Lost to churn: \$1.6M
- •Remaining after churn: \$3.8M

Machine Learning Model

Our **machine learning model** was able to predict customer churn with an accuracy of **80%**, correctly identifying the characteristics of customers most likely to leave. This means that in **8 out of 10** cases, the model successfully distinguished between customers who stayed and those who churned. While this is not a perfect prediction rate, it provides a reliable foundation for **identifying at-risk customers** and offers valuable direction for potential retention strategies.

HIGH-RISK CUSTOMER IDENTIFICATION

Our model identified **109 high-risk customers**, representing **7.7% of the test group**. These customers account for a potential **\$8,743 in monthly revenue at risk**, which scales to approximately **\$104,922 annually**. On average, high-risk customers have **monthly charges of \$80.22** and a short **tenure of 3.4 months**, highlighting that newer customers with higher bills are more likely to churn.

Recommendations

Target high-risk customers

New customers with high monthly charges (avg. \$80.22, tenure 3.4 months) churn fastest—especially seniors (41.7% churn) and fibre users (41.9% churn).

Develop retention incentives

Offer early discounts, loyalty perks, or personalized outreach in the first 3 months. This is critical for seniors, customers without partners/dependents, and those paying by electronic check (45% churn).

Leverage predictive modeling

Use the ML model (80% accuracy) to proactively flag at-risk customers. Cross-reference with demographics (senior status, contract type, billing method) for targeted interventions.

Unify TV & Movie strategy

Churn rates differ by < 0.1% — treat them as one segment to simplify retention campaigns.

Quantify the financial upside

With ~\$105K annual revenue at risk, churn reduction initiatives could significantly increase profitability.

Closing statement

By combining demographic insights with predictive modelling, we can not only understand who is most likely to churn, but act early to prevent it—turning a \$105K risk into a major opportunity for growth.