Customer Lifetime Value Prediction Model

Notebook by Gaurav Tawri

1. Setup & Imports

In [18]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from xgboost import XGBRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error
from IPython.display import Markdown, display
```

2. Data Loading & Initial Exploration

2.1. Data Loading & Initial Exploration

In [19]:
```
# Loading the dataset with specified encoding
df = pd.read_csv('C:\\Users\\gaura\\Downloads\\Data Analyst (Elevate Labs)\\Projects\\Project 2\\E-commerce Data.csv', pars
```

2.2 Preview Data

In [20]:
```
display(df.head())
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom

2.3 Data Info & Missing Values

In [21]:
```
df.info()
print(df.isnull().sum())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    541909 non-null  object
 1   StockCode    541909 non-null  object
 2   Description  540455 non-null  object
 3   Quantity     541909 non-null  int64
 4   InvoiceDate  541909 non-null  datetime64[ns]
 5   UnitPrice    541909 non-null  float64
 6   CustomerID   406829 non-null  float64
 7   Country      541909 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 33.1+ MB
InvoiceNo           0
StockCode           0
Description      1454
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     135080
Country             0
dtype: int64
```

3. Data Cleaning & Feature Engineering

3.1 Droping rows without CustomerID and invalid transactions

In [22]:
```
df = df.dropna(subset=['CustomerID'])
df = df[(df['Quantity'] > 0) & (df['UnitPrice'] > 0)]
```

3.2 Computing OrderValue

In [23]:
```
df['OrderValue'] = df['Quantity'] * df['UnitPrice']
```

3.3 RFM aggregation

In [24]:
```
reference_date = df['InvoiceDate'].max() + pd.Timedelta(days=1)
rfm = df.groupby('CustomerID').agg({
    'InvoiceDate': lambda x: (reference_date - x.max()).days,
    'InvoiceNo': 'nunique',
    'OrderValue': 'sum'
}).reset_index()
rfm.columns = ['CustomerID', 'Recency', 'Frequency', 'Monetary']
rfm['AOV'] = rfm['Monetary'] / rfm['Frequency']
print('### 3.1 RFM Features')
display(rfm.head())
```

```
### 3.1 RFM Features
```

	CustomerID	Recency	Frequency	Monetary	AOV
0	12346.0	326	1	77183.60	77183.600000
1	12347.0	2	7	4310.00	615.714286
2	12348.0	75	4	1797.24	449.310000
3	12349.0	19	1	1757.55	1757.550000
4	12350.0	310	1	334.40	334.400000

4. Model Training & Evaluation

4.1 Model Training & Evaluation

In [25]:
```
X = rfm[['Recency', 'Frequency', 'AOV']]
y = rfm['Monetary']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
model = XGBRegressor(objective='reg:squarederror', random_state=42)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

4.2 Metrics

In [26]:
```
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
print(f'**MAE:** {mae:.2f} | **RMSE:** {rmse:.2f}\n')
```

```
**MAE:** 245.43 | **RMSE:** 2365.48
```

5. Save Predictions

5.1 Save Predictions

In [27]:
```
rfm['Predicted_LTV'] = model.predict(X)
rfm.to_csv('Customer_LTV_Predictions.csv', index=False)
print('Saved Customer_LTV_Predictions.csv')
```

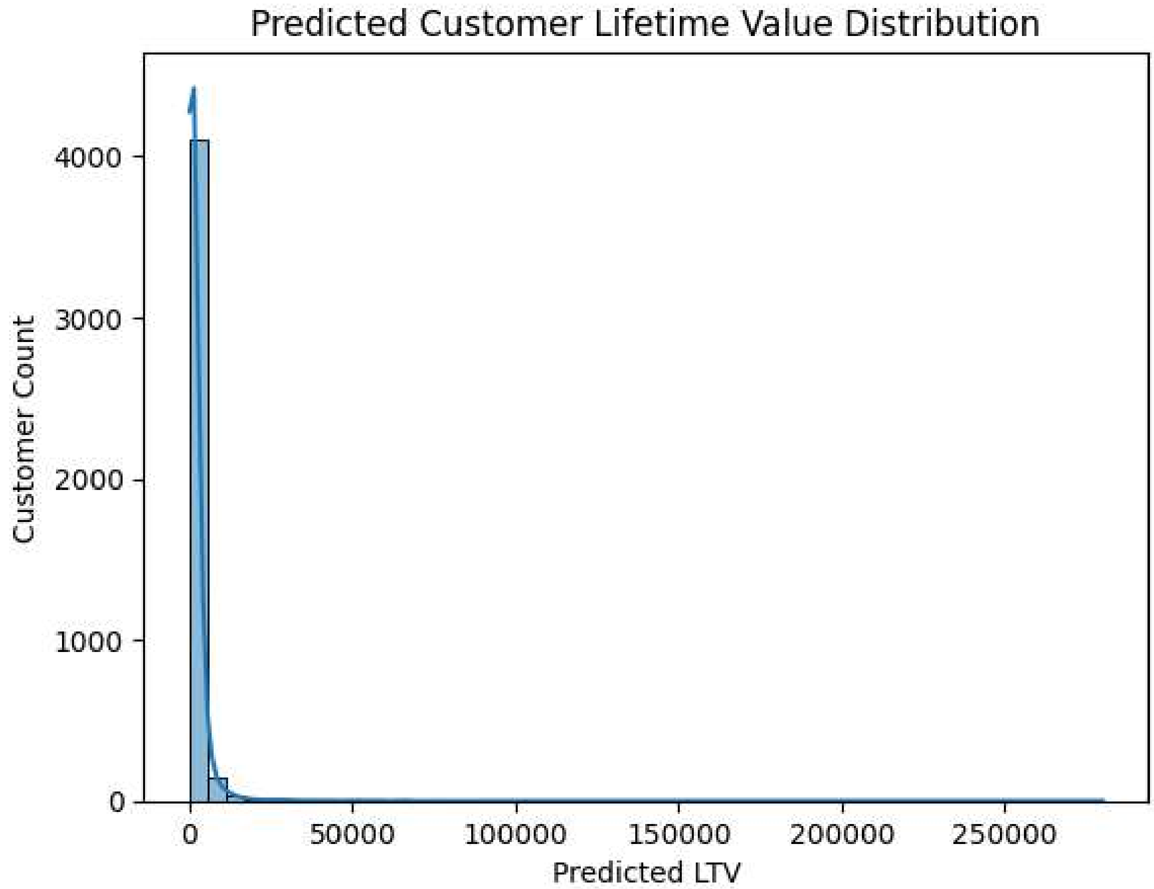
```
Saved Customer_LTV_Predictions.csv
```

6. Visualizations

6.1 Visualizations

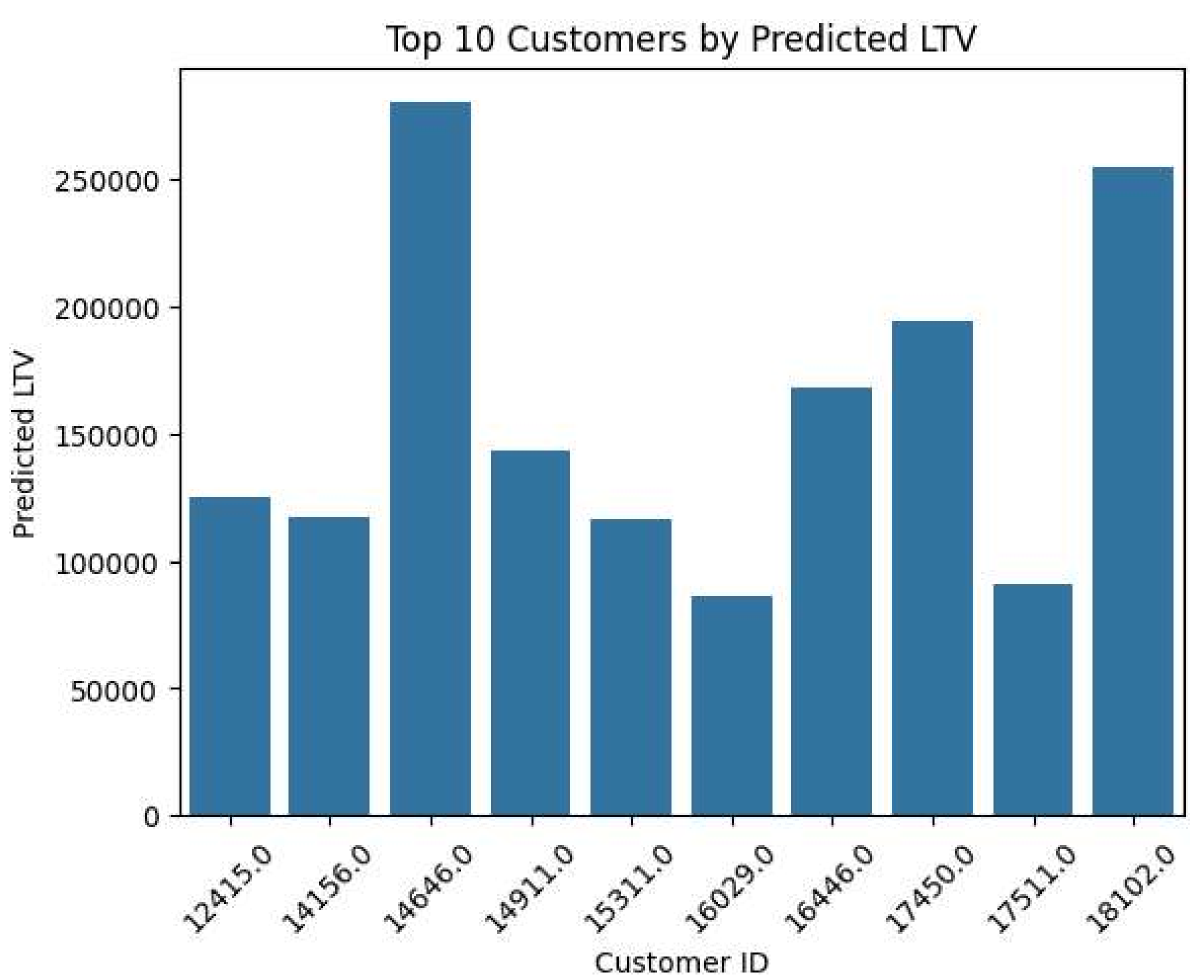
1. Distribution of Predicted LTV

In [28]:
```
sns.histplot(rfm['Predicted_LTV'], bins=50, kde=True)
plt.title('Predicted Customer Lifetime Value Distribution')
plt.xlabel('Predicted LTV')
plt.ylabel('Customer Count')
plt.show()
```



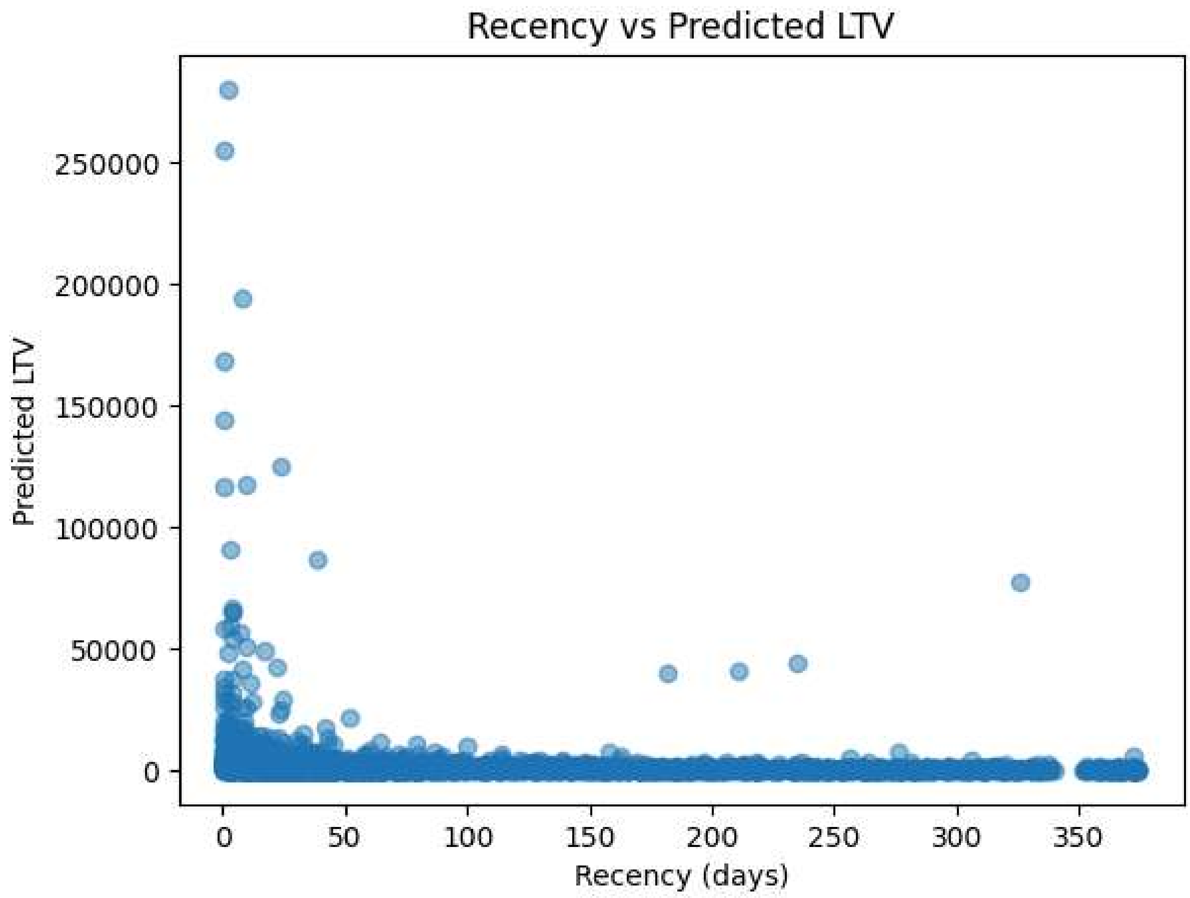
2. Top 10 Customers by Predicted LTV

In [29]:
```
top10 = rfm.nlargest(10, 'Predicted_LTV')
sns.barplot(data=top10, x='CustomerID', y='Predicted_LTV')
plt.title('Top 10 Customers by Predicted LTV')
plt.xlabel('Customer ID')
plt.xticks(rotation=45)
plt.ylabel('Predicted LTV')
plt.show()
```



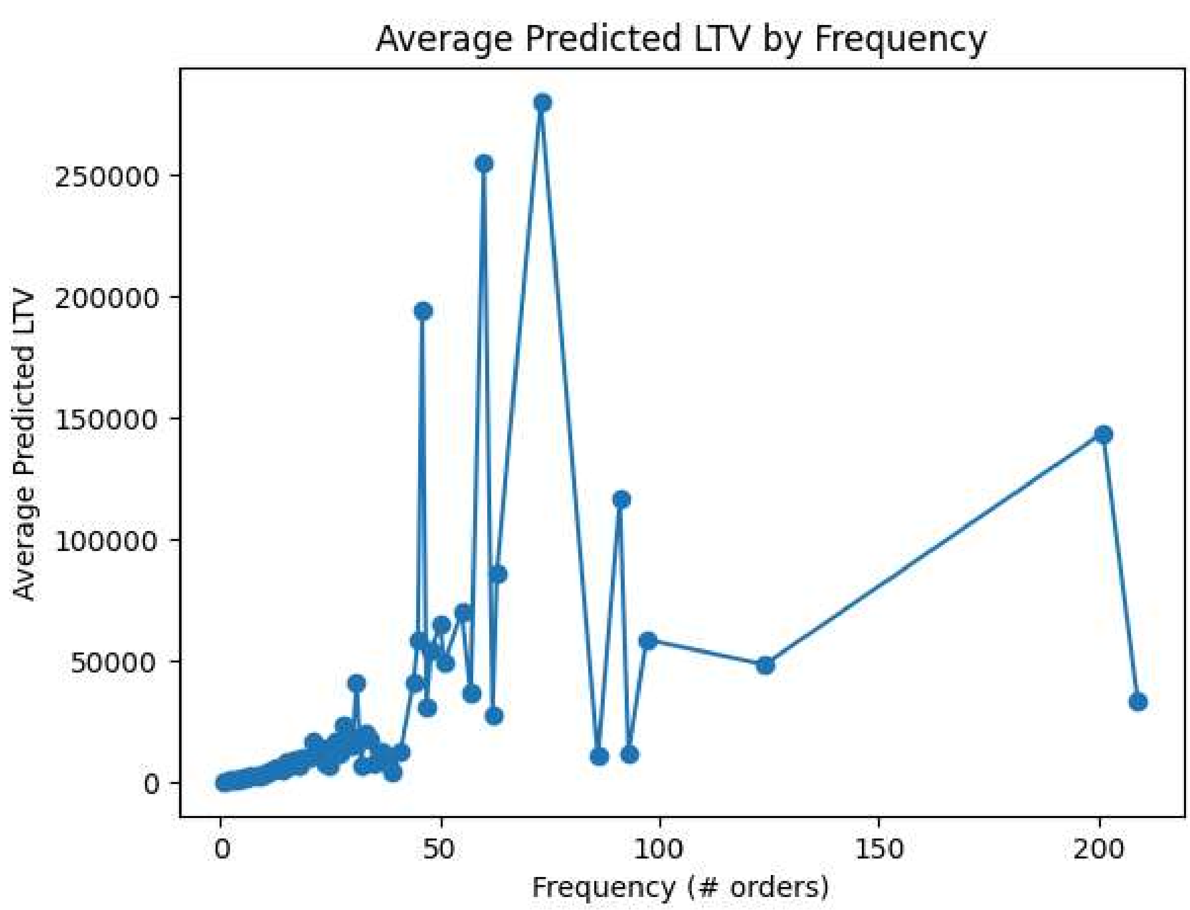
3. Recency vs Predicted LTV Scatter

In [30]:
```
plt.scatter(rfm['Recency'], rfm['Predicted_LTV'], alpha=0.5)
plt.title('Recency vs Predicted LTV')
plt.xlabel('Recency (days)')
plt.ylabel('Predicted LTV')
plt.show()
```



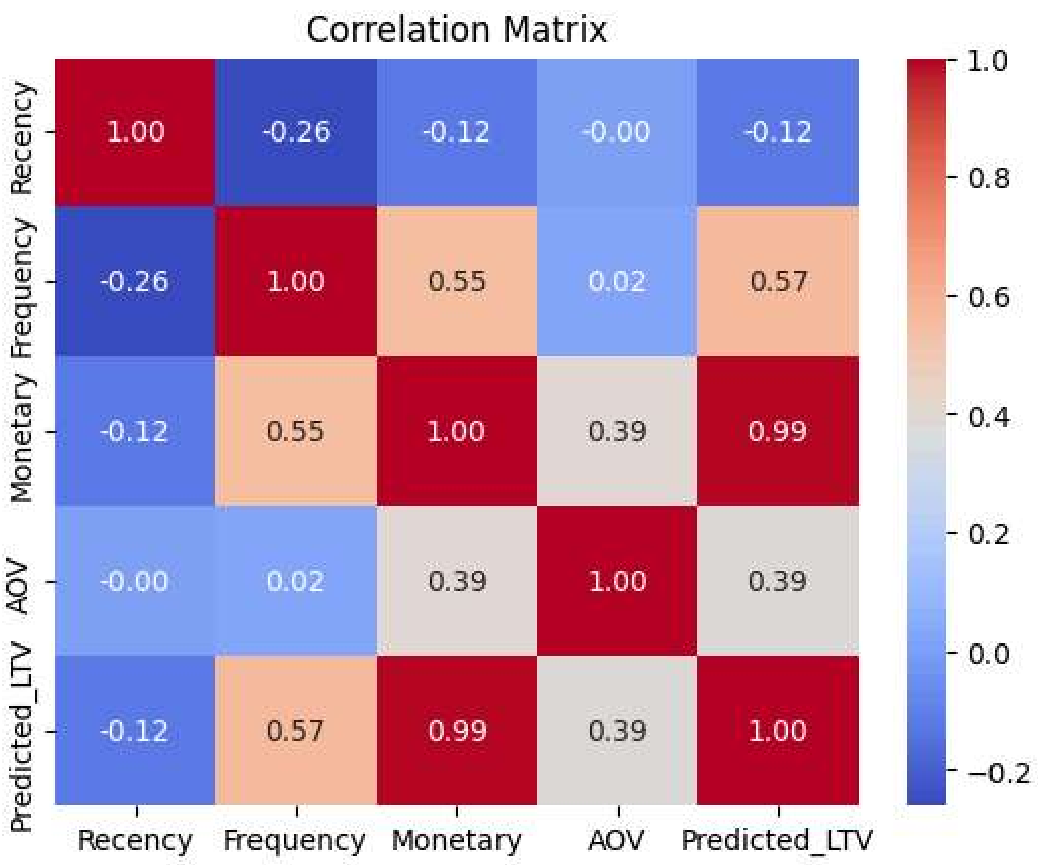
4. Average LTV by Frequency

In [31]:
```
freq_pivot = rfm.groupby('Frequency')['Predicted_LTV'].mean().reset_index()
plt.plot(freq_pivot['Frequency'], freq_pivot['Predicted_LTV'], marker='o')
plt.title('Average Predicted LTV by Frequency')
plt.xlabel('Frequency (# orders)')
plt.ylabel('Average Predicted LTV')
plt.show()
```



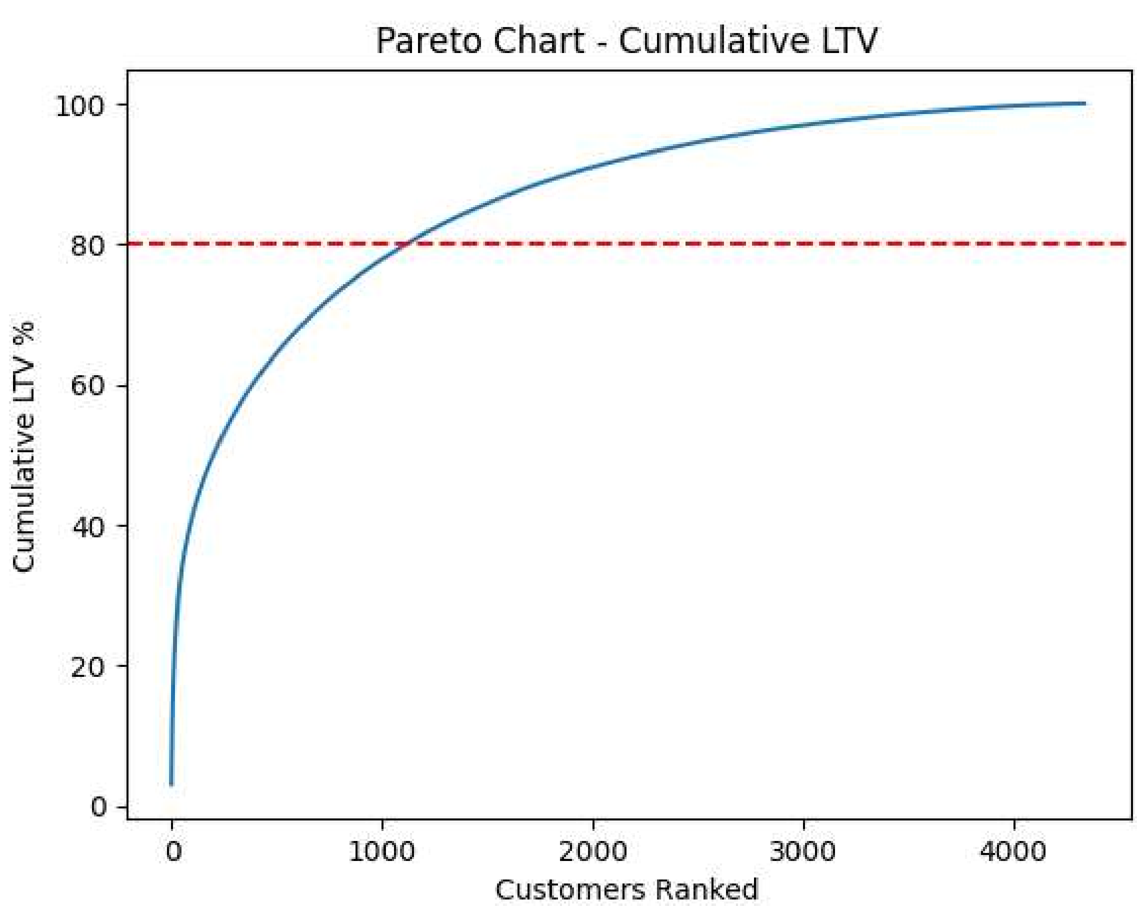
5. Correlation Heatmap

In [32]:
```
corr = rfm[['Recency', 'Frequency', 'Monetary', 'AOV', 'Predicted_LTV']].corr()
sns.heatmap(corr, annot=True, fmt='.2f', cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



6. Pareto Chart

In [33]:
```
rfm_sorted = rfm.sort_values('Predicted_LTV', ascending=False)
rfm_sorted['CumSum'] = rfm_sorted['Predicted_LTV'].cumsum()
rfm_sorted['CumPerc'] = 100 * rfm_sorted['CumSum'] / rfm_sorted['Predicted_LTV'].sum()
plt.plot(rfm_sorted['CumPerc'].values)
plt.axhline(80, color='red', linestyle='--')
plt.title('Pareto Chart - Cumulative LTV')
plt.xlabel('Customers Ranked')
plt.ylabel('Cumulative LTV %')
plt.show()
```



7. Conclusion

Conclusion & Next Steps

1. High-frequency customers drive majority of LTV
2. Negative recency correlates with higher LTV
3. Next: Integrate predictions into BI for segmentation
4. Consider SHAP for model explainability