1. Executive Summary

Over the past quarter, our customer base exhibits a **26.54% churn rate**, with an **average projected lifetime value (CLTV)** of **$2,279.58**. A baseline logistic regression model—leveraging tenure and billing metrics—delivered **79% accuracy**, **66% precision**, and **45% recall** in identifying at-risk customers. These insights underscore immediate opportunities to refine our retention strategies and elevate predictive capabilities.

2. Analysis Methodology

1. **Data Ingestion & Cleansing**
   - Imported the Telco Customer Churn dataset.
   - Standardized monetary fields (TotalCharges) and encoded churn status into a binary flag.
2. **KPI Derivation**
   - **Churn Rate**: Percentage of customers who discontinued service.
   - **CLTV Proxy**: Tenure × MonthlyCharges.
3. **Predictive Model Baseline**
   - **Features**: Tenure, MonthlyCharges, TotalCharges.
   - **Model**: Logistic Regression (70/30 train/test split, threshold = 0.5).
   - **Performance Metrics**: Accuracy, Precision, Recall.

3. Key Findings

Metric	Value	Interpretation
Customer Churn Rate	26.54%	Nearly 1 in 4 customers are leaving; immediate focus required on retention levers.
Average CLTV	$2,279.58	Represents our average revenue per customer over their lifecycle—critical for ROI modeling.
Model Accuracy	79%	Baseline classifier correctly labels ~4 out of 5 customers; provides foundational predictive power.
Model Precision	66%	Two-thirds of customers flagged as “at-risk” truly churn—sufficient for targeted interventions.
Model Recall	45%	Captures fewer than half of actual churners; indicates need for richer features or threshold tuning.

4. Strategic Implications

- **Retention Playbooks**
  - With 26.5% churn, segment high-value cohorts (CLTV > $3,000) and deploy proactive win-back campaigns.
  - Leverage model precision to minimize outreach to false positives.
- **Revenue Optimization**
  - CLTV benchmarks guide budget allocation: invest up to 25% of $2,279 in customer success initiatives per account.
- **Predictive Maturity**
  - 79% accuracy validates our modeling pipeline; however, 45% recall signals the need for enhanced data sources—service usage, support interactions, and NPS scores—to capture more at-risk customers.

5. Recommendations & Next Steps

1. **Data Enrichment**
   - Integrate survey (CSAT/NPS) and support-ticket logs (ART, FCR) to enrich feature set and drive more nuanced predictive signals.
2. **Model Optimization**
   - Incorporate additional variables (contract type, service add-ons, network performance) and iterate with ensemble techniques to boost recall above 60%.
3. **Operationalize KPIs**
   - Automate KPI dashboards in Power BI/Tableau, with real-time alerts when monthly churn exceeds 2% MoM.
4. **Targeted Retention Campaigns**
   - Launch pilot outreach to top 10% CLTV segment flagged by model; measure uplift and refine approach.

Conclusion
This analysis demonstrates our ability to quantify churn, project lifetime value, and underpin retention efforts with predictive modeling. By expanding data inputs and operationalizing insights, we can materially reduce churn, optimize spend, and secure long-term revenue stability.