CUSTOMER CHURN PREDICTION AND RETENTION STRATEGY

OVERVIEW:

Growth for subscription-based businesses starts there and doesn't end there. In addition to lost money, each departing client also represents lost future value, increased acquisition expenses, and lost chances to establish enduring partnerships.

In this case study, I take on the role of an analyst for a B2C subscription company that has begun to see early indicators of client attrition. Although the leadership is aware that churn is occurring, they are unable to clearly see who is leaving, why, or how much income is actually at risk.

This project approaches churn as a forward-looking business challenge rather than as a past indicator. The objective is to identify early warning signs and turn them into insights that business teams can act upon by merging customer behavior data with churn probability forecasts.

I created an interactive analytics solution using Power BI that provides a comprehensive churn story:

- Which clients are most likely to leave?
- Which plan-related and behavioral factors increase the probability of churn?
- How customer categories differ in terms of turnover risk
- How much of the monthly income is in danger from high-risk clients?

This study focuses on converting predictions into decisions rather than the machine learning model per se. The final dashboards are designed to help marketing, CRM, and customer success teams prioritize retention initiatives, allocate resources wisely, and take action before churn occurs rather than after.

BUSINESS PROBLEM:

The business operates on a subscription-based revenue model, where customer retention directly impacts Monthly Recurring Revenue (MRR), Customer Lifetime Value (LTV), and acquisition efficiency. Over time, leadership has observed a steady rise in customer churn occurring within the first 30 days of subscription, signaling early dissatisfaction and increased revenue leakage.

While churn events are tracked, the organization currently lacks a mechanism to predict and prioritize churn risk in advance. Existing reports focus on historical churn rates, offering limited value for proactive intervention. As a result, key business KPIs are being negatively impacted:

- **Monthly Recurring Revenue (MRR):** High-risk customers are churning before contributing long-term revenue, leading to avoidable MRR loss.
- **Revenue at Risk:** The business has no consolidated view of how much subscription revenue is exposed to imminent churn.
- **Customer Lifetime Value (LTV):** Early churn significantly reduces average LTV, weakening the return on acquisition investments.
- **Customer Acquisition Cost (CAC) Efficiency:** Marketing and sales efforts are diluted when newly acquired customers churn before breakeven.
- **Retention Effectiveness:** Retention teams lack a data-driven way to identify and prioritize customers who require immediate intervention.

Although a churn prediction model exists, its outputs are not translated into business-friendly insights. Churn probabilities remain abstract numbers, disconnected from customer segments, subscription plans, and revenue contribution. This prevents stakeholders from answering critical questions such as

- Which customers pose the highest financial risk?
- How much revenue is at stake if no action is taken?
- Which customer behaviors and plan types are most strongly associated with churn risk?

The goal of this project is to build an analytics solution that converts churn predictions into actionable KPIs and decision-ready insights. Specifically, the solution aims to:

- Categorize customers into Low, Medium, and High churn risk segments
- Quantify Revenue at Risk by aggregating subscription value for high-risk customers
- Monitor Overall Churn Rate and Average Churn Probability as early warning indicators
- Identify the top churn drivers impacting high-value customers
- Enable retention teams to focus efforts where they can maximize MRR protection and LTV preservation

By aligning churn analytics with core business KPIs, the organization can transition from reactive churn reporting to a proactive, revenue-focused churn prevention strategy.

OBJECTIVE:

The aim of this project is to develop a decision-oriented churn analytics solution that empowers business teams to proactively identify, prioritize, and address customer churn prior to the occurrence of revenue loss.

Instead of considering churn as a historical metric, this project reinterprets churn as a prospective risk indicator directly associated with revenue, customer value, and retention strategy.

Specifically, the project aims to:

- **Identify customers at imminent risk of churn** by translating churn probability outputs into clear, business-friendly risk categories (Low, Medium, High)
- **Quantify revenue exposure** by calculating Revenue at Risk from high-risk customers, enabling leadership to understand the financial impact of inaction
- **Highlight key behavioral and plan-level churn drivers** that disproportionately affect high-value and early-tenure customers
- **Enable prioritization of retention efforts** by helping marketing, CRM, and customer success teams focus on customers where intervention can protect the most MRR and

LTV

- **Provide early-warning KPIs** such as average churn probability and risk distribution to detect churn trends before they materialize in actual losses
- **Deliver insights through interactive Power BI dashboards** designed for non-technical stakeholders, ensuring churn analytics are accessible, interpretable, and action-ready.

In order to enable the company to transition from reactive churn reporting to a proactive, revenue-driven retention strategy, the ultimate objective is to close the gap between churn prediction and business action.

DATA OVERVIEW:

The analysis is based on customer-level data from a B2C subscription-based business and is intended to reflect real-world churn behavior during the first 30 days of subscription.

Each record in the dataset represents a unique customer and contains demographic, subscription, behavioral, and transactional data collected during the customer's active period.

Dataset Structure

The dataset consists of the following key data categories:

1. Customer & Subscription Attributes

- Customer ID
- Subscription plan type (Legacy, Standard, Premium)
- Contract tenure (in days)
- Monthly subscription value
- Age & Gender

These fields establish customer value, pricing exposure, and tenure stage—critical for understanding early churn patterns.

2. Usage & Engagement Metrics

- Product usage frequency
- Activity count
- Days since last activity
- Feature adoption indicators

Engagement metrics serve as early behavioral signals, as reduced or declining usage often precedes churn events.

3. Billing & Payment Behavior

- Payment delays or failed transactions
- Billing issues or disputes
- Auto-renewal status

Payment-related friction is a strong churn indicator, particularly for early-tenure customers.

4. Customer Support Interactions

- Number of support tickets raised
- Complaint frequency
- Resolution status and response time (where applicable)
- High support interaction combined with low engagement often signals dissatisfaction.

5. Churn Indicator

- Churn flag (1 / 0), indicating whether the customer discontinued their subscription within the 30-day observation window

This variable serves as the target outcome for churn risk analysis and prediction.

Data Assumptions & Constraints

To align the analysis with business reality, the following assumptions were applied:

- Churn is defined as subscription cancellation or non-renewal within 30 days
- Customer behavior prior to churn is assumed to be fully observable within the dataset
- External factors such as competitor offers or macroeconomic conditions are not captured
- The dataset represents a snapshot in time and does not include longitudinal behavior beyond the observation window

These assumptions were documented to ensure transparency and prevent overinterpretation of results.

Data Preparation Summary

Before analysis and visualization, the data was prepared to ensure accuracy and usability:

- Missing values were handled using business-appropriate imputation techniques
- Categorical variables were standardized for consistency
- Outliers in usage and billing metrics were reviewed to avoid skewed insights
- Derived metrics such as Revenue at Risk and Churn Risk Bands were created for downstream analysis.

This prepared dataset forms the foundation for churn risk segmentation, revenue exposure analysis, and interactive Power BI dashboards.

DATA PREPARATION AND MODELLING LOGIC:

This stage focuses on converting raw customer data and churn model outputs into dependable, decision-ready analytics. The emphasis is not on model complexity but on ensuring that churn risk signals are accurate, understandable, and consistent with business KPIs.

Data Preparation

Prior to analysis and dashboard development, the dataset was prepared to ensure consistency, accuracy, and analytical usability.

Key preparation steps included:

- **Data validation and cleaning**
    - Removed duplicate customer records
    - Ensured one-to-one mapping between Customer ID and subscription
    - Standardized categorical fields such as plan type and payment method
- **Handling missing and inconsistent values**
    - Missing usage and engagement values were treated as potential inactivity signals rather than dropped
    - Billing-related nulls were reviewed to distinguish between true non-events and data gaps
- **Tenure and time-based normalization**
    - Customer tenure was normalized to enable fair comparison across new and existing customers
    - Early-tenure customers were flagged separately to analyze first-30-day churn behavior
- **Metric standardization**
    - Usage, complaints, and payment events were scaled or bucketed where required to support aggregation and segmentation in Power BI

These steps ensured the data reflected real customer behavior, not artifacts of poor data quality.

Churn Modelling Logic

A churn prediction model was used to assign a churn probability score to each customer, representing the likelihood of churn within the specified observation window.

Instead of treating the model as a black box, the outputs were intentionally simplified for business use.

Churn Risk Segmentation

Customers were categorized into three churn risk groups based on probability thresholds:

- **Low Risk** – Customers with stable engagement and low likelihood of churn
- **Medium Risk** – Customers showing early warning signals
- **High Risk** – Customers with strong churn indicators requiring immediate attention

This risk banding allows non-technical teams to quickly prioritize actions without interpreting raw probabilities.

Revenue at Risk Calculation

To correlate churn risk with financial impact, Revenue at Risk was calculated by aggregating the monthly subscription value of High Risk customers.

This metric enables stakeholders to answer critical questions such as

- How much MRR is exposed to potential churn?
- Which plans or customer segments contribute most to revenue risk?
- Where should retention efforts be focused to protect revenue?

Analytical Integration in Power BI

The prepared dataset and churn risk outputs were integrated into Power BI using a star-schema-friendly structure to support performance and scalability.

Key analytical logic implemented in Power BI includes:

- Dynamic churn risk distribution by plan, tenure, and usage behavior
- Revenue at Risk slicing across customer segments
- Drill-down analysis from overall churn risk to individual customer profiles
- KPI tracking for overall churn rate and average churn probability

This ensures that churn analytics are more than just static reports; they are interactive tools for making ongoing decisions.

Design Philosophy

The modelling and preparation logic were intentionally designed to:

- Favor interpretability over complexity
- Align churn insights with MRR, LTV, and retention priorities
- Enable action, not just observation

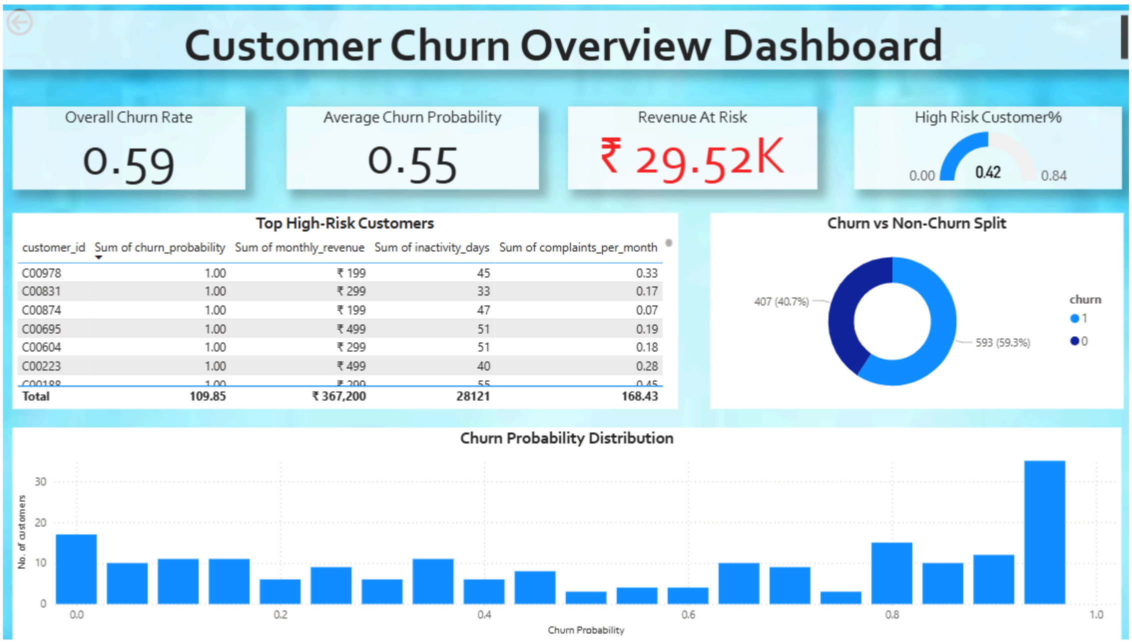
By grounding predictive outputs in business logic, the solution bridges the gap between data science and real-world retention strategy.

DASHBOARD DESIGN AND INSIGHTS:

The Power BI dashboard was designed with a decision-first approach, ensuring that each visual answers a specific business question related to churn prevention and revenue protection. Rather than overwhelming users with metrics, the dashboard emphasizes clarity, prioritization, and actionability.

The dashboard is divided into three main analytical views, each tailored to a different stakeholder need.

1. Executive Churn Overview



What this dashboard shows

This executive-level dashboard provides a high-level snapshot of customer churn health, combining churn risk, revenue exposure, and customer distribution into a single view.

It is designed for leadership, strategy, and decision-makers to quickly assess churn severity and prioritize immediate actions.

It answers the question:

> *"How serious is our churn problem, where is the revenue risk, and which customers need immediate attention?"*

Key Visuals & Insights

1) Overall Churn Rate & Average Churn Probability

These KPIs summarize the overall churn landscape across the customer base.

Insights:

- The overall churn rate of 0.59 indicates that a significant portion of customers are at risk of churning
- The average churn probability of 0.55 suggests elevated churn risk even among non-churned customers

Business takeaway:
Churn is a systemic issue, not limited to a small subset of customers, requiring proactive and scalable retention strategies.

2) Revenue at Risk

This KPI quantifies the potential revenue exposure from customers with high churn probability.

Insights:

- Approximately ₹29.52K in monthly revenue is currently at risk due to churn-prone customers

Business takeaway:
Even small improvements in retention among high-risk customers can lead to meaningful revenue protection.

3) High-Risk Customer Percentage

This indicator highlights the proportion of customers falling into the high-risk churn segment.

Insights:

- A substantial share of customers fall into the high churn risk category, signaling urgency for intervention

Business takeaway:
Targeted outreach programs are required to prevent further escalation into actual churn events.

4) Top High-Risk Customers Table

This table identifies customers with the highest churn probability along with their behavioral indicators.

Insights:

- High-risk customers often exhibit extended inactivity periods and frequent complaints
- These customers contribute disproportionately to revenue at risk

Business takeaway:
Customer-level prioritization enables focused retention actions such as personalized outreach, service recovery, or incentives.

5) Churn vs Non-Churn Split

This donut chart shows the distribution of churned versus retained customers.

Insights:

- A sizable portion of customers have already churned, while a slightly larger segment remains active

Business takeaway:
Retention efforts should focus on preventing further migration from the active to the churned segment.

6) Churn Probability Distribution

This distribution highlights how churn risk is spread across the customer base.

Insights:

- Customers are spread across the churn probability spectrum, with noticeable clustering at higher risk levels

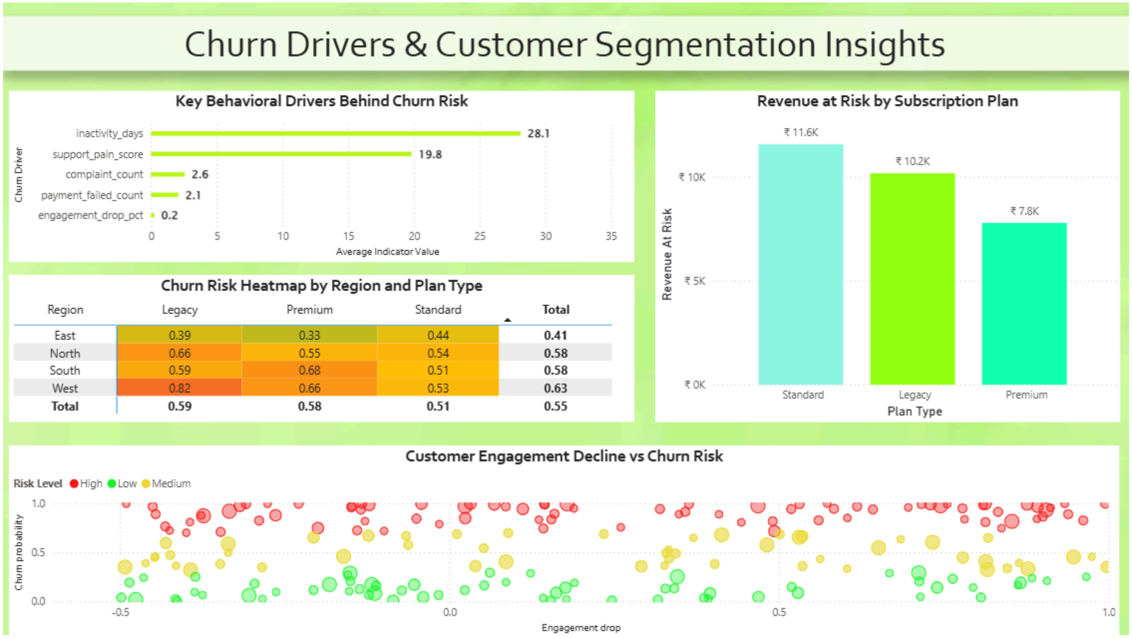
Business takeaway:
Churn probability can be used as a prioritization metric, enabling tiered intervention strategies rather than blanket actions.

Who This Dashboard Is For

- Business leaders and executives
- Strategy and growth teams
- Customer success leadership

This dashboard serves as a decision-making control panel, enabling rapid assessment of churn risk and revenue exposure before diving into deeper diagnostic views.

2. Churn Drivers & Customer Segmentation



What this dashboard shows

This view is designed to help marketing, CRM, and product teams understand the key drivers behind churn risk and how that risk varies across customer segments, regions, and subscription plans.

It answers the question:

> *"Why are customers churning, and which segments require different retention strategies?"*

Key Visuals & Insights

1) Key Behavioral Drivers Behind Churn Risk

The driver analysis highlights the strongest behavioral signals associated with churn probability.

Insights:

- Inactivity days emerge as the most influential churn driver, indicating disengagement as a primary risk factor
- Support pain score and complaint count show a strong relationship with churn, suggesting service friction plays a critical role
- Payment failures and engagement drop contribute to churn risk, but to a lesser extent compared to inactivity and support issues

Business takeaway:
Churn prevention efforts should prioritize re-engagement and service quality improvements over purely price-based interventions.

2) Revenue at Risk by Subscription Plan

This visual connects churn risk with financial exposure at the plan level.

Insights:

- Standard and Legacy plans account for the highest share of Revenue at Risk
- Premium plans, while higher priced, show relatively lower churn risk concentration

Business takeaway:
Retention strategies should be plan-specific, with targeted interventions for plans contributing the most revenue exposure.

3) Churn Risk Heatmap by Region and Plan Type

The heatmap reveals geographic and plan-level variations in churn probability.

Insights:

- Certain regions consistently show higher churn risk across plans
- Plan performance varies by region, indicating that churn drivers are not uniform

Business takeaway:
A one-size-fits-all retention approach is ineffective; regional and plan-level customization is required.

4) Customer Engagement Decline vs Churn Risk

This scatter plot visualizes the relationship between declining engagement and churn probability.

Insights:

- Customers with higher engagement decline cluster heavily in the high-risk churn zone
- Low-risk customers show stable or improving engagement patterns

Business takeaway:
Engagement metrics act as early behavioral warning signals, enabling intervention before churn occurs.

Who This Dashboard Is For

- Marketing & CRM teams
- Product managers
- Customer success and support teams

This view supports root-cause analysis and segmentation-driven decision-making.

3. Churn Risk Action Plan & Retention Strategy

What this dashboard shows

This action-oriented dashboard translates churn predictions into clear, revenue-focused retention priorities.

It is designed to help customer success, retention, and growth teams identify:

- Customers requiring immediate intervention
- Revenue exposure by churn risk
- High-value customers at high risk of churn

It answers the question:

> *"Which customers should we act on first, and where will retention efforts have the highest business impact?"*

Key Visuals & Insights

1) High-Risk Customers Requiring Immediate Action

This table highlights customers with very high churn probability, along with their revenue contribution, plan type, and region.

Insights:

- Multiple customers show a churn probability of 1.0, indicating near-certain churn risk
- A large proportion of these customers are on legacy plans
- Several high-risk customers contribute moderate to high monthly revenue

Business takeaway:
These customers should be prioritized for immediate, personalized retention actions such as proactive outreach, plan upgrades, or service recovery interventions.

2) Customer Distribution by Churn Risk Level

This bar chart shows how customers are distributed across High, Medium, and Low churn risk segments.

Insights:

- The high-risk segment is the largest, followed by low- and medium-risk customers

Business takeaway:
Churn risk is not isolated, a significant portion of the customer base requires urgent attention, making prioritization critical.

3) Revenue Exposure by Churn Risk Level

This chart visualizes monthly revenue at risk across different churn risk segments.

Insights:

- High-risk customers account for the largest revenue exposure (~₹30K)

- Medium- and low-risk segments still contribute meaningful revenue (~₹23K each)

Business takeaway:
Retention efforts should focus first on high-risk customers to protect revenue, while preventive engagement can be applied to medium-risk customers.

4) High-Value vs High-Risk Customer Segmentation

This scatter plot maps customers by churn probability vs. monthly revenue, segmented by churn risk level.

Insights:

- A visible cluster of high-revenue customers with churn probability above 0.7 represents the most critical risk segment
- Low-risk customers are largely concentrated at lower churn probabilities and stable revenue levels
- Medium-risk customers act as a transition segment, offering early intervention opportunities

Business takeaway:
This visualization enables precision targeting, ensuring retention resources are focused on customers where both revenue impact and churn risk are high.

Impact

This dashboard enables teams to:

- Prioritize retention actions based on churn risk and revenue impact
- Reduce reactive churn handling by enabling proactive intervention
- Allocate customer success resources more efficiently

By combining predictive churn signals with revenue insights, the dashboard directly supports measurable revenue protection.

KEY BUSINESS RECOMMENDATIONS:

Based on insights from the Executive Overview, Churn Drivers & Segmentation, and Action & Retention Strategy dashboards, the following recommendations are proposed to reduce churn risk and protect recurring revenue.

1) Prioritize Immediate Intervention for High-Risk Customers

What to do:

- Launch proactive outreach campaigns for customers with churn probability ≥ 0.7
- Assign these customers to customer success or retention specialists
- Use personalized messaging addressing recent issues (complaints, inactivity, failed payments)

Why this matters:

- High-risk customers form the largest risk segment
- They account for the highest revenue exposure (~₹30K/month)

Expected impact:

- Rapid churn reduction
- Immediate revenue protection with minimal acquisition cost

2) Address Core Behavioral Drivers of Churn

What to do:

- Monitor and act on early churn signals such as
    - Rising inactivity days
    - Increasing support pain score
    - Frequent complaints
- Trigger automated alerts when these metrics cross risk thresholds

Why this matters:

- Inactivity and support pain are the strongest churn drivers

- Churn is often preceded by behavioral deterioration, not sudden exits

Expected impact:

- Early intervention before customers enter high-risk zones
- Reduced dependency on last-minute retention offers

3) Redesign Retention Strategy by Subscription Plan

What to do:

- Review and modernize legacy plans, which show:
  - Higher churn risk
  - Disproportionate revenue at risk
- Incentivize migration to standard or premium plans through:
  - Feature upgrades
  - Loyalty discounts
  - Flexible pricing

Why this matters:

- Legacy plan customers contribute heavily to churn risk
- Plan structure is a controllable business lever

Expected impact:

- Improved customer experience
- Lower churn driven by outdated offerings

4) Focus Retention Efforts on High-Value, High-Risk Customers

What to do:

- Segment customers using both:
  - Churn probability
  - Monthly revenue
- Prioritize high-revenue customers with high churn risk for white-glove retention strategies

Why this matters:

- Losing a small number of high-value customers creates outsized revenue loss
- These customers justify higher retention investment

Expected impact:

- Stronger ROI on retention spend
- Improved long-term customer lifetime value (CLV)

5) Implement Tiered Retention Strategies by Risk Level

What to do:

Risk Level	Strategy
High	Direct outreach, incentives, service recovery
Medium	Engagement nudges, usage education, check-ins
Low	Loyalty programs, feature adoption campaigns

Why this matters:

- Churn risk is distributed across the customer base
- A one-size-fits-all approach is inefficient and costly

Expected impact:

- Scalable churn prevention
- Better allocation of customer success resources

6) Use Churn Probability as a Core Business Metric

What to do:

- Integrate churn probability into:
    - Weekly customer success reviews

    - Revenue forecasting
    - Account health scoring
- Track churn probability movement over time, not just churn events

Why this matters:

- Churn probability provides forward-looking insight
- Enables proactive decision-making rather than reactive analysis

Expected impact:

- Predictable revenue
- Stronger alignment between analytics and business teams

Overall Business Impact

If implemented effectively, these recommendations will:

- Reduce preventable churn
- Protect high-risk revenue
- Enable proactive, data-driven retention strategies
- Improve customer lifetime value and long-term growth

BUSINESS IMPACT:

By implementing the Customer Churn Prevention Engine and the recommended retention strategies, the business can transition from reactive churn management to a proactive, data-driven retention model.

The expected business impact spans revenue protection, operational efficiency, and strategic decision-making.

1) Revenue Protection & Growth

Impact:

- Identification of ~₹30K in monthly revenue at immediate churn risk
- Focused retention of high-risk, high-value customers prevents disproportionate revenue loss

Business value:

- Even a 20–30% reduction in high-risk churn can protect a significant portion of recurring revenue
- Retention costs are substantially lower than new customer acquisition costs

Outcome:

- Improved revenue predictability
- Stronger monthly recurring revenue (MRR) stability

2) Higher ROI on Retention & Marketing Spend

Impact:

- Retention efforts are targeted only at customers with:
    - High churn probability
    - Meaningful revenue contribution
- Reduced blanket discounting and untargeted campaigns

Business value:

- Marketing and retention budgets are allocated where they deliver maximum impact
- Avoids revenue leakage from unnecessary incentives to low-risk customers

Outcome:

- Increased campaign efficiency
- Better return on retention investments

3) Operational Efficiency for Customer Success Teams

Impact:

- Clear prioritization of customers by churn risk and revenue value
- Automated identification of customers requiring immediate intervention

Business value:

- Customer success teams spend time on high-impact accounts
- Reduced firefighting and manual monitoring

Outcome:

- Faster response times
- More structured and scalable customer success operations

4) Improved Customer Experience & Satisfaction

Impact:

- Early identification of churn signals such as inactivity, complaints, and support pain
- Timely, personalized outreach before dissatisfaction escalates

Business value:

- Customers feel supported rather than ignored
- Issues are resolved before they lead to churn

Outcome:

- Higher customer satisfaction
- Increased loyalty and engagement

5) **Data-Driven Decision Making Across Teams**

Impact:

- Leadership gains real-time visibility into:
    - Churn risk distribution
    - Revenue exposure
    - Key churn drivers
- Product, marketing, and support teams align around shared metrics

Business value:

- Decisions are based on predictive signals, not lagging indicators
- Clear accountability across functions

Outcome:

- Faster, more confident strategic decisions
- Better cross-functional alignment

6) **Long-Term Strategic Impact**

Impact:

- Churn probability becomes a core KPI for:
    - Revenue forecasting
    - Customer health scoring
    - Product prioritization

Business value:

- Enables continuous improvement of retention strategies
- Builds a scalable churn prevention framework applicable across products and regions

Outcome:

- Sustainable customer growth
- Stronger customer lifetime value (CLV)

Summary of Business Impact

Area	**Impact**
Revenue	Reduced churn-related revenue loss
Marketing	Higher ROI through targeted retention
Operations	Efficient customer success prioritization
Customer Experience	Proactive issue resolution
Strategy	Predictive, data-driven decision-making

WHY THIS PROJECT MATTERS:

Customer churn is often treated as a historical metric—measured after revenue has already been lost. This project challenges that approach by repositioning churn as a forward-looking business risk that can be anticipated, quantified, and actively managed.

What makes this project meaningful is not the prediction of churn itself, but the translation of churn signals into business decisions.

1. Moves Analytics Closer to Business Impact

Because their outputs are still disconnected from revenue, customer value, and operational workflows, many churn models fail in real-world scenarios. By directly connecting churn risk to MRR, LTV, and Revenue at Risk, this project closes that gap and guarantees that insights are both financially relevant and prepared for decision-making.

It illustrates how analytics can actively influence business outcomes in addition to reporting.

2. Emphasizes Action Over Accuracy

The solution puts interpretability and usability ahead of model performance optimization alone. Churn probabilities are transformed into distinct risk categories that non-technical teams can respond to right away.

This illustrates the maturity of real-world analytics, where a model's usefulness is determined by its uptake rather than its intricacy.

3. Addresses a High-Impact, Universal Business Problem

SaaS, fintech, telecom, and e-commerce are just a few of the industries that struggle with churn. This project addresses an issue that directly impacts growth, profitability, and customer experience in almost all subscription-based businesses by concentrating on early-stage churn and revenue exposure.

The framework and insights are scalable across domains and widely applicable.

4. Demonstrates End-to-End Analytical Thinking

The project showcases the complete analytics lifecycle:

- Problem framing from a business perspective
- Data preparation and modeling logic
- Insight generation through dashboards
- Translation of insights into strategic recommendations

This end-to-end approach reflects how analytics functions in real organizations—not in isolation, but as a driver of decision-making.

5. Highlights the Role of Analytics in Proactive Decision-Making

By introducing early-warning indicators such as churn risk distribution and Revenue at Risk, the solution enables teams to act before churn occurs, not after it is recorded.

This proactive mindset is critical for organizations seeking to move from reactive reporting to predictive and prescriptive analytics.

Summary

This project matters because it demonstrates how data can be used to anticipate risk, protect revenue, and improve customer experience, not just measure outcomes. It reflects the mindset of an analyst who understands both data and business and who builds solutions designed to be used, trusted, and acted upon.

CONCLUSION

In a subscription-based setting, this project provides a comprehensive, business-focused approach to understanding and reducing customer attrition. The analysis goes beyond traditional reporting to enable proactive, revenue-driven decision-making by redefining churn as a predictive risk rather than a past outcome.

The solution uses structured data preparation, churn risk segmentation, and interactive Power BI dashboards to transform abstract churn probabilities into understandable, useful insights that align with key business KPIs such as MRR, LTV, and Revenue at Risk. In addition to identifying the customers who are most likely to leave, stakeholders can see why these customers are at risk and where intervention will have the biggest financial impact.

The project demonstrates how analytics can serve as a strategic function—bridging data.

Overall, this case study highlights the role of analytics in driving proactive churn prevention, reinforcing how data-driven insights can directly influence business outcomes and long-term growth.