Churn Analysis

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Approach

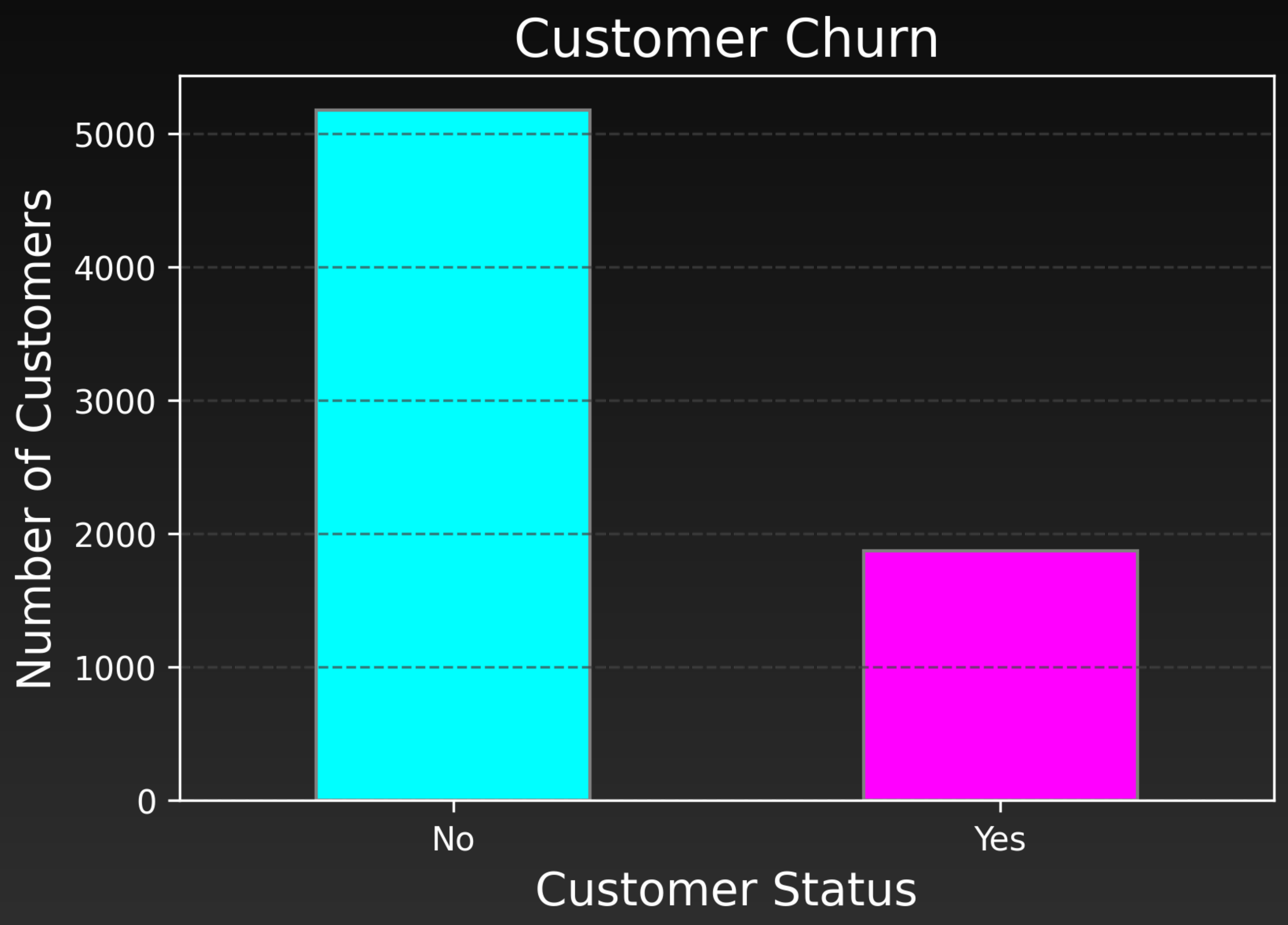
- **Data Preparation** → Collected 7,043 telecom customer records; cleaned missing values, encoded categorical variables, and engineered features (e.g., tenure groups, contract type).
- **Exploratory Analysis** → Used summary statistics and visualizations to uncover churn patterns across demographics, 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

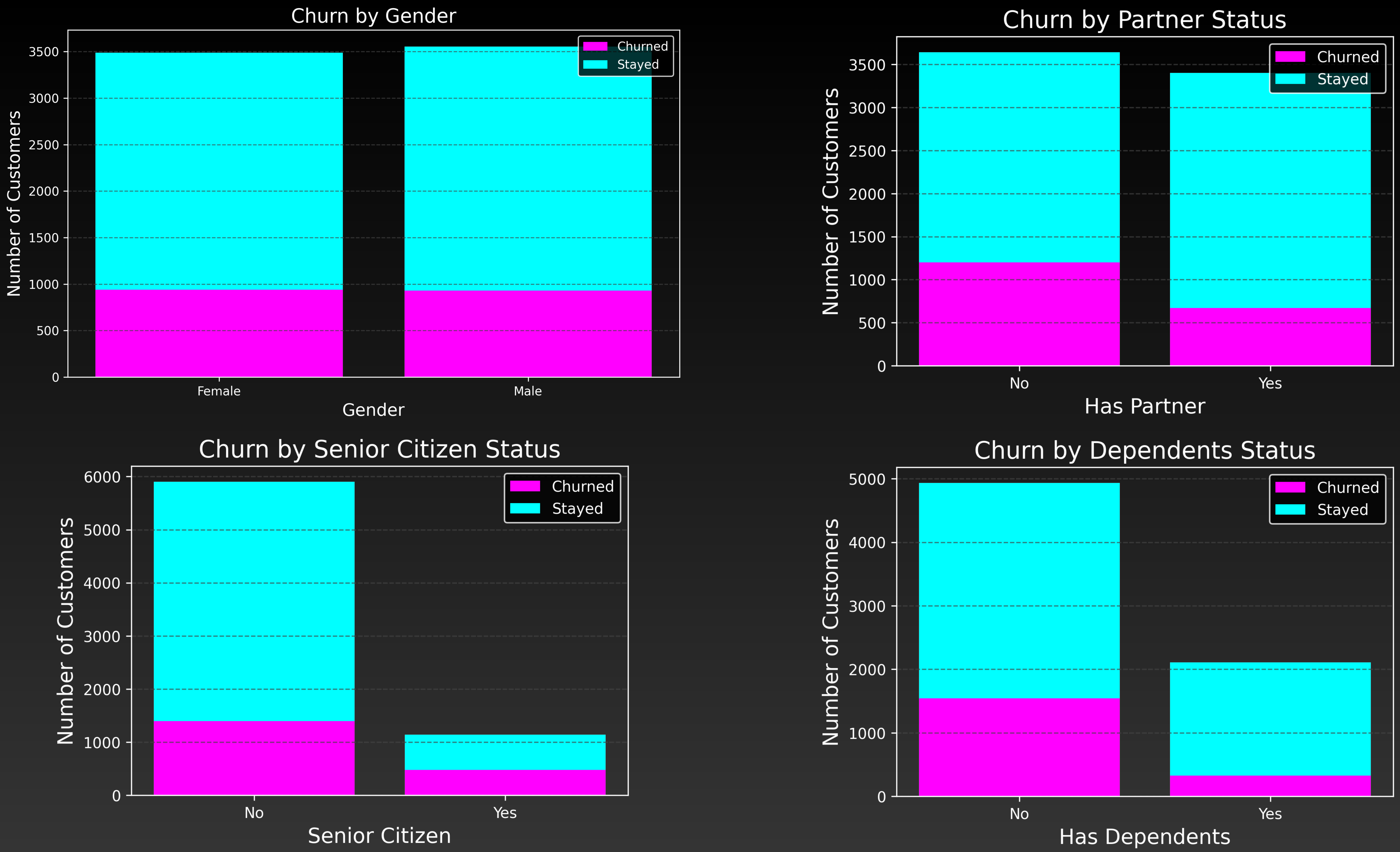
- **Dataset size:** 7,043 telecom customer records
- **Variables:**
  - **Demographics** → gender, age, senior citizen status
  - **Services** → internet, phone, streaming, add-ons
  - **Account details** → tenure, contract type, payment method
  - **Billing** → monthly charges, total charges
- **Target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

Overall Churners

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



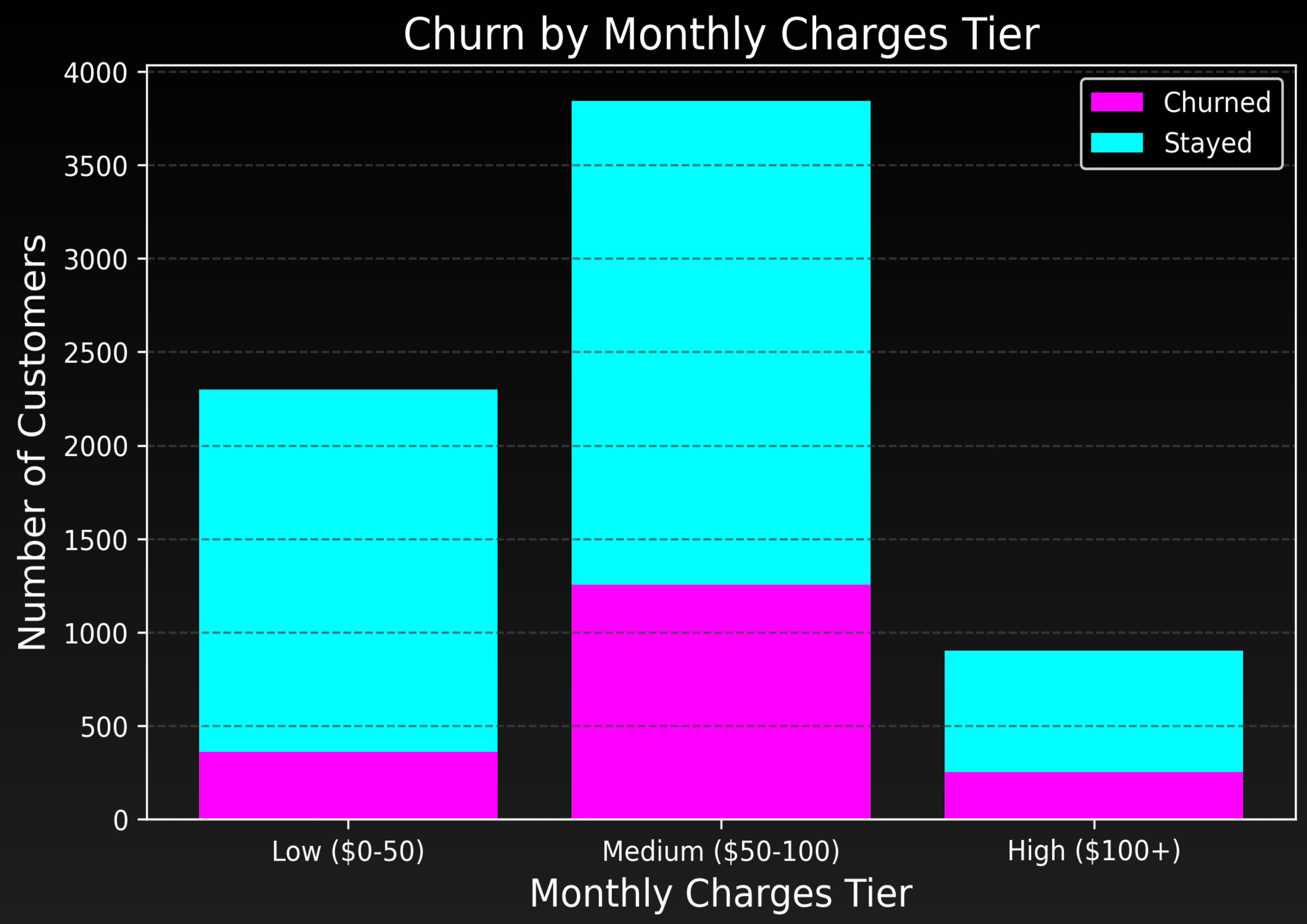
Demographics

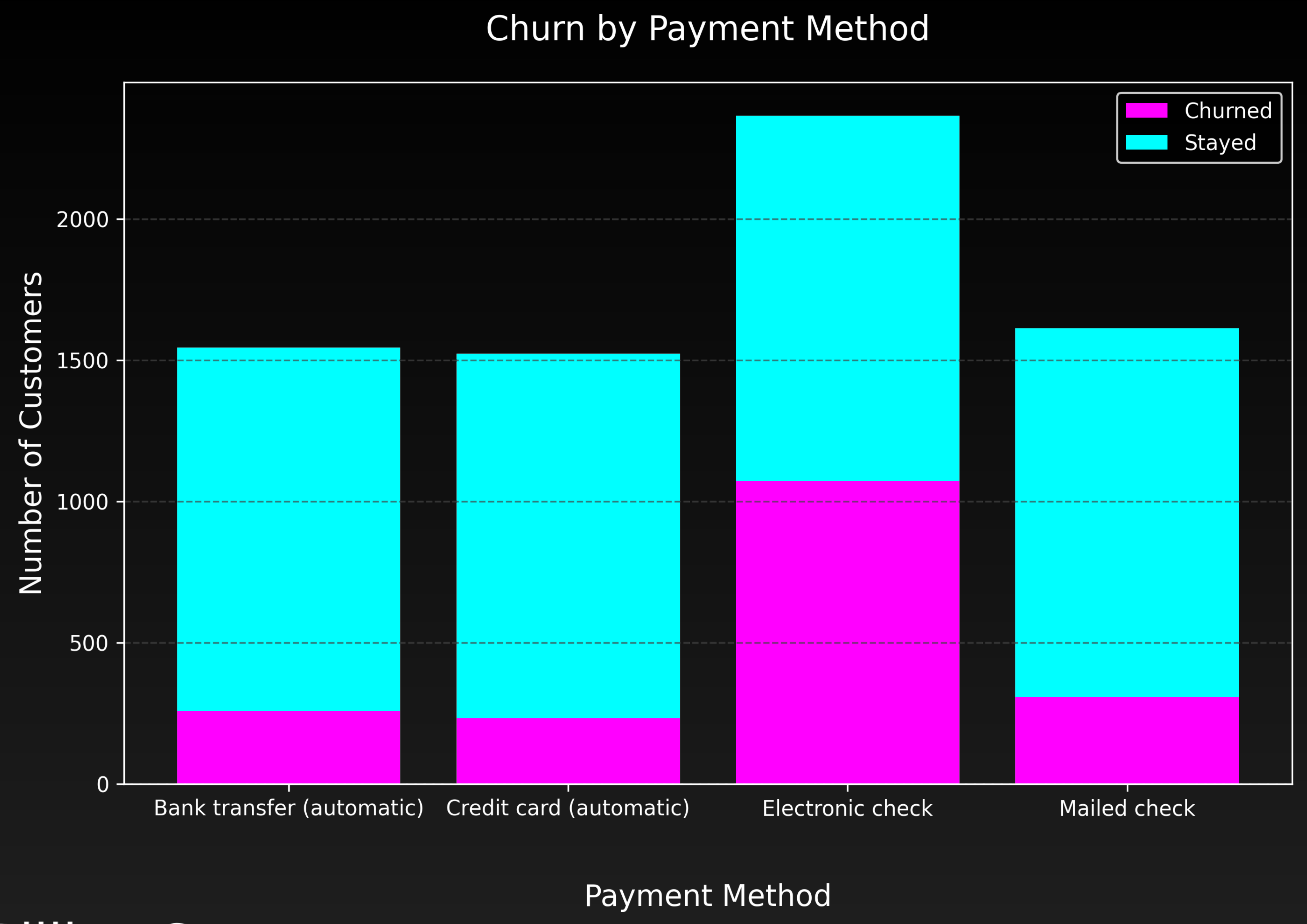

Churn by Gender
Churned
Stayed
Number of Customers
0
500
1000
1500
2000
2500
3000
3500
Female
Male
Gender
Churn by Partner Status
Churned
Stayed
Number of Customers
0
500
1000
1500
2000
2500
3000
3500
No
Yes
Has Partner
Churn by Senior Citizen Status
Churned
Stayed
Number of Customers
0
1000
2000
3000
4000
5000
6000
No
Yes
Senior Citizen
Churn by Dependents Status
Churned
Stayed
Number of Customers
0
1000
2000
3000
4000
5000
No
Yes
Has Dependents

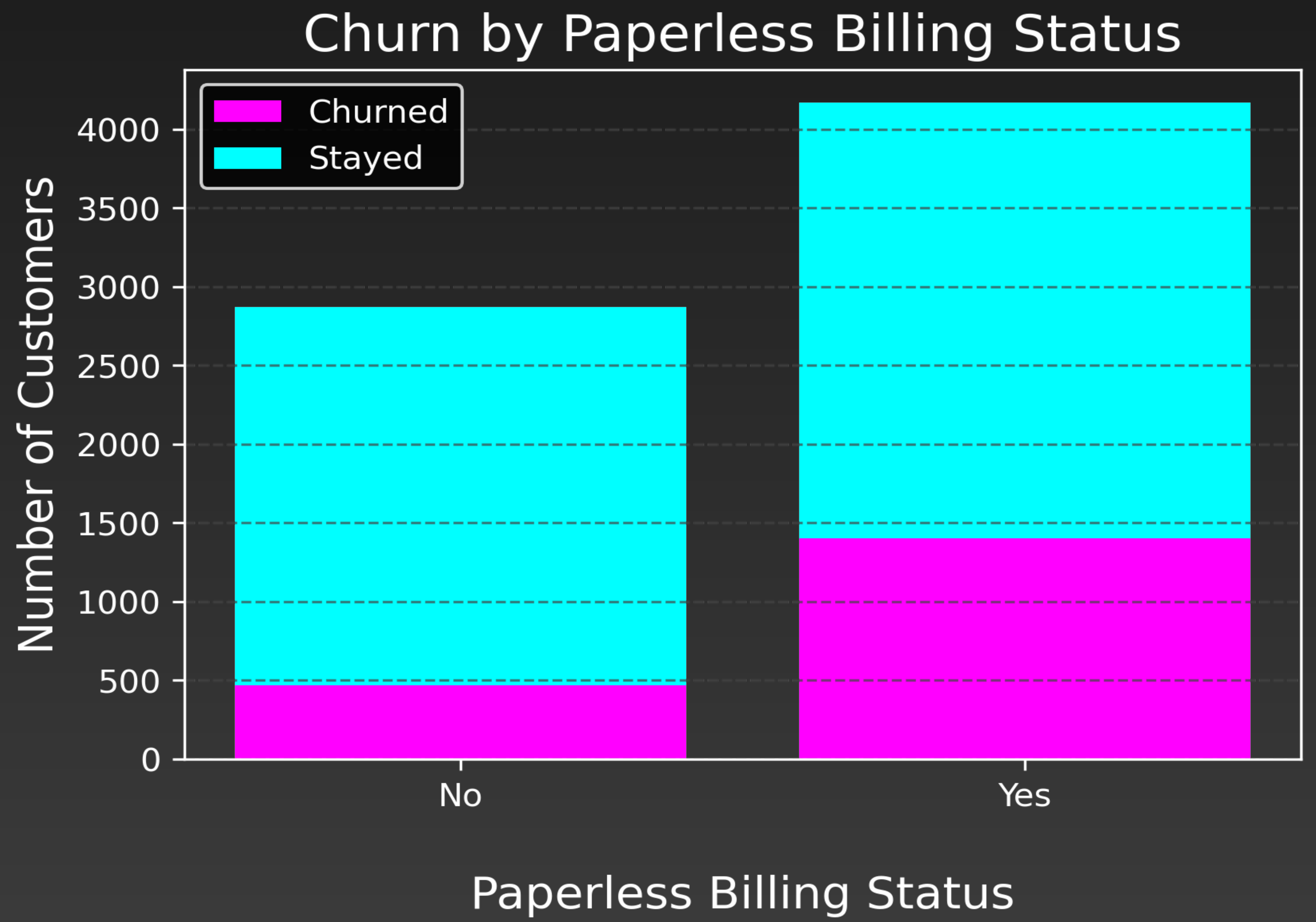
Insights

- **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


Churn by Monthly Charges Tier
Number of Customers
Churned
Stayed
0
500
1000
1500
2000
2500
3000
3500
4000
Low ($0-50)
Medium ($50-100)
High ($100+)
Monthly Charges Tier

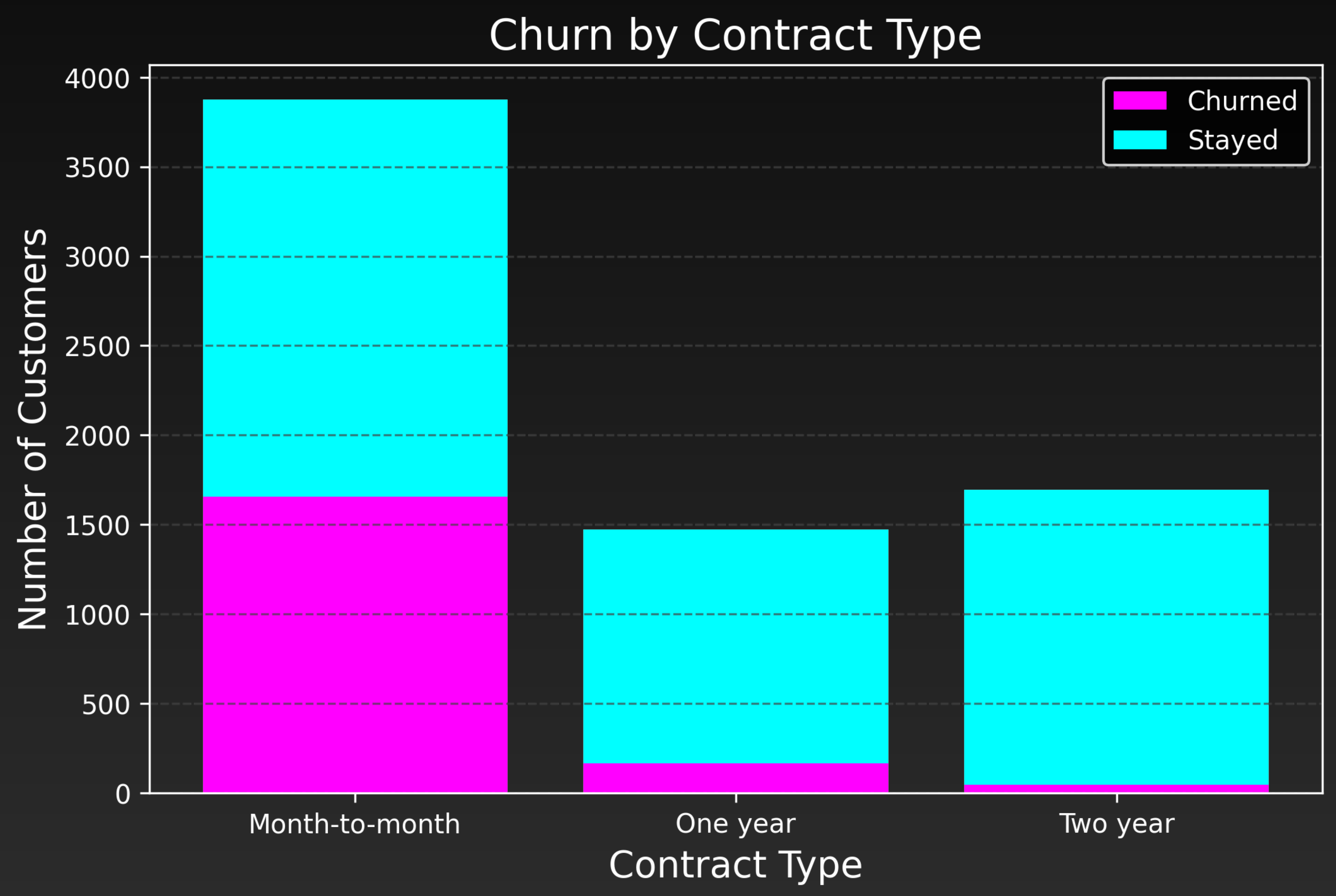

Churn by Payment Method
Number of Customers
Churned
Stayed
0
500
1000
1500
2000
Bank transfer (automatic)
Credit card (automatic)
Electronic check
Mailed check
Payment Method

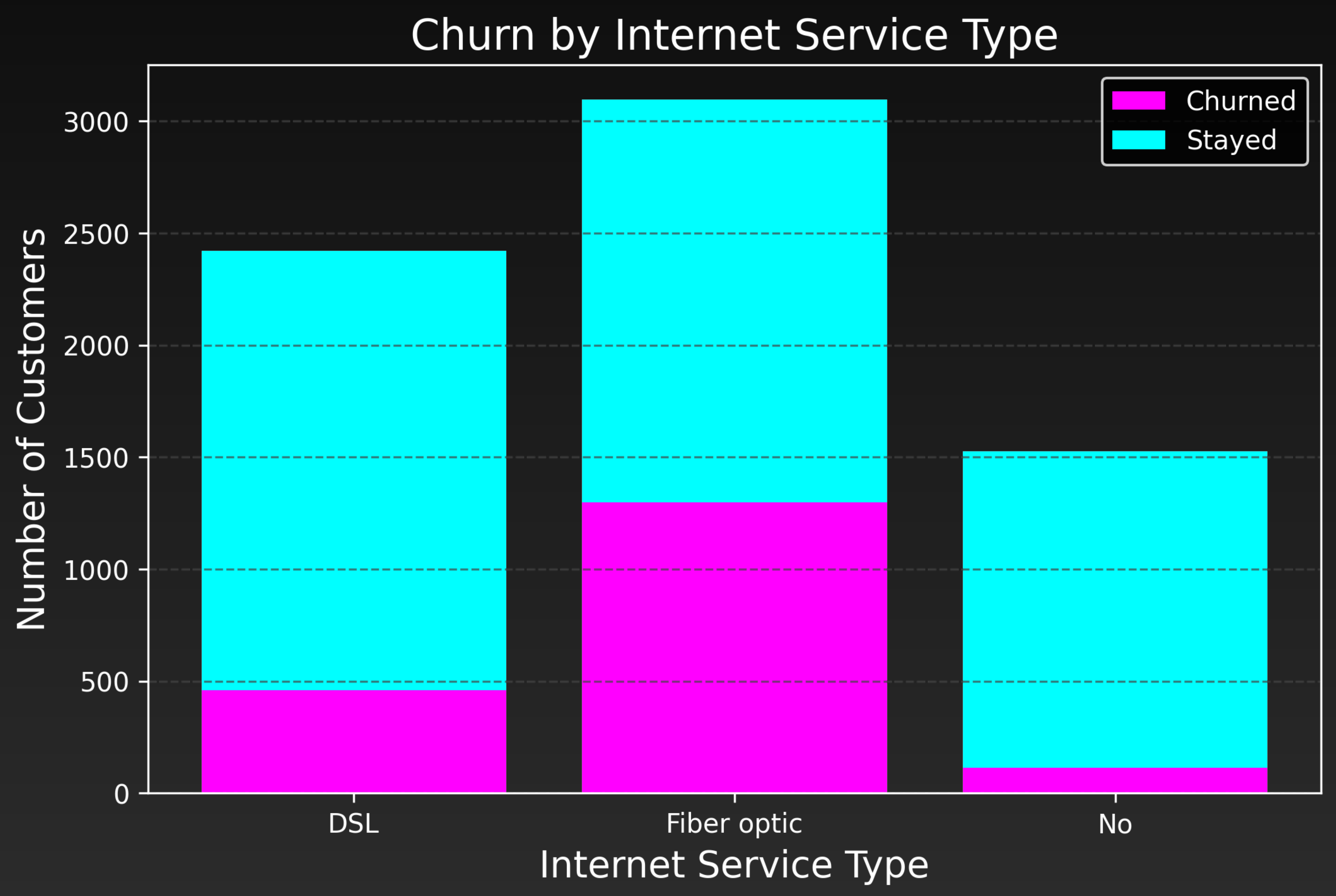

Churn by Paperless Billing Status
Number of Customers
Churned
Stayed
0
500
1000
1500
2000
2500
3000
3500
4000
No
Yes
Paperless Billing Status

Insights

- **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

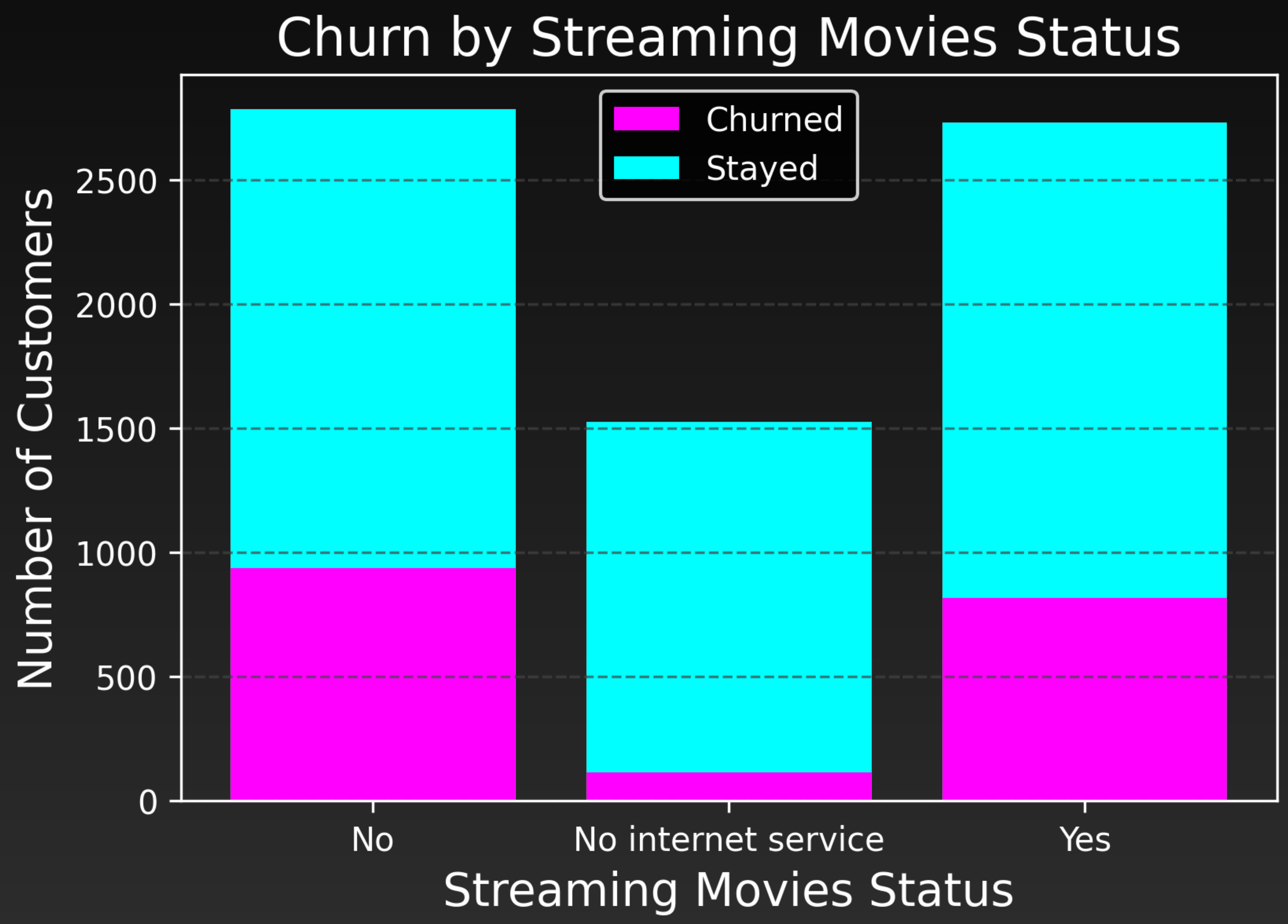

Churn by Contract Type
Churned
Stayed
Number of Customers
4000
3500
3000
2500
2000
1500
1000
500
0
Month-to-month
One year
Two year
Contract Type

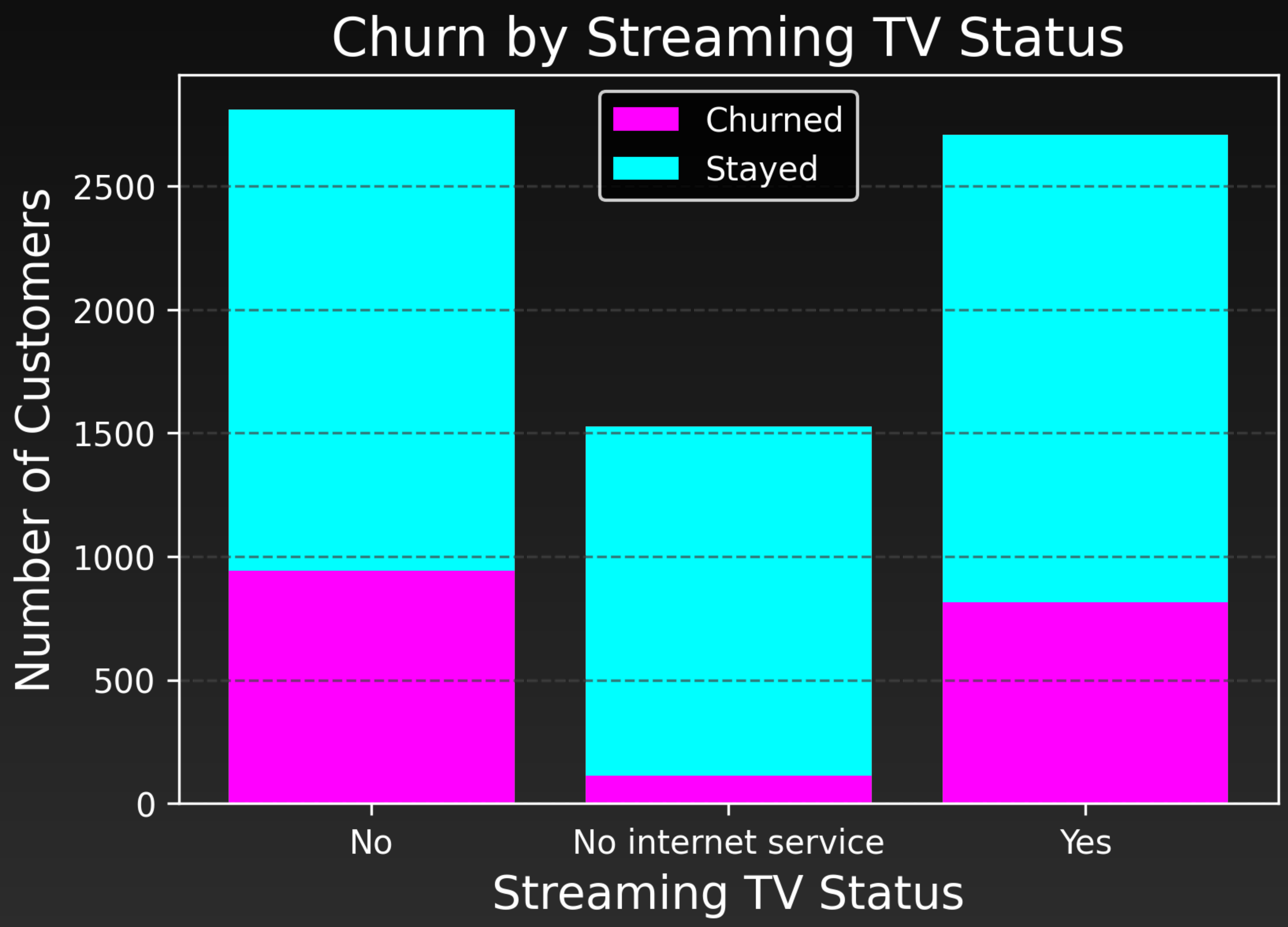

Churn by Internet Service Type
Churned
Stayed
Number of Customers
3000
2500
2000
1500
1000
500
0
DSL
Fiber optic
No
Internet Service Type

Insights

- **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


Churn by Streaming Movies Status
Churned
Stayed
Number of Customers
0
500
1000
1500
2000
2500
No
No internet service
Yes
Streaming Movies Status

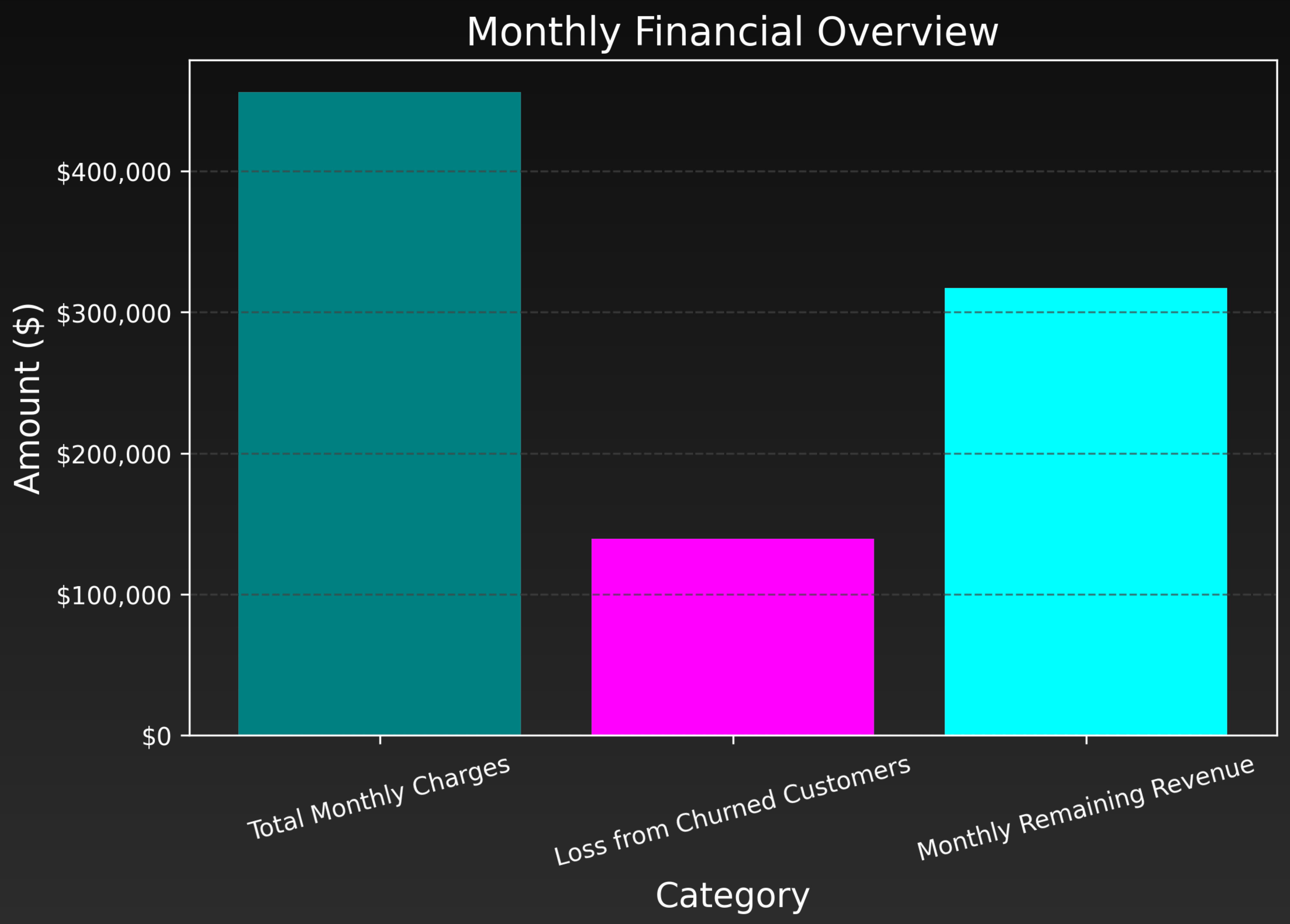

Churn by Streaming TV Status
Churned
Stayed
Number of Customers
0
500
1000
1500
2000
2500
No
No internet service
Yes
Streaming TV Status

Insights

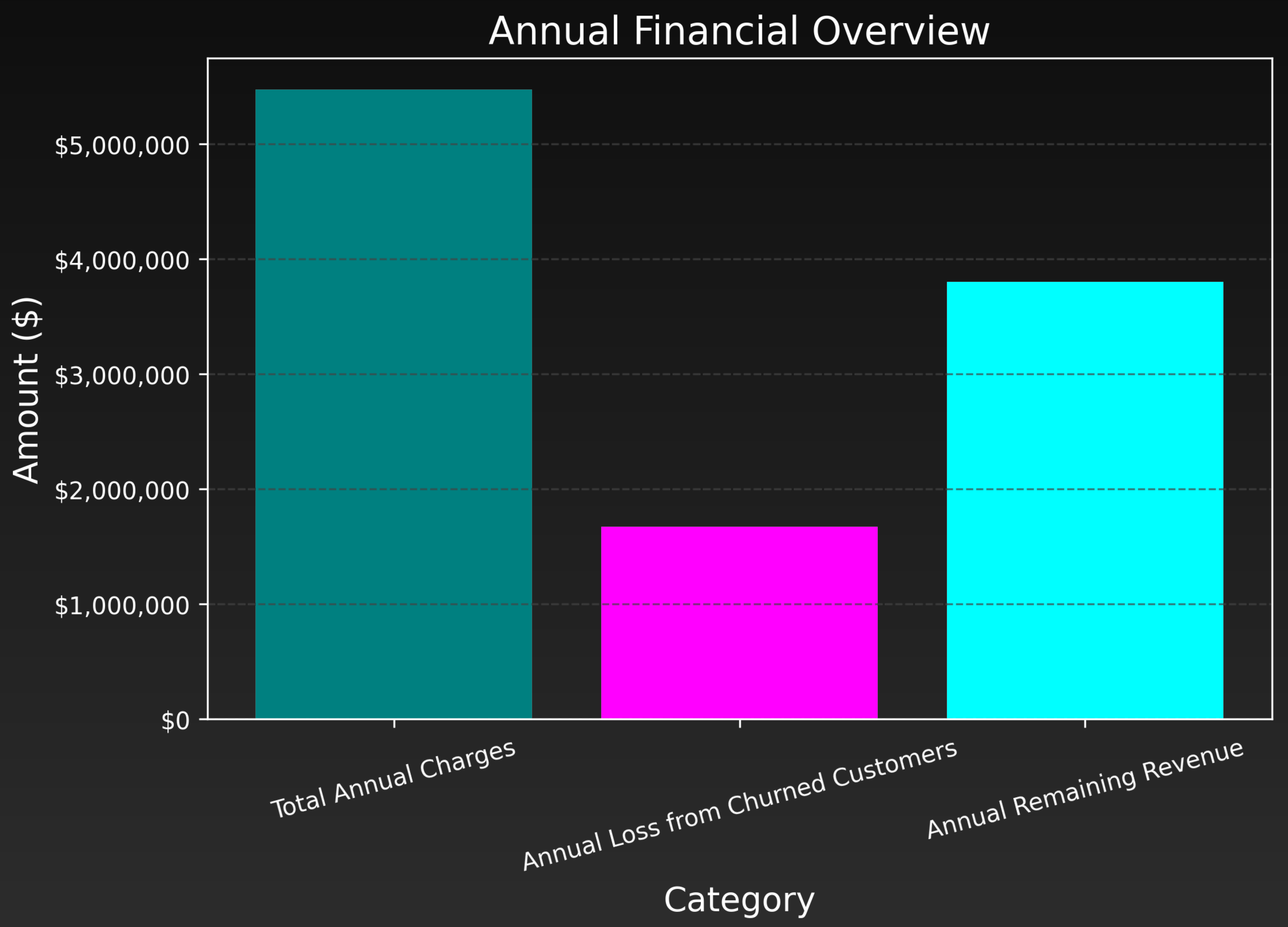
TV & Movie Streaming Churn Patterns:

- 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 Financial Overview
$400,000
$300,000
$200,000
$100,000
$0
Amount ($)
Total Monthly Charges
Loss from Churned Customers
Monthly Remaining Revenue
Category



Annual Financial Overview
$5,000,000
$4,000,000
$3,000,000
$2,000,000
$1,000,000
$0
Amount ($)
Total Annual Charges
Annual Loss from Churned Customers
Annual Remaining Revenue
Category

Insights

- **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

80%

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 **$8,743.50 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.