# EMAIL

### Subject: Plan to Address Power-Co's Customer Churn – Business Understanding & Problem Framing

Hi AD,

Following our discussion, Estelle and I have begun the business understanding and problem framing phase of the data science methodology to address PowerCo’s issue with customer churn. Below is our initial breakdown:

**1. Define the Problem (Step 1)**

PowerCo is experiencing a decline in customer retention and needs to understand why customers are switching providers. Our goal is to identify the key drivers of customer churn and provide actionable insights to reduce it.

**2. Understand the Data Requirements (Step 2)**

To investigate this, we will need access to the following data:

Customer Demographics : Age, location, type (residential/commercial), contract type.

Usage Data : Historical energy consumption patterns (monthly/yearly).

Billing Data : Pricing plans, rate changes over time, discounts, and total cost paid by customers.

Service Interaction Logs : Number and type of customer service interactions, complaints, resolution times.

Satisfaction Metrics : Survey responses, NPS scores, online reviews.

Competitor Data : Publicly available pricing or services from competitors (if accessible).

Clean Energy Preferences : Whether the customer opted for green energy plans.

Churn Flag : A binary indicator of whether the customer left in the past (historical churn data).

**3. Collect and Prepare the Data (Step 3)**

Once the data is obtained, we will:

Clean missing values and outliers.

Merge datasets (e.g., usage + billing + churn flag).

Create derived features such as average monthly spend, change in usage over time, frequency of support tickets.

**4. Analyze and Model the Data (Step 4)**

We plan to use the following techniques:

Exploratory Data Analysis (EDA):

Visualize churn rates by age group, location, and contract type.

Compare average prices between churned and retained customers.

Look at trends in customer service complaints before churn.

Statistical Testing:

Use chi-square tests or t-tests to determine if differences in groups (e.g., price, clean energy preference) are statistically significant.

Predictive Modeling:

Train classification models (e.g., logistic regression, random forest) to predict churn based on features.

Use feature importance to identify which factors most influence churn.

**5. Interpret Results and Present Findings (Step 5)**

We will summarize the top predictors of churn and recommend targeted strategies to improve retention, such as adjusting pricing structures, improving customer service response times, or promoting clean energy options.

**Key Reasons for Customer Churn (Hypotheses):**

We believe the main reasons customers may leave include:

* Price competitiveness
* Quality of customer service
* Preference for clean/renewable energy
* Contract flexibility
* Geographic coverage or local competition

**How We’ll Test These Hypotheses Using Data:**

Price Sensitivity: Compare churn rate vs. average price per kWh across segments.

Customer Service Impact: Analyze churn vs. number of service tickets or average resolution time.

Clean Energy Effect: Segment users by green plan participation and compare churn.

Location Trends: Map churn geographically to spot regional clusters.

Visualization Tools: Use tools like Tableau or Python libraries (Matplotlib, Seaborn) to create bar charts, scatter plots, heatmaps, and time series graphs.

We’re ready to move forward once we receive the required data from the client.

Best regards,  
Fouzia  
Estelle