Our exploratory data analysis aimed to uncover relationships between various factors and customer churn. Here's what we found:

Consumption Patterns: Higher electricity consumption (cons_12m) tends to be associated with lower churn rates, suggesting that higher-usage customers are less likely to leave.

Client Tenure: Longer tenure correlates with lower churn, indicating that more established customers are more likely to stay.

Contract Renewal: Customers are more likely to churn around the time of contract renewal, highlighting a critical period for retention efforts.

Seasonality: No significant seasonal trends in churn were observed based on contract renewal month.

Product Modification: Customers who have not modified their products for an extended time show very low churn rates, suggesting satisfaction or low engagement levels.

Price Sensitivity: The analysis showed no strong correlation between our calculated price sensitivity score and churn. Unexpectedly, customers classified with low price sensitivity had the highest churn rate.

Suggestions for Data Augmentation:

To deepen the analysis and improve the predictive power of churn modeling, we might need augmenting the dataset with:

Customer Interaction Data: Records of customer service interactions, support ticket history, and satisfaction ratings post-interaction could give insights into service quality's impact on churn.

Competitive Market Data: Information on competitor pricing, promotions, and market share could help understand churn in the context of competitive actions.

Demographic and Psychographic Data: Age, location, industry, and behavioral data could help create more nuanced customer segments and understand differing needs and churn risks.

By integrating these additional data sources, we can build a more holistic view of the factors driving churn and refine our predictive models for more accurate forecasting and targeted retention strategies.