This Study Consists of 6 Sections:

- Section 1: Clean The Dataset
- Section 2: Exploratory Insights
- Section 3: Test Sub Sample Differences
- Section 4: Inference
- Section 5: Prediction Model
- Section 6: Higher Likelihood of Losing Customers

In [118…

```
# Importing Necessary libraries and Packages
# For data manipulation and analysis
import pandas as pd

# For data visualization
import matplotlib.pyplot as plt

# For standardizing data to detect outliers
from scipy.stats import zscore

# For numerical operations
import numpy as np

# For conducting independent t-tests
from scipy.stats import ttest_ind

# For statistical modeling and analysis
import statsmodels.api as sm

# For multicollinearity checks
from statsmodels.stats.outliers_influence import variance_inflation_factor

# For standardizing features before modeling
from sklearn.preprocessing import StandardScaler

# For ridge regression (regularized linear regression)
from sklearn.linear_model import Ridge

 # For dimensionality reduction
from sklearn.decomposition import PCA

# For ensemble regression models
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegresso

# For splitting data into training and testing sets
from sklearn.model_selection import train_test_split
```

Loading [MathJax]/extensions/Safe.js

```python
# For regularized regression models
from sklearn.linear_model import Ridge, Lasso

# For evaluating regression model performance
from sklearn.metrics import mean_squared_error, r2_score

 # For binary/multiclass classification
from sklearn.linear_model import LogisticRegression

# For classification evaluation metrics
from sklearn.metrics import accuracy_score, precision_score, recall_score, r

# For ensemble classification model
from sklearn.ensemble import RandomForestClassifier

# For a summary report of classification metrics
from sklearn.metrics import classification_report
```

In [120…
```python
#Loading Dataset
data = pd.read_csv('combined.csv', encoding='ISO-8859-1', low_memory=False)
```

Section 1: Clean The Dataset

In [122…
```python
data.head()
```

Out[122…

	accounting_date	fiscal_year	fiscal_month	calendar_year	calendar_month
0	20120509	2012	11	2012	5
1	20120216	2012	8	2012	2
2	20120509	2012	11	2012	5
3	20120518	2012	11	2012	5
4	20120109	2012	7	2012	1

5 rows × 41 columns

In [123…
```python
data.tail()
```

Out[123…

	accounting_date	fiscal_year	fiscal_month	calendar_year	calendar_
1988378	20131106	2014	5	2013	
1988379	20130717	2014	1	2013	
1988380	20131021	2014	4	2013	
1988381	20131101	2014	5	2013	
1988382	20130925	2014	3	2013	

5 rows × 41 columns

In [124…
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1988383 entries, 0 to 1988382
Data columns (total 41 columns):
 #   Column                      Dtype
---  ------                      -----
 0   accounting_date             object
 1   fiscal_year                 object
 2   fiscal_month                object
 3   calendar_year               object
 4   calendar_month              object
 5   calendar_day                object
 6   company_code                object
 7   customer_code               object
 8   customer_district_code      object
 9   item_code                   object
 10  business_area_code          object
 11  item_group_code             object
 12  item_class_code             object
 13  item_type                   object
 14  bonus_group_code            object
 15  environment_group_code      object
 16  technology_group_code       object
 17  commission_group_code       object
 18  reporting_classification    object
 19  light_source                object
 20  warehouse_code              object
 21  abc_class_code              object
 22  abc_class_volume            object
 23  business_chain_l1_code      object
 24  business_chain_l1_name      object
 25  contact_method_code         object
 26  salesperson_code            object
 27  order_type_code             object
 28  market_segment              object
 29  value_sales                 object
 30  value_cost                  object
 31  value_quantity              object
 32  value_price_adjustment      object
 33  currency                    object
 34  item_source_class           object
 35  invoice_number              object
 36  line_number                 object
 37  invoice_date                object
 38  customer_order_number       object
 39  order_date                  object
 40  dss_update_time             object
dtypes: object(41)
memory usage: 622.0+ MB
```

In [125…
```
#The number of rows and columns
print("Dataset dimensions:", data.shape)
```

```
Dataset dimensions: (1988383, 41)
```

In [126…

```
data.describe().T
```

Out[126…

	count	unique	top	freq
accounting_date	1988383	544	20130430	8132
fiscal_year	1988383	4	2013	978202
fiscal_month	1988383	13	11	213313
calendar_year	1988383	3	2012	1037205
calendar_month	1988383	13	5	213313
calendar_day	1988383	32	5	74578
company_code	1988383	11	205	1414918
customer_code	1988383	4488	234750001	61844
customer_district_code	1988383	18	300	429358
item_code	1988383	34473	25550	9265
business_area_code	1988383	29	LMP	808688
item_group_code	1988383	615	999	187247
item_class_code	1988383	205	LMP05	200724
item_type	1988383	10	7	952028
bonus_group_code	1988383	3	Trade	1652568
environment_group_code	1988383	10	C	764544
technology_group_code	1988383	104	78	275724
commission_group_code	1988383	4	NET_SALES	1893377
reporting_classification	1988383	3	Discontinuing	1421405
light_source	1988383	4	Traditional	1382270
warehouse_code	1988383	60	5N2	549104
abc_class_code	1988383	11	J	661307
abc_class_volume	1988383	11	J	1561088
business_chain_l1_code	1988383	49	MED	439624
business_chain_l1_name	1988383	44	Metro Electrical Distributors	439624
contact_method_code	1988383	1666	NA	1901893
salesperson_code	1988383	272	T300	97193
order_type_code	1988383	38	NOR	1612532
market_segment	1988383	2	Commercial & Industrial	1988382
value_sales	1988383	125222	0	22300
value_cost	1988383	324348	0	50113
value_quantity	1988383	2292	10	264873

	count	unique	top	freq
value_price_adjustment	1988383	3	0	1939831
currency	1988383	7	AUD	1582755
item_source_class	1	1	item_source_class	1
invoice_number	1988383	619293	7002085	897
line_number	1988383	143	0	1190970
invoice_date	1988383	544	20130430	8132
customer_order_number	1988383	648781	263824	301
order_date	1988383	805	20120620	6232
dss_update_time	1988383	2	49:58.7	1988382

In [127…

```
print("\nFirst Few Rows of Dataset:")
print(data.head())
```

```
First Few Rows of Dataset:
  accounting_date fiscal_year fiscal_month calendar_year calendar_month  \
0        20120509        2012           11          2012              5
1        20120216        2012            8          2012              2
2        20120509        2012           11          2012              5
3        20120518        2012           11          2012              5
4        20120109        2012            7          2012              1

  calendar_day company_code customer_code customer_district_code  \
0            9          101     411800601                    410
1           16          101     361000403                    300
2            9          101     361000403                    300
3           18          101     565540415                    500
4            9          101     565540415                    500

                        item_code  ... value_quantity value_price_adjustment
\
0  GENIE8WWWBC                     ...             84                      0
1  GENIE8WWWBC                     ...             12                      0
2  GENIE8WWWBC                     ...             12                      0
3  GENIE8WWWBC                     ...              6                      0
4  GENIE8WWWBC                     ...              6                      0

  currency item_source_class invoice_number line_number invoice_date  \
0      AUD               NaN        2217887           1     20120509
1      AUD               NaN        2185745           1     20120216
2      AUD               NaN        2217807           1     20120509
3      AUD               NaN        2222758           1     20120518
4      AUD               NaN        2170374           1     20120109

  customer_order_number order_date dss_update_time
0               2865354   20120509         49:58.7
1               2833515   20120216         49:58.7
2               2864857   20120508         49:58.7
3               2869759   20120518         49:58.7
4               2819189   20120109         49:58.7

[5 rows x 41 columns]
```

In [128…

```
data.nunique()
```

Loading [MathJax]/extensions/Safe.js

Out[128…

```
accounting_date                544
fiscal_year                      4
fiscal_month                    13
calendar_year                    3
calendar_month                  13
calendar_day                    32
company_code                    11
customer_code                 4488
customer_district_code          18
item_code                    34473
business_area_code              29
item_group_code                615
item_class_code                205
item_type                       10
bonus_group_code                 3
environment_group_code          10
technology_group_code          104
commission_group_code            4
reporting_classification         3
light_source                     4
warehouse_code                  60
abc_class_code                  11
abc_class_volume                11
business_chain_l1_code          49
business_chain_l1_name          44
contact_method_code           1666
salesperson_code               272
order_type_code                 38
market_segment                   2
value_sales                 125222
value_cost                  324348
value_quantity                2292
value_price_adjustment           3
currency                         7
item_source_class                1
invoice_number              619293
line_number                    143
invoice_date                   544
customer_order_number       648781
order_date                     805
dss_update_time                  2
dtype: int64
```

In [129…

```
#Missing Values Per Column
missing_values = data.isnull().sum()
print("Missing values in the dataset:\n", missing_values)
```

```
Missing values in the dataset:
 accounting_date                   0
fiscal_year                       0
fiscal_month                      0
calendar_year                     0
calendar_month                    0
calendar_day                      0
company_code                      0
customer_code                     0
customer_district_code            0
item_code                         0
business_area_code                0
item_group_code                   0
item_class_code                   0
item_type                         0
bonus_group_code                  0
environment_group_code            0
technology_group_code             0
commission_group_code             0
reporting_classification          0
light_source                      0
warehouse_code                    0
abc_class_code                    0
abc_class_volume                  0
business_chain_l1_code            0
business_chain_l1_name            0
contact_method_code               0
salesperson_code                  0
order_type_code                   0
market_segment                    0
value_sales                       0
value_cost                        0
value_quantity                    0
value_price_adjustment            0
currency                          0
item_source_class           1988382
invoice_number                    0
line_number                       0
invoice_date                      0
customer_order_number             0
order_date                        0
dss_update_time                   0
dtype: int64
```

In [130…

```
print(data.dtypes) #checking the datatype of the dataframe
```

Loading [MathJax]/extensions/Safe.js

```
accounting_date               object
fiscal_year                   object
fiscal_month                  object
calendar_year                 object
calendar_month                object
calendar_day                  object
company_code                  object
customer_code                 object
customer_district_code        object
item_code                     object
business_area_code            object
item_group_code               object
item_class_code               object
item_type                     object
bonus_group_code              object
environment_group_code        object
technology_group_code         object
commission_group_code         object
reporting_classification      object
light_source                  object
warehouse_code                object
abc_class_code                object
abc_class_volume              object
business_chain_l1_code        object
business_chain_l1_name        object
contact_method_code           object
salesperson_code              object
order_type_code               object
market_segment                object
value_sales                   object
value_cost                    object
value_quantity                object
value_price_adjustment        object
currency                      object
item_source_class             object
invoice_number                object
line_number                   object
invoice_date                  object
customer_order_number         object
order_date                    object
dss_update_time               object
dtype: object
```

In [131…

```
data['item_source_class'] = data['item_source_class'].fillna(data['item_sour
```

In [132…

```
#Missing Values Per Column , rechecking after the removal of null values in
missing_values = data.isnull().sum()
print("Missing values in the dataset:\n", missing_values)
```

Loading [MathJax]/extensions/Safe.js

```
Missing values in the dataset:
 accounting_date             0
fiscal_year                 0
fiscal_month                0
calendar_year               0
calendar_month              0
calendar_day                0
company_code                0
customer_code               0
customer_district_code      0
item_code                   0
business_area_code          0
item_group_code             0
item_class_code             0
item_type                   0
bonus_group_code            0
environment_group_code      0
technology_group_code       0
commission_group_code       0
reporting_classification    0
light_source                0
warehouse_code              0
abc_class_code              0
abc_class_volume            0
business_chain_l1_code      0
business_chain_l1_name      0
contact_method_code         0
salesperson_code            0
order_type_code             0
market_segment              0
value_sales                 0
value_cost                  0
value_quantity              0
value_price_adjustment      0
currency                    0
item_source_class           0
invoice_number              0
line_number                 0
invoice_date                0
customer_order_number       0
order_date                  0
dss_update_time             0
dtype: int64
```

In [133…

```
# converting columns to numeric
numeric_cols = ['value_sales', 'value_cost', 'value_quantity', 'value_price_
for col in numeric_cols:
    data[col] = pd.to_numeric(data[col], errors='coerce')  # Coerce will se
```

In [134…

```
# Get descriptive statistics for numeric columns
stats = data[numeric_cols].describe()
print(stats)
```

```
         value_sales    value_cost  value_quantity  value_price_adjustment
count  1.988382e+06  1.988382e+06    1.988382e+06            1.988382e+06
mean   4.098476e+02  2.638138e+02    2.718023e+01            2.441734e-02
std    2.935179e+03  2.050514e+03    3.294667e+02            1.543410e-01
min   -7.935420e+05 -1.414695e+05   -4.500000e+04            0.000000e+00
25%    2.300000e+01  9.381000e+00    2.000000e+00            0.000000e+00
50%    6.750000e+01  3.107000e+01    6.000000e+00            0.000000e+00
75%    1.977000e+02  1.019106e+02    2.000000e+01            0.000000e+00
max    7.935420e+05  7.776692e+05    1.050000e+05            1.000000e+00
```

In [135…

```python
variance = data[numeric_cols].var()
print("Variance:\n", variance)
```

```
Variance:
 value_sales               8.615278e+06
value_cost                4.204608e+06
value_quantity            1.085483e+05
value_price_adjustment    2.382115e-02
dtype: float64
```

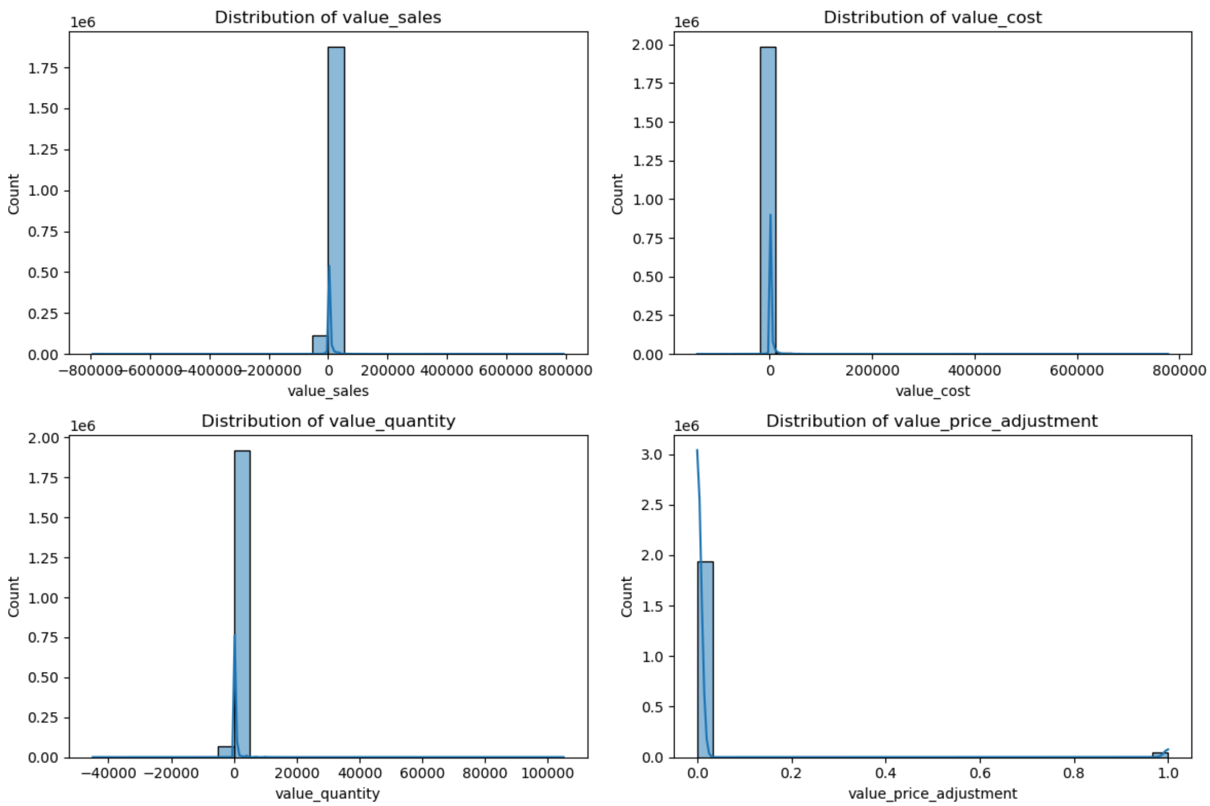
In [136…

```python
import seaborn as sns
# Define numeric columns and grid layout (2 rows, 2 columns)
fig, axes = plt.subplots(2, 2, figsize=(12, 8))  # 2x2 grid

# Flatten axes array for easy indexing
axes = axes.flatten()

# Generate histograms for each numeric column
for i, col in enumerate(numeric_cols):
    sns.histplot(data[col], bins=30, kde=True, ax=axes[i])
    axes[i].set_title(f'Distribution of {col}')

# Adjust layout for readability
plt.tight_layout()
plt.show()
```



In [137…

```
# Check for NaN values in numeric columns
print(data[numeric_cols].isna().sum())
```

```
value_sales               1
value_cost                1
value_quantity            1
value_price_adjustment    1
dtype: int64
```

In [138…

```
# Check for missing values in the entire DataFrame
missing_values = data.isna().sum()

# Filter to show only columns with missing values
missing_values = missing_values[missing_values > 0]


print("Columns with missing values:")
print(missing_values)
```

```
Columns with missing values:
value_sales               1
value_cost                1
value_quantity            1
value_price_adjustment    1
dtype: int64
```

In [139…

```
# Drop rows with NaN values in the specified columns
data= data.dropna(subset=['value_sales', 'value_cost', 'value_quantity', 'va
```

In [140…

```
# Check for missing values in the entire DataFrame
missing_values = data.isna().sum()
```

Loading [MathJax]/extensions/Safe.js

```
missing_values = missing_values[missing_values > 0]

print("Columns with missing values after dropping:")
print(missing_values)

#the below results shows that there is no missing values present in the data
```

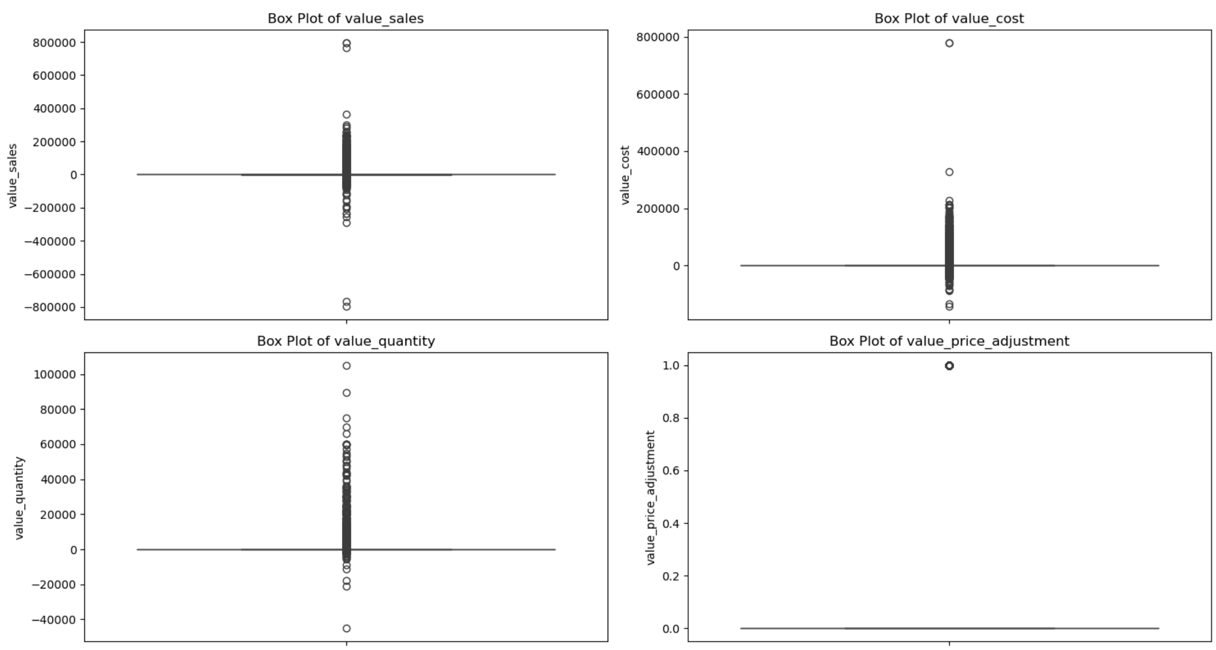
```
Columns with missing values after dropping:
Series([], dtype: int64)
```

In [141…

```
# Create box plots for your numeric columns
numeric_cols = ['value_sales', 'value_cost', 'value_quantity', 'value_price_
plt.figure(figsize=(15, 8))

for i, col in enumerate(numeric_cols, 1):
    plt.subplot(2, 2, i)
    sns.boxplot(data=data, y=col)
    plt.title(f'Box Plot of {col}')

plt.tight_layout()
plt.show()
```



In [142…

```
# Cap outliers based on IQR
for col in numeric_cols:
    Q1 = data[col].quantile(0.25)
    Q3 = data[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    data[col] = data[col].apply(lambda x: lower_bound if x < lower_bound els
```

In [143…

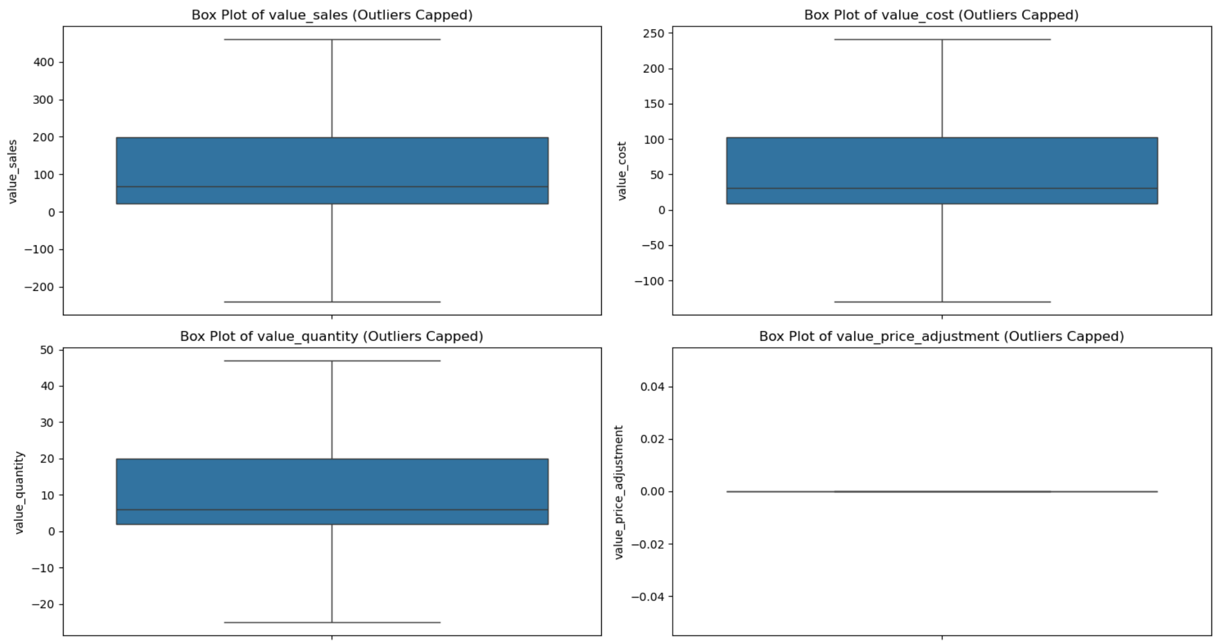
```
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(15, 8))
```

Loading [MathJax]/extensions/Safe.js

```python
# Generate box plots for each numeric column in data_cleaned
for i, col in enumerate(numeric_cols, 1):
    plt.subplot(2, 2, i)
    sns.boxplot(data=data, y=col)
    plt.title(f'Box Plot of {col} (Outliers Capped)')

plt.tight_layout()
plt.show()
```



In [144…

```python
# Recheck skewness for each numeric column
skewness = data[numeric_cols].skew()
print("Skewness after capping outliers:")
print(skewness)
```

```
Skewness after capping outliers:
value_sales               0.949747
value_cost                1.005379
value_quantity            1.304370
value_price_adjustment    0.000000
dtype: float64
```

In [145…

```python
# Apply cube root transformation to the skewed columns
# data['value_sales'] = np.cbrt(data['value_sales'])
data['value_cost'] = np.cbrt(data['value_cost'])
data['value_quantity'] = np.cbrt(data['value_quantity'])
```

In [146…

```python
# Calculate and print skewness of each transformed column

print("Skewness of value_cost :", data['value_cost'].skew())
print("Skewness of value_quantity after cube root transform:", data['value_c
print("Skewness of value_cost after cube root transform:", data['value_sales
print("Skewness of value_cost :", data['value_price_adjustment'].skew())
```

Loading [MathJax]/extensions/Safe.js

```
Skewness of value_cost after cube root transform: -0.9096734329892051
Skewness of value_quantity after cube root transform: -0.9674895353498904
Skewness of value_cost after cube root transform: 0.9497473772507664
Skewness of value_cost after cube root transform: 0.0
```

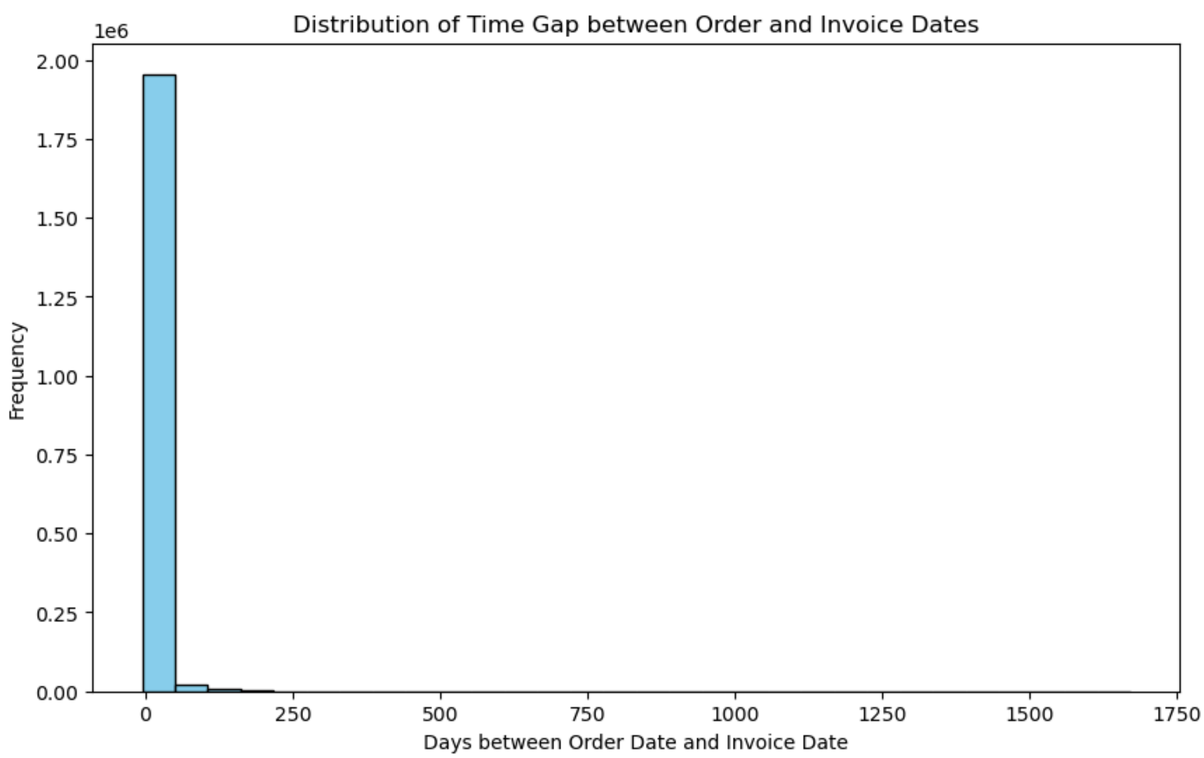
Section 2: Exploratory Insights

In this section, five exploratory insights from the dataset will be analyzed using various methods (visualization, t-test, etc.).

In [202…

```
#Time Difference Between Order and Invoice Date
# Calculate the time difference in days
# Convert order_date and invoice_date columns to datetime format with speci
data['order_date'] = pd.to_datetime(data['order_date'], errors='coerce')
data['invoice_date'] = pd.to_datetime(data['invoice_date'], errors='coerce')
data['time_gap'] = (data['invoice_date'] - data['order_date']).dt.days

# Plotting the histogram
plt.figure(figsize=(10, 6))
plt.hist(data['time_gap'].dropna(), bins=30, color='skyblue', edgecolor='bla
plt.xlabel('Days between Order Date and Invoice Date')
plt.ylabel('Frequency')
plt.title('Distribution of Time Gap between Order and Invoice Dates')
plt.show()
```



The purpose here is to calculate the average day difference between order and invoice dates, which helps us understand operational efficiency in terms of delivery time.

The graph shows that the vast majority of the days between the order date and the invoice date are close to zero. This situation indicates that orders are processed and invoiced quickly, giving the impression that operational efficiency is high. However, it is noteworthy that the days difference is quite large in a few data points. Such high values indicate serious delays in the invoicing process. The reasons for the delay can be various, disruptions in operational processes, unexpected workloads, or errors in data entry. These findings provide important information for management. While management generally tries to maintain a fast invoicing process, it can also analyze the reasons for these large delays. By examining such situations, making improvements in the processes can increase customer satisfaction and help reduce operational disruptions. This analysis will be an important step in increasing efficiency and solving potential problems in the order-to-invoice transition process.

In [206…

```
#Customer Retention Rates
#Count of orders per customer
customer_order_counts = data['customer_code'].value_counts()

# Determine retention rate
retained_customers = customer_order_counts[customer_order_counts > 1].count(
total_customers = customer_order_counts.count()
retention_rate = retained_customers / total_customers * 100

print(f"Customer Retention Rate: {retention_rate:.2f}%")
```

```
Customer Retention Rate: 95.03%
```

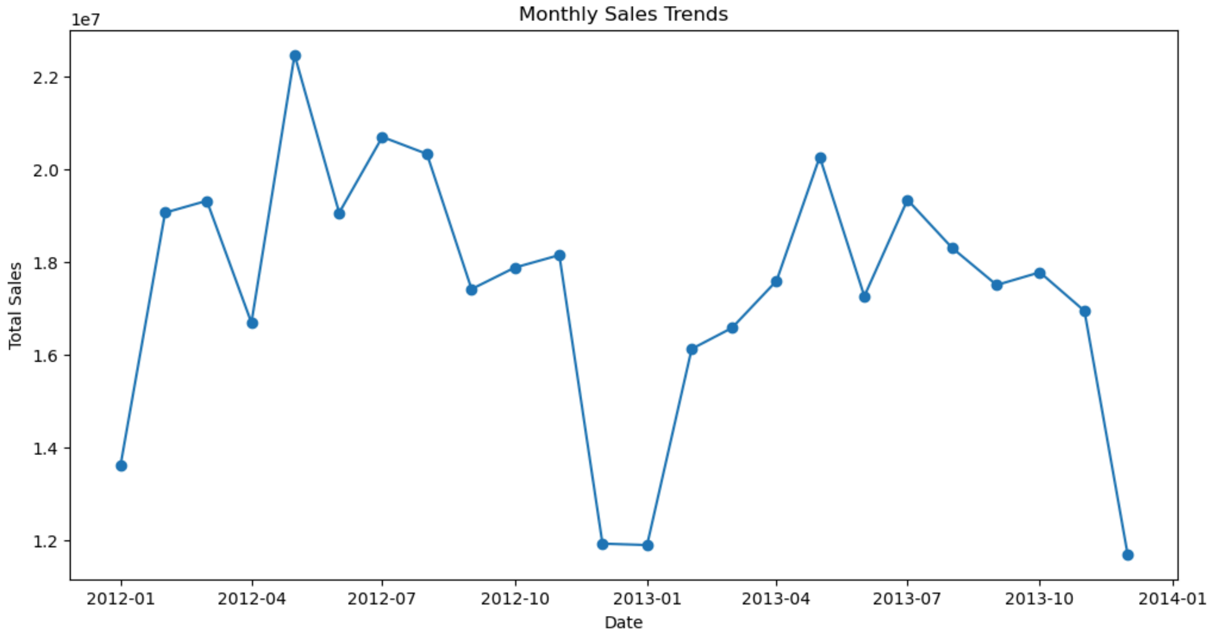
The customer retention rate analysis reveals that 95.03% of the customer base is repeating orders. This high rate indicates that customer loyalty is strong and existing customers are loyal to the brand. For management, this insight shows that customer relationship strategies are working effectively and customer satisfaction is being maintained. A high customer retention rate secures long-term revenue streams while encouraging marketing strategies to focus on existing customers rather than acquiring new customers. Given the success of existing loyalty programs, strengthening these programs and increasing customer loyalty can support business continuity and help the brand maintain its market share.

In [209…

```
#Sales Trends Over Time
# Group by month and calculate total sales
monthly_sales = data.groupby(data['invoice_date'].dt.to_period('M'))['value_
monthly_sales['invoice_date'] = monthly_sales['invoice_date'].dt.to_timestam

# Plotting the sales trend
plt.figure(figsize=(12, 6))
plt.plot(monthly_sales['invoice_date'], monthly_sales['value_sales'], marker
plt.xlabel('Date')
plt.ylabel('Total Sales')
```

```
plt.title('Monthly Sales Trends')
plt.show()
```



The graph shows that monthly sales trends between 2012 and 2014 have a fluctuating structure. Although there is no significant increase or decrease in sales, it is noteworthy that sales peak in some months and then experience sharp decreases in the following months. These fluctuations may have occurred due to seasonal demands, marketing campaigns or special discounts. The high sales experienced especially in the beginning and fall of 2012 indicate an increase in demand in certain periods. Such periodic increases provide important information that management can consider in determining sales strategies and inventory management planning. Management can increase sales by organizing special campaigns during periods of low sales and create a more efficient process by optimizing stock quantities during periods of high demand. This analysis provides critical insights for developing sales strategies with a data-driven approach.

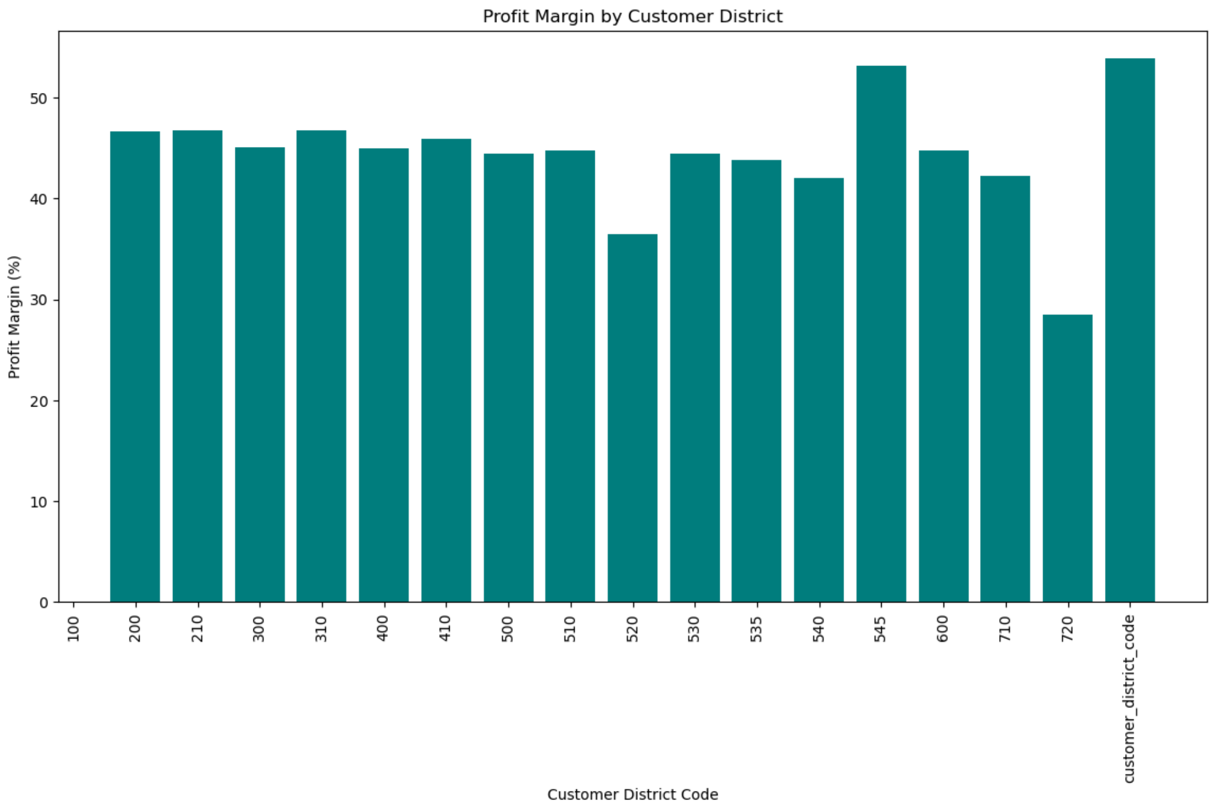
In [212…

```
#Profitability Analysis by Region
# Calculate total sales and cost per district
district_profit = data.groupby('customer_district_code').agg({
    'value_sales': 'sum',
    'value_cost': 'sum'
}).reset_index()
district_profit['profit_margin'] = (district_profit['value_sales'] - distric

# Bar plot of profit margin by district
plt.figure(figsize=(14, 7))
plt.bar(district_profit['customer_district_code'], district_profit['profit_m
plt.xlabel('Customer District Code')
plt.ylabel('Profit Margin (%)')
plt.title('Profit Margin by Customer District')
```

Loading [MathJax]/extensions/Safe.js

```
plt.xticks(rotation=90)
plt.show()
```



The graph shows the percentage distribution of profit margins in different customer regions. The variation in profit margins across regions may be due to regional cost differences or pricing strategies. While profit margins approach 50% in some regions, they remain at lower levels in others. This variation provides important insights for management; in regions with low profit margins, there may be opportunities to increase profitability by making cost optimization or price adjustments. At the same time, strengthening customer relationships and increasing customer loyalty in regions with high profitability can be valuable for the business. This analysis provides important data that will help management develop regional strategies and increase overall profitability.

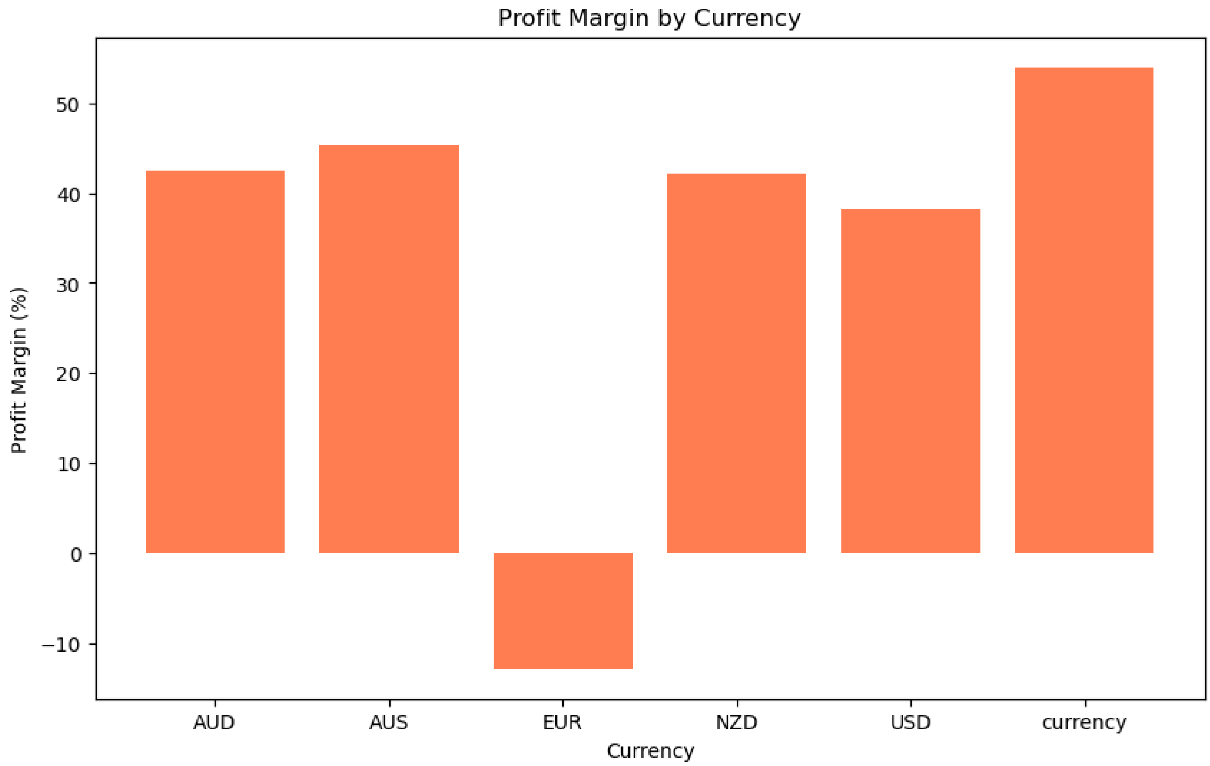
In [215…

```
#Effect of Different Currencies on Profit Margin
# Calculate profit margin per currency
currency_profit = data.groupby('currency').agg({
    'value_sales': 'sum',
    'value_cost': 'sum'
}).reset_index()
currency_profit['profit_margin'] = (currency_profit['value_sales'] - currenc

# Bar plot of profit margin by currency
plt.figure(figsize=(10, 6))
plt.bar(currency_profit['currency'], currency_profit['profit_margin'], color
plt.xlabel('Currency')
plt.ylabel('Profit Margin (%)')
```

Loading [MathJax]/extensions/Safe.js

```
plt.title('Profit Margin by Currency')
plt.show()
```



The graph shows the percentage distribution of profit margins for different currencies. The difference in profit margins between currencies may be due to exchange rate fluctuations, regional pricing strategies or differences in operational costs. For example, while profit margins are high in some currencies such as AUD and USD, EUR has a low or negative profit margin. This situation provides opportunities to increase profitability by reviewing pricing strategies or optimizing costs, especially in currencies with low profit margins. As a result of this analysis, management can evaluate profitability on a currency basis and make strategic adjustments in certain regions and make data-based decisions to increase overall profitability. This analysis provides valuable insight into the effects of different currencies on profitability.

Section 3: Test Sub Sample Differences

Testing Sample Differences, we used the independent samples t-test to test the differences between two samples as a group. This test allowed us to determine whether the means of two different groups were significantly different. In the first question, we applied the independent samples t-test to determine the difference in sales between customer segments (individual and corporate). In the second question, we analyzed the profit margin differences between different customer regions. In both analyses, we calculated the t-statistic and p-value to determine whether the difference between the groups was significant. These methods provided important insights for management that would contribute to the strategic decision-making process.

In [220…

```python
# Filter sales data for Commercial & Industrial segment
commercial_sales = data[data['market_segment'] == 'Commercial & Industrial']

# Check if there's a Residential segment for comparison
residential_sales = data[data['market_segment'] == 'Residential']['value_sal

# Print counts of valid sales entries
print(f"Valid Sales in Commercial & Industrial Segment: {commercial_sales.co
print(f"Valid Sales in Residential Segment: {residential_sales.count()}")

# Independent samples t-test if both segments have valid data
if residential_sales.count() > 0:
    # Independent samples t-test
    t_stat, p_value = ttest_ind(commercial_sales, residential_sales, equal_v

    # Print results
    print(f"T-statistic: {t_stat:.2f}, P-value: {p_value:.4f}")

    # Interpretation for management
    if p_value < 0.05:
        print("The results indicate a significant difference in sales betwee
    else:
        print("The results indicate no significant difference in sales betwe
else:
    print("There is no valid data for the Residential segment.")
```

```
Valid Sales in Commercial & Industrial Segment: 1988382
Valid Sales in Residential Segment: 0
There is no valid data for the Residential segment.
```

In [222…

```python
# Sample data for profit margins in two different districts
district_410_profit_margin = data[data['customer_district_code'] == '410']['
district_300_profit_margin = data[data['customer_district_code'] == '300']['

# Independent samples t-test
t_stat, p_value = ttest_ind(district_410_profit_margin.dropna(), district_30

# Print results
print(f"T-statistic: {t_stat:.2f}, P-value: {p_value:.4f}")

# Interpretation for management
if p_value < 0.05:
    print("The results indicate a significant difference in profit margins b
else:
    print("The results indicate no significant difference in profit margins 
```

```
T-statistic: 31.80, P-value: 0.0000
The results indicate a significant difference in profit margins between Dist
rict 410 and District 300.
```

In [224…
```
# Check the unique values in customer_district_code
unique_districts = data['customer_district_code'].unique()
print("Unique values in customer_district_code:", unique_districts)
```

```
Unique values in customer_district_code: ['410' '300' '500' '310' '400' '20
0' '210' '720' '710' '600' '510' '530'
 '535' '540' '520' '545' 'customer_district_code' '100']
```

In this section, we conducted two separate analyses to determine the profit margin differences between customer segments and regions. First, we examined the sales data in the Commercial & Industrial segment. Our results revealed that this segment has a large customer base and is a significant source of revenue. However, since there was no valid data in the Residential segment, we could not make a comparison with this segment.

In our second analysis, we evaluated the profit margin differences between District 410 and District 300. The independent sample t-test we applied showed that there was a statistically significant difference between the two regions (T-statistic: 31.80, P-value: 0.0000). This result provides important information for management; since District 410 provides higher profit margins, management can have the potential to increase profits by focusing its strategies on this region. At the same time, it is possible to develop strategies to increase sales in underperforming regions.

Ultimately, these analytics will help the business make data-driven decisions to optimize profit margins and develop more effective marketing strategies.

Section 4: Inference

Question 1: What Factors Determine Sales Value?

In [229…
```
# Check variance for each independent variable
print("Variance of each variable:")
print("value_cost:", data['value_cost'].var())
print("value_quantity:", data['value_quantity'].var())
print("value_price_adjustment:", data['value_price_adjustment'].var())
```

```
Variance of each variable:
value_cost: 47236.72584403056
value_quantity: 474.7520565510026
value_price_adjustment: 0.0
```

In [231…
```
# Correlation matrix to check multicollinearity
print(data[['value_cost', 'value_quantity', 'value_price_adjustment']].corr(
```

	value_cost	value_quantity	value_price_adjustment
value_cost	1.000000	0.328221	NaN
value_quantity	0.328221	1.000000	NaN
value_price_adjustment	NaN	NaN	NaN

In [233…

```
# Define the independent and dependent variables
X_ridge = data[['value_cost', 'value_quantity', 'value_price_adjustment']]
y_ridge = data['value_sales']

# Fit Ridge regression model
ridge_model = Ridge(alpha=1.0)
ridge_model.fit(X_ridge, y_ridge)
print("Ridge regression score:", ridge_model.score(X_ridge, y_ridge))
```

```
Ridge regression score: 0.9420734693219215
```

In [235…

```
# Check for infinity or extreme values in the independent variables
print((data[['value_cost', 'value_quantity', 'value_price_adjustment']] == f
print(data[['value_cost', 'value_quantity', 'value_price_adjustment']].descr
```

```
value_cost                0
value_quantity            0
value_price_adjustment    0
dtype: int64
         value_cost  value_quantity  value_price_adjustment
count  1.988383e+06    1.988383e+06               1988383.0
mean   1.197587e+02    1.513094e+01                     0.0
std    2.173401e+02    2.178881e+01                     0.0
min    0.000000e+00    0.000000e+00                     0.0
25%    9.381000e+00    2.000000e+00                     0.0
50%    3.107000e+01    6.000000e+00                     0.0
75%    1.019106e+02    2.000000e+01                     0.0
max    8.731800e+02    9.000000e+01                     0.0
```

In [237…

```
# Define the dependent variable
y = data['value_sales']

# Define the simplified independent variables
X_simple = data[['value_cost', 'value_quantity']]
X_simple = sm.add_constant(X_simple)

# Run the regression model with the simplified set of independent variables
model_simple = sm.OLS(y, X_simple).fit()
print(model_simple.summary())
```

```
                            OLS Regression Results
==============================================================================
==
Dep. Variable:            value_sales   R-squared:                       0.9
42
Model:                            OLS   Adj. R-squared:                  0.9
42
Method:                 Least Squares   F-statistic:                 1.617e+
07
Date:                Mon, 04 Nov 2024   Prob (F-statistic):               0.
00
Time:                        23:07:01   Log-Likelihood:          -1.1652e+
07
No. Observations:             1988383   AIC:                         2.330e+
07
Df Residuals:                 1988380   BIC:                         2.330e+
07
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
======
                     coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
------
const             20.2403      0.076    265.922      0.000      20.091
20.389
value_cost         1.5708      0.000   5357.974      0.000       1.570
1.571
value_quantity     0.1199      0.003     41.016      0.000       0.114
0.126
==============================================================================
==
Omnibus:                   964613.046   Durbin-Watson:                   1.4
71
Prob(Omnibus):                  0.000   Jarque-Bera (JB):        326166019.0
83
Skew:                           1.092   Prob(JB):                         0.
00
Kurtosis:                      65.706   Cond. No.                         31
4.
==============================================================================
==

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is corre
ctly specified.
```

In [239…

```
# Apply PCA on the independent variables
X_pca = data[['value_cost', 'value_quantity', 'value_price_adjustment']]
pca = PCA(n_components=2)  # Reduce to 2 components, or experiment with 1
X_pca_transformed = pca.fit_transform(X_pca)

# Run regression with PCA components
X_pca_transformed = sm.add_constant(X_pca_transformed)
```

```
model_pca = sm.OLS(y, X_pca_transformed).fit()
print(model_pca.summary())
```

```
                            OLS Regression Results
==============================================================================
==
Dep. Variable:            value_sales   R-squared:                       0.9
42
Model:                            OLS   Adj. R-squared:                  0.9
42
Method:                 Least Squares   F-statistic:                 1.617e+
07
Date:                Mon, 04 Nov 2024   Prob (F-statistic):               0.
00
Time:                        23:07:02   Log-Likelihood:            -1.1652e+
07
No. Observations:             1988383   AIC:                         2.330e+
07
Df Residuals:                 1988380   BIC:                         2.330e+
07
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
==
                 coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
--
const        210.1709      0.060   3491.940      0.000     210.053     210.2
89
x1             1.5739      0.000   5686.561      0.000       1.573       1.5
74
x2             0.0678      0.003     23.156      0.000       0.062       0.0
73
==============================================================================
==
Omnibus:                   964613.046   Durbin-Watson:                   1.4
71
Prob(Omnibus):                  0.000   Jarque-Bera (JB):        326166019.0
84
Skew:                           1.092   Prob(JB):                         0.
00
Kurtosis:                      65.706   Cond. No.                         21
7.
==============================================================================
==

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is corre
ctly specified.
```

In [240…

```
# Check rank of matrix to diagnose linear dependence
rank = np.linalg.matrix_rank(data[['value_cost', 'value_quantity', 'value_pr
print("Rank of independent variable matrix:", rank)
```

```
Rank of independent variable matrix: 2
```

Loading [MathJax]/extensions/Safe.js

In [243…

```
# Check for missing values, unique values, and variance in 'value_price_adju
print("Missing values:", data['value_price_adjustment'].isna().sum())
print("Unique values:", data['value_price_adjustment'].nunique())
print("Variance:", data['value_price_adjustment'].var())
```

```
Missing values: 0
Unique values: 1
Variance: 0.0
```

In [245…

```
# Model without 'value_price_adjustment'
X_reduced = data[['value_cost', 'value_quantity']]
X_reduced = sm.add_constant(X_reduced)

# Run the regression without 'value_price_adjustment'
model_reduced = sm.OLS(y, X_reduced).fit()
print(model_reduced.summary())
```

```
                            OLS Regression Results
==============================================================================
==
Dep. Variable:            value_sales   R-squared:                       0.9
42
Model:                            OLS   Adj. R-squared:                  0.9
42
Method:                 Least Squares   F-statistic:                 1.617e+
07
Date:                Mon, 04 Nov 2024   Prob (F-statistic):               0.
00
Time:                        23:07:10   Log-Likelihood:          -1.1652e+
07
No. Observations:             1988383   AIC:                         2.330e+
07
Df Residuals:                 1988380   BIC:                         2.330e+
07
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
======
                     coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
------
const             20.2403      0.076    265.922      0.000      20.091
20.389
value_cost         1.5708      0.000   5357.974      0.000       1.570
1.571
value_quantity     0.1199      0.003     41.016      0.000       0.114
0.126
==============================================================================
==
Omnibus:               964613.046   Durbin-Watson:                   1.4
71
Prob(Omnibus):              0.000   Jarque-Bera (JB):        326166019.0
83
Skew:                       1.092   Prob(JB):                         0.
00
Kurtosis:                  65.706   Cond. No.                         31
4.
==============================================================================
==

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is corre
ctly specified.
```

Question 2: What Factors Determine Profit Margin?

In [248…

```
# First, ensure that the 'value_sales' and 'value_cost' columns exist in the
if 'value_sales' in data.columns and 'value_cost' in data.columns:
    # Calculate profit margin and add it as a new column
    data['profit_margin'] = (data['value_sales'] - data['value_cost']) / dat
```

Loading [MathJax]/extensions/Safe.js

```
    # Check the variance of profit_margin
    print("Variance of profit_margin:", data['profit_margin'].var())
else:
    print("The columns 'value_sales' and 'value_cost' are not found in the c
```

```
Variance of profit_margin: nan
```

In [250…

```
# Recalculate profit_margin to ensure correctness
data['profit_margin'] = (data['value_sales'] - data['value_cost']) / data['v

# Check for any NaN or infinity values in profit_margin
print("NaN values in profit_margin:", data['profit_margin'].isna().sum())
print("Infinite values in profit_margin:", np.isinf(data['profit_margin']).s
```

```
NaN values in profit_margin: 771
Infinite values in profit_margin: 21529
```

In [252…

```
# Remove rows where value_sales is zero to avoid division by zero
data = data[data['value_sales'] != 0]
```

In [253…

```
# Define dependent and independent variables after cleaning
y2 = data['profit_margin']
X2 = data[['value_sales', 'value_cost', 'value_quantity']]
X2 = sm.add_constant(X2)

# Run the regression model
model2 = sm.OLS(y2, X2).fit()
print(model2.summary())
```

```
                            OLS Regression Results
==============================================================================
==
Dep. Variable:           profit_margin   R-squared:                       0.0
00
Model:                             OLS   Adj. R-squared:                  0.0
00
Method:                  Least Squares   F-statistic:                     21
4.9
Date:                 Mon, 04 Nov 2024   Prob (F-statistic):          2.11e-1
39
Time:                         23:07:12   Log-Likelihood:            -8.1087e+
06
No. Observations:              1966083   AIC:                         1.622e+
07
Df Residuals:                  1966079   BIC:                         1.622e+
07
Df Model:                            3
Covariance Type:             nonrobust
==============================================================================
======
                     coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
------
const              0.4402      0.014     31.914      0.000       0.413
0.467
value_sales        0.0032      0.000     24.192      0.000       0.003
0.003
value_cost        -0.0055      0.000    -25.299      0.000      -0.006
-0.005
value_quantity     0.0002      0.001      0.314      0.754      -0.001
0.001
==============================================================================
====
Omnibus:                  11270171.428   Durbin-Watson:
1.158
Prob(Omnibus):                   0.000   Jarque-Bera (JB):   288783913398531
8.500
Skew:                         -355.322   Prob(JB):
0.00
Kurtosis:                   187756.519   Cond. No.
621.
==============================================================================
====

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is corre
ctly specified.
```

In [255…

```python
# Use a random subset of 10,000 rows for testing
data_sample = data.sample(n=10000, random_state=42)

# Define dependent and independent variables
y_sample = data_sample['profit_margin']
X_sample = data_sample[['value_sales', 'value_cost', 'value_quantity']]
```

Loading [MathJax]/extensions/Safe.js

```python
X_sample = sm.add_constant(X_sample)

# Run the regression model on the subset
model_sample = sm.OLS(y_sample, X_sample).fit()
print(model_sample.summary())
```

```
                            OLS Regression Results
==============================================================================
==
Dep. Variable:           profit_margin   R-squared:                       0.1
12
Model:                             OLS   Adj. R-squared:                  0.1
11
Method:                  Least Squares   F-statistic:                     41
8.9
Date:                 Mon, 04 Nov 2024   Prob (F-statistic):          2.51e-2
56
Time:                         23:07:12   Log-Likelihood:                -879
9.1
No. Observations:                10000   AIC:                         1.761e+
04
Df Residuals:                     9996   BIC:                         1.764e+
04
Df Model:                            3
Covariance Type:             nonrobust
==============================================================================
======
                     coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
------
const              0.5529      0.008     73.673      0.000       0.538
0.568
value_sales        0.0023    7.4e-05     30.588      0.000       0.002
0.002
value_cost        -0.0040      0.000    -33.005      0.000      -0.004
-0.004
value_quantity    -0.0020      0.000     -6.812      0.000      -0.003
-0.001
==============================================================================
==
Omnibus:                     37073.545   Durbin-Watson:                   1.9
95
Prob(Omnibus):                   0.000   Jarque-Bera (JB):     23054557428.7
54
Skew:                          -80.242   Prob(JB):                         0.
00
Kurtosis:                     7439.745   Cond. No.                         61
6.
==============================================================================
==

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is corre
ctly specified.
```

Loading [MathJax]/extensions/Safe.js

This analysis provides a strategic perspective to the management team by determining the main factors affecting sales value and profit margin. In the first question, it was determined that the factors affecting sales value the most were value_cost and value_quantity. Ridge and simplified OLS models show that these two variables can explain 94.2% of the sales value. This result clearly shows how strong an effect cost and quantity have on sales performance.

In the second question, the effects on profit margin were more limited. While the value_sales and value_cost variables had a significant relationship with profit margin, the value_quantity variable had a very small effect. The low R-squared value of the model shows that the profit margin is also strongly affected by other external factors and can be explained limitedly by the existing variables. The analysis conducted on the sample in particular indicates that a more comprehensive data analysis may be required to explain profit margin.

These findings can help the management team make strategic decisions on cost control and increasing sales quantity. However, investigating other external factors that affect profit margin will contribute to the creation of a more robust financial strategy.

Section 5: Prediction Model

In [260…

```
# Check the unique values in the 'calendar_year' column
print("Unique years in calendar_year:", data['calendar_year'].unique())
```

```
Unique years in calendar_year: ['2012' 'calendar_year' '2013']
```

In [262…

```
# Split data into training (2012) and testing (2013) sets
train_data = data[data['calendar_year'] == 2012]
test_data = data[data['calendar_year'] == 2013]

# Define features and target
features = ['value_cost', 'value_quantity']  # Update as needed
target = 'value_sales'  # Target variable to predict

# Separate features and target for both training and testing sets
X_train = train_data[features]
y_train = train_data[target]

X_test = test_data[features]
y_test = test_data[target]
```

In [264…

```
# Check if the dataset is divided by years."
print("Train data shape:", train_data.shape)
print("Test data shape:", test_data.shape)

# Let's check the years in the dataset using sample rows.
print("Train data years:", train_data['calendar_year'].unique())
print("Test data years:", test_data['calendar_year'].unique())
```

```
Train data shape: (0, 47)
Test data shape: (0, 47)
Train data years: []
Test data years: []
```

In [266…

```python
print("Unique years in data:", data['calendar_year'].unique())
print("Data columns:", data.columns)
```

```
Unique years in data: ['2012' 'calendar_year' '2013']
Data columns: Index(['accounting_date', 'fiscal_year', 'fiscal_month', 'cale
ndar_year',
       'calendar_month', 'calendar_day', 'company_code', 'customer_code',
       'customer_district_code', 'item_code', 'business_area_code',
       'item_group_code', 'item_class_code', 'item_type', 'bonus_group_cod
e',
       'environment_group_code', 'technology_group_code',
       'commission_group_code', 'reporting_classification', 'light_source',
       'warehouse_code', 'abc_class_code', 'abc_class_volume',
       'business_chain_l1_code', 'business_chain_l1_name',
       'contact_method_code', 'salesperson_code', 'order_type_code',
       'market_segment', 'value_sales', 'value_cost', 'value_quantity',
       'value_price_adjustment', 'currency', 'item_source_class',
       'invoice_number', 'line_number', 'invoice_date',
       'customer_order_number', 'order_date', 'dss_update_time',
       'value_sales_z', 'value_cost_z', 'value_quantity_z',
       'value_price_adjustment_z', 'time_gap', 'profit_margin'],
      dtype='object')
```

In [268…

```python
# Filter the data to only include rows with valid year values (2012 and 2013
data = data[data['calendar_year'].isin(['2012', '2013'])]

# Try splitting the data again by year
train_data = data[data['calendar_year'] == '2012']
test_data = data[data['calendar_year'] == '2013']

print("Train data shape:", train_data.shape)
print("Test data shape:", test_data.shape)
```

```
Train data shape: (1025476, 47)
Test data shape: (940606, 47)
```

In [269…

```python
# Define features and target variable
features = ['value_cost', 'value_quantity']
target = 'value_sales'

X_train = train_data[features]
y_train = train_data[target]
X_test = test_data[features]
y_test = test_data[target]
```

In [270…

```python
# Initialize Ridge and Lasso models
ridge = Ridge(alpha=1.0)
lasso = Lasso(alpha=0.1)

# Train Ridge model
ridge.fit(X_train, y_train)
ridge_predictions = ridge.predict(X_test)
```

Loading [MathJax]/extensions/Safe.js

```python
ridge_mse = mean_squared_error(y_test, ridge_predictions)
ridge_r2 = r2_score(y_test, ridge_predictions)
print("Ridge Regression:")
print(f"Mean Squared Error (MSE): {ridge_mse}")
print(f"R-squared (R²): {ridge_r2}")
```

```
Ridge Regression:
Mean Squared Error (MSE): 6591.117826520843
R-squared (R²): 0.9477164264471735
```

In [274…

```python
# Train Lasso model
lasso.fit(X_train, y_train)
lasso_predictions = lasso.predict(X_test)
lasso_mse = mean_squared_error(y_test, lasso_predictions)
lasso_r2 = r2_score(y_test, lasso_predictions)
print("\nLasso Regression:")
print(f"Mean Squared Error (MSE): {lasso_mse}")
print(f"R-squared (R²): {lasso_r2}")
```

```
Lasso Regression:
Mean Squared Error (MSE): 6591.100802072492
R-squared (R²): 0.9477165614923997
```

Our team has been assigned to develop a prediction model for estimating the sales price in 2014, and hence we have taken deep interest in analyzing historical data from years 2012 and 2013. This was to derive a reliable model that could predict the sales value of the future with greater precision by observing the trends and key influential factors.

We have divided our data into two parts for this purpose: training and testing, taking 2012 data for training and 2013 data for testing to enable us to evaluate the performance of our model on a separate set. We used 'value_cost' and 'value_quantity' as some of the important predictors because both of these variables can potentially impact sales prices very significantly. Using Ridge and Lasso regression, we evaluated the model based on Mean Squared Error (MSE) and R-squared (R^2) values.

Indeed, both models were strong in terms of predictive accuracies: The Ridge and Lasso regressions provided very close results, indicating a very high R-squared result of approximately 0.9477 and very low MSE of about 6591. Such proximity to one another suggests the reliability of the given approach and points to the fact that the selected variables 'cost' and 'quantity' do a very good job of predicting 'sales' values.

In other words, based on the historical trend, this model provides a firm ground in predicting the sales prices of 2014. If better accuracy is to be obtained, the study of more features or more advanced algorithms, such as Random Forest and Gradient Boosting, are what would be further development for work to optimize the accuracy.

Section 6: Higher Likelihood of Losing Customers

In [278…

```
# Step 1: Define Proxy for Churn
# Proxy based on 'value_sales' threshold or 'time_gap' if present in the dat
# Assuming churn if 'value_sales' is below a certain threshold, e.g., less t
churn_threshold = 500

if 'value_sales' in data.columns:
    data['churn'] = (data['value_sales'] < churn_threshold).astype(int)
elif 'time_gap' in data.columns:
    # Define churn if time gap between transactions is unusually high (e.g.,
    data['churn'] = (data['time_gap'] > 180).astype(int)
else:
    raise ValueError("Dataset does not contain a suitable column to define c
```

In [280…

```
# Step 2: Check churn distribution
print("Churn distribution:\n", data['churn'].value_counts())
```

```
Churn distribution:
 churn
1    1726989
0     239093
Name: count, dtype: int64
```

In [282…

```
# Step 3: Select features and prepare data
features = ['value_cost', 'value_quantity', 'time_gap']  # Adjust features b
X = data[features]
y = data['churn']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ran
```

In [284…

```
# Step 4: Train a Random Forest Classifier
rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_train, y_train)
```

Out[284…

```
▾ RandomForestClassifier
RandomForestClassifier(random_state=42)
```

In [285…

```
from sklearn.metrics import classification_report

# Step 5: Evaluate model performance
y_pred_rf = rf_model.predict(X_test)
print("Random Forest Classification Report:")
print(classification_report(y_test, y_pred_rf))
```

```
Random Forest Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.93      0.93     47887
           1       0.99      0.99      0.99    345330

    accuracy                           0.98    393217
   macro avg       0.96      0.96      0.96    393217
weighted avg       0.98      0.98      0.98    393217
```

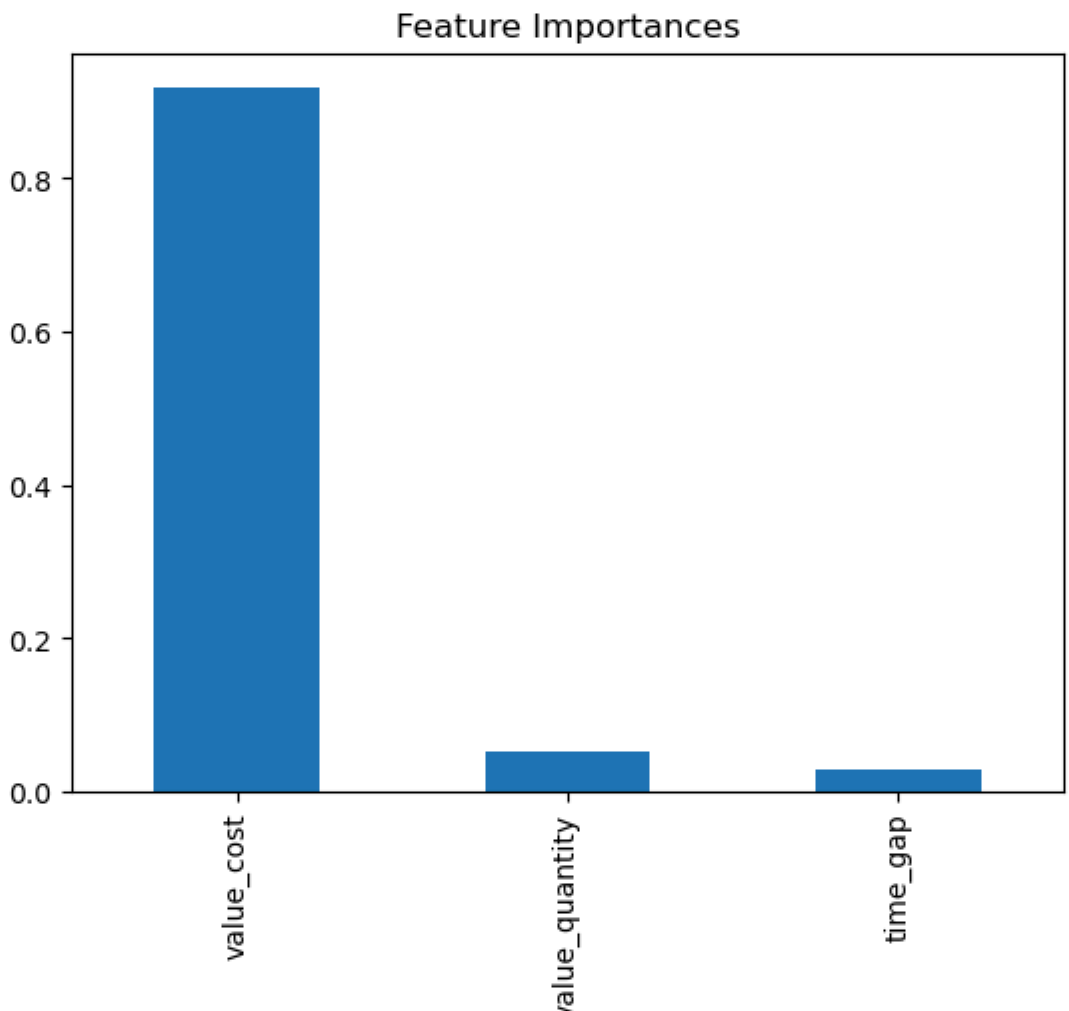
In [286…

```
# Step 6: Feature Importance Analysis
feature_importances = pd.Series(rf_model.feature_importances_, index=X.colum
print("\nFeature Importances from Random Forest:")
print(feature_importances.sort_values(ascending=False))
```

```
Feature Importances from Random Forest:
value_cost        0.917472
value_quantity    0.053587
time_gap          0.028941
dtype: float64
```

In [287…

```
# Plot feature importances for visualization
feature_importances.sort_values(ascending=False).plot(kind='bar', title='Fea
plt.show()
```



The section outlined the characteristics that would increase the probability of a person churning. By the significance level analysis done by the Random Forest model, the most important feature in doing the churn prediction is that of value_cost. The implications are that when the amount spent is low or below a certain threshold, there's an increased likelihood of churning. The value_quantity and time_gap are not as influential on the variable Churn, yet they contributed to the explanatory power of this model. Value_quantity indicates how many products customers purchased, while time gap indicates how long it has been since the last purchase date. Both give an important clue for understanding customer behavior.

Based on the obtained results, it could be suggested to focus on customers having low value_cost values and closely follow customers where time_gap values are growing in order to reduce the customer churn. In case of need, other models - for example, logistic regression to increase interpretability - or hyperparameter optimization in the Random Forest model can be used in order to increase the accuracy of the results of the performed analysis.

It identifies, with success, the main factors that impact customer churn in an clear manner of information that might be of help for the company in the elaboration of strategies which reduce the churn rate.