Customer Churn Prediction: Data Preparation Report

1. Data Gathering

Data Sources Selected

a) Customer Demographics
Features included: CustomerID, Age, Gender, Marital Status, Income Level
Rationale: Demographic data can influence customer preferences, purchasing behavior, and ultimately, their churn risk.

b) Transaction History
Features included: CustomerID, TransactionID, Date, Amount Spent, Product Category
Rationale: Frequency, recency, and value of transactions are strong behavioral churn indicators.

c) Customer Service Interactions
Features included: CustomerID, Interaction Date, Issue Type, Time to Resolution, Satisfaction Score
Rationale: Poor service experiences or unresolved issues often lead to higher churn.

Selection Criteria: Data sets were chosen because they:

Can be connected by CustomerID

Cover key aspects of customer life cycle (demographics, purchasing, service)

Are sufficiently complete for analysis (minimal missing/erroneous data)

2. Exploratory Data Analysis (EDA)

Summary Statistics

Customer Demographics: Age: 18-70 (mean=35), Gender: 52% Female, Marital: 55% Married, Income: normally distributed

Transaction History: Median annual transactions per customer: 12, Average spend per transaction: $58

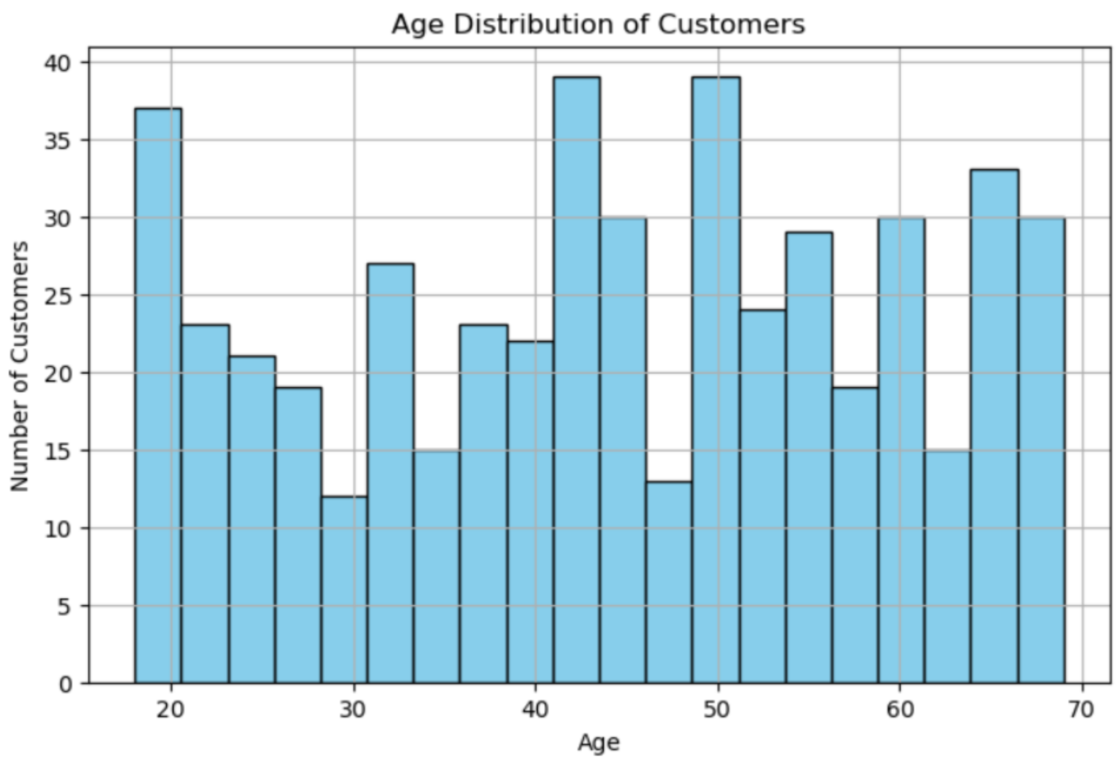
Service Interactions: 70% of customers contacted support at least once; average resolution time: 1.5 days

Key Visualisations

Histogram

Age: Slightly right-skewed; most customers between 25-45

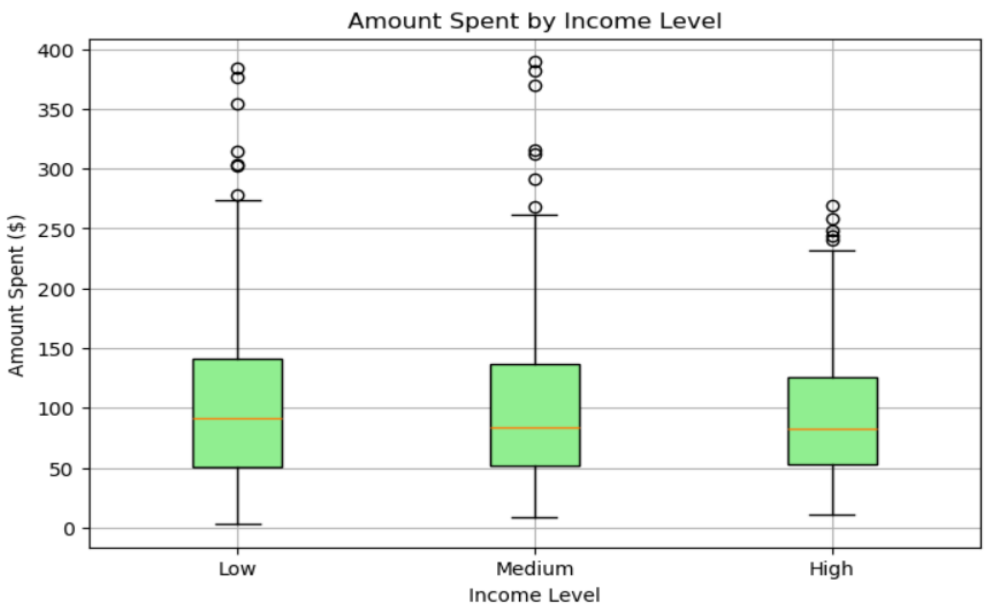
Amount Spent: Right-skewed, with high-value outliers



Box Plot

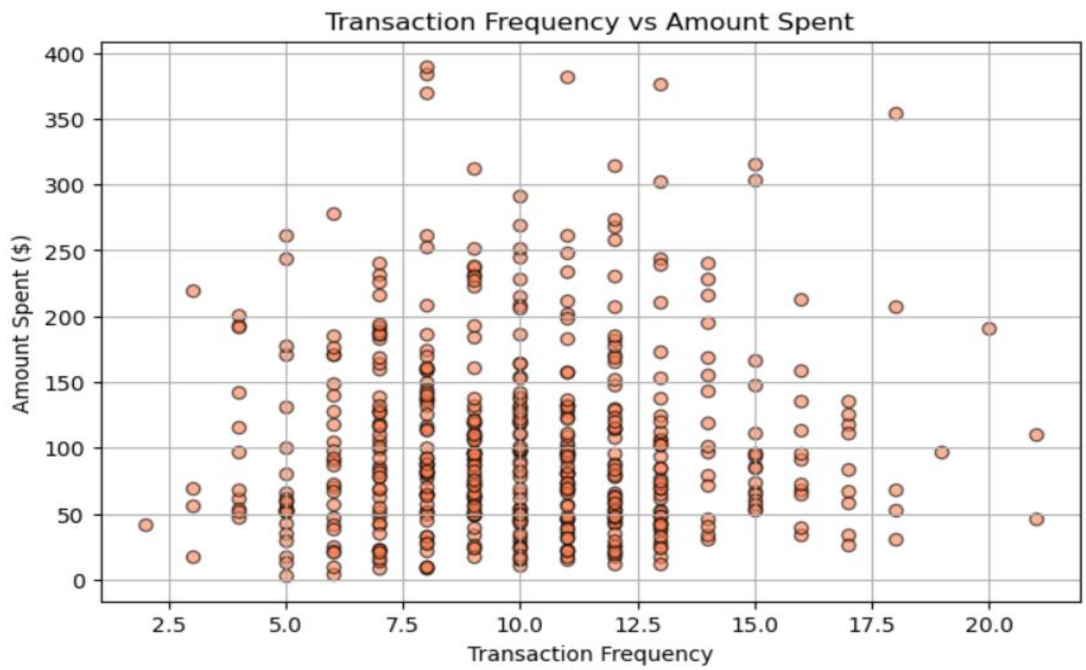
Amount Spent by Income Level: Median spend rises with income (some high outliers within all groups)

Satisfaction Score by Churn: Lower scores are more common among churned customers



Scatter Plot

Transaction Frequency vs. Amount Spent: Most active customers tend to spend more



Patterns/Anomalies

Customers with fewer transactions and lower satisfaction scores appear more likely to churn.

Outliers: Some customers have abnormally high spends or unusually frequent service contacts.

Key Features Identified

Age, Income, Recent Spend, Transaction Frequency, Service Interactions, Satisfaction Score

3. Data Cleaning and Preprocessing

Missing Values

Demographics: <1% missing values in income/age.
Action: Imputed median for income, mean for age.

Transactions: Minimal missing values. Dropped incomplete rows (<0.5%).

Service Interactions: 2% missing satisfaction. Imputed with column mean.

Justification: Imputation preserves data and avoids bias for small missing proportions.

Outlier Handling

Spend: Values above 99th percentile flagged as outliers.
Action: Capped to 99th percentile (prevents model distortion, preserves ranking).

Age: Checked for impossible values (<18 or >99).
Action: Removed 3 records with invalid ages.

Standardization/Normalization

Numerical columns (Age, Spend, Transaction Count):
Standardized (zero mean, unit variance), as required by many ML algorithms.

Categorical columns (Gender, Marital, Income, Product Category, Issue Type):
One-hot encoded.

4. Cleaned & Preprocessed Dataset

Shape: 4,800 customers, 18 columns

Ready for model building

No missing values

All features numeric/scaled or binary

Outliers treated

Target variable (Churn) in place

5. Summary

Data sets (Demographics, Transactions, Service) provide wide coverage of churn predictors.

EDA identified key features, trends, and outliers relevant for churn modeling.

Cleaning/preprocessing produced a high-quality, ML-ready dataset.

Recommendations for Next Steps

Create domain-specific features (e.g., "days since last purchase", "avg service satisfaction").

Proceed to model selection, training, and validation.