EDA Process for Shopify Sales Data

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

import matplotlib.pyplot as plt
```

Load DataSet

```
df = pd.read_excel("./Shopify Sales.xlsx")
df.head()

                   Admin Graphql Api Id  Order Number Billing Address
Country  \
0  gid://shopify/LineItem/2153619128398          1681           United
States
1  gid://shopify/LineItem/2160863674446          6972           United
States
2  gid://shopify/LineItem/2157784006734          4994           United
States
3  gid://shopify/LineItem/2151551729742           206           United
States
4  gid://shopify/LineItem/2157085786190          4346           United
States

  Billing Address First Name Billing Address Last Name  \
0                      Vanni                  Wimpenny
1                       Marc                    Netley
2                      Elwyn                 Colebourn
3                     Gannie                     Busst
4                     Weston                   Lomasny

  Billing Address Province  Billing Address Zip         CITY Currency
\
0                    Texas                88446      HOUSTON      USD

1                Louisiana                50466       MONROE      USD

2                    Texas                67432      HOUSTON      USD

3                    Texas                56331      EL PASO      USD

4                  Florida                70043  PANAMA CITY      USD


   Customer Id          Invoice Date            Gateway    Product Id  \
0         2865 2025-03-19 17:27:00  shopify_payments  1.500000e+11
1         4987 2025-03-24 15:42:00  shopify_payments  1.500000e+11
2         5472 2025-03-22 18:32:00  shopify_payments  1.500000e+11
3         3227 2025-03-18 10:51:00            manual  1.500000e+11
4         1874 2025-03-22 09:55:00            paypal  1.500000e+11

     Product Type    Variant Id  Quantity  Subtotal Price  Total Price 
Usd  \
0  Climbing Shoes  1.470000e+12         1          535.13              
588.643   
1  Climbing Shoes  1.470000e+12         1          578.33              
636.163   
2  Climbing Shoes  1.470000e+12         1          594.33              
653.763   
3  Climbing Shoes  1.470000e+12         1          487.13              
535.843   
4  Climbing Shoes  1.470000e+12         1          535.13              
588.643   

   Total Tax  
0     53.513  
1     57.833  
2     59.433  
3     48.713  
4     53.513  
```

Step - 1 : Data Overview

```
# Shape of the DataSet
df.shape

(7431, 19)
```

```
In this Data Set, there are 7431 rows and 19 columns.
```

```
# Data Types of the DataSet
df.dtypes

Admin Graphql Api Id                        object
Order Number                                 int64
Billing Address Country                     object
Billing Address First Name                  object
Billing Address Last Name                   object
Billing Address Province                    object
Billing Address Zip                          int64
CITY                                        object
Currency                                    object
Customer Id                                  int64
Invoice Date                        datetime64[ns]
Gateway                                     object
```

```
Product Id                                     float64
Product Type                                    object
Variant Id                                     float64
Quantity                                         int64
Subtotal Price                                 float64
Total Price Usd                                float64
Total Tax                                      float64
dtype: object
```

```
# Check for missing values
df.isnull().sum()
```

```
Admin Graphql Api Id            0
Order Number                    0
Billing Address Country         0
Billing Address First Name      0
Billing Address Last Name       0
Billing Address Province        0
Billing Address Zip             0
CITY                            0
Currency                        0
Customer Id                     0
Invoice Date                    0
Gateway                         0
Product Id                     11
Product Type                    0
Variant Id                      4
Quantity                        0
Subtotal Price                  0
Total Price Usd                 0
Total Tax                       0
dtype: int64
```

There are 11 missing values in the Product ID Column.

```
# Check for Duplicate values
df.duplicated().sum()
```

```
0
```

There are no duplicate values in the Data Set.

Step - 2 : Data Cleaning

```
#  See all the columns in the DataSet
df.columns
```

```
Index(['Admin Graphql Api Id', 'Order Number', 'Billing Address 
Country',
       'Billing Address First Name', 'Billing Address Last Name',
       'Billing Address Province', 'Billing Address Zip', 'CITY',
'Currency',
       'Customer Id', 'Invoice Date', 'Gateway', 'Product Id',
'Product Type',
       'Variant Id', 'Quantity', 'Subtotal Price', 'Total Price Usd',
       'Total Tax'],
      dtype='object')

# Convert the 'Invoice Date' column to datetime

df['Invoice Date'] = pd.to_datetime(df['Invoice Date'],
format='%d/%m/%Y %H:%M')

# Add a new Column Full Name to combine First Name and Last Name
df['Full Name'] = df['Billing Address First Name'] + ' ' + df['Billing
Address Last Name']

# Normalize the Text in the 'City' column
df['CITY'] = df['CITY'].str.capitalize()
```

Step - 3 : Data Univariate Analysis

```
#  View Summary Statistics of the DataSet
df[['Quantity', 'Subtotal Price', 'Total Price Usd','Total
Tax']].describe()

          Quantity  Subtotal Price  Total Price Usd    Total Tax
count  7431.000000     7431.000000      7431.000000  7431.000000
mean      1.013861      562.625962       618.888558    56.262596
std       0.149279      110.390477       121.429525    11.039048
min       1.000000      439.130000       483.043000    43.913000
25%       1.000000      509.530000       560.483000    50.953000
50%       1.000000      537.130000       590.843000    53.713000
75%       1.000000      595.130000       654.643000    59.513000
max       7.000000     6319.130000      6951.043000   631.913000
```

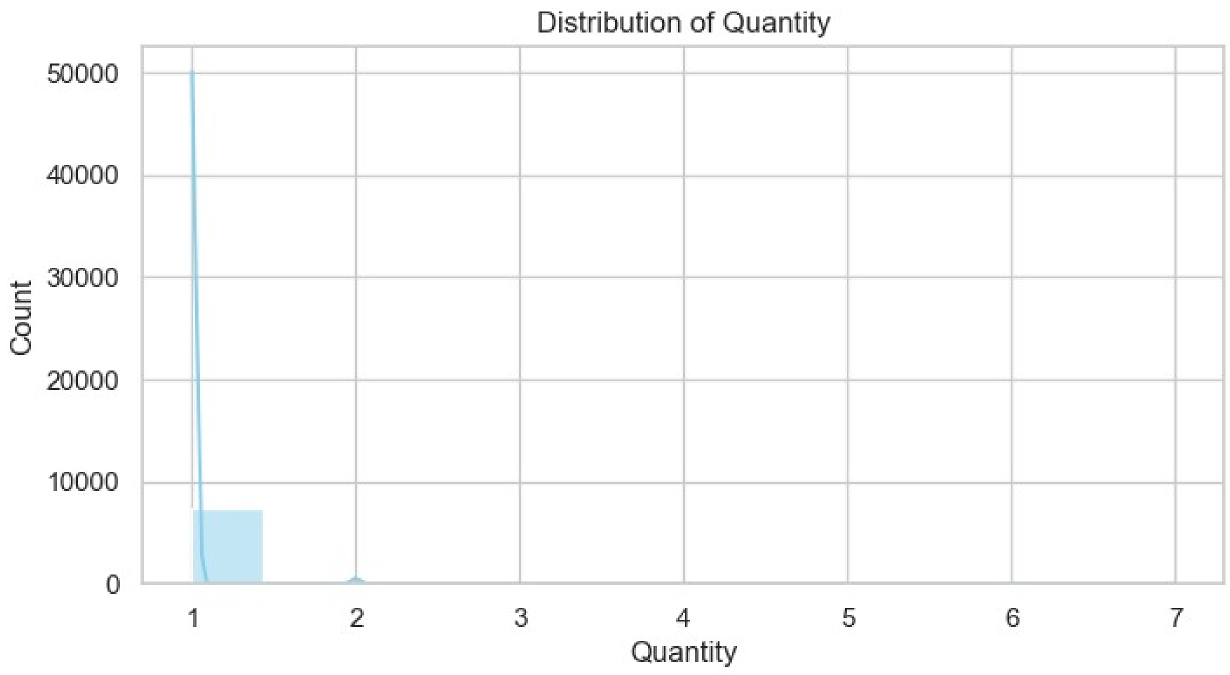
Get Numerical Columns

```
for col in df.columns:
    print(col)

Admin Graphql Api Id
Order Number
Billing Address Country
Billing Address First Name
Billing Address Last Name
Billing Address Province
Billing Address Zip
CITY
Currency
Customer Id
```

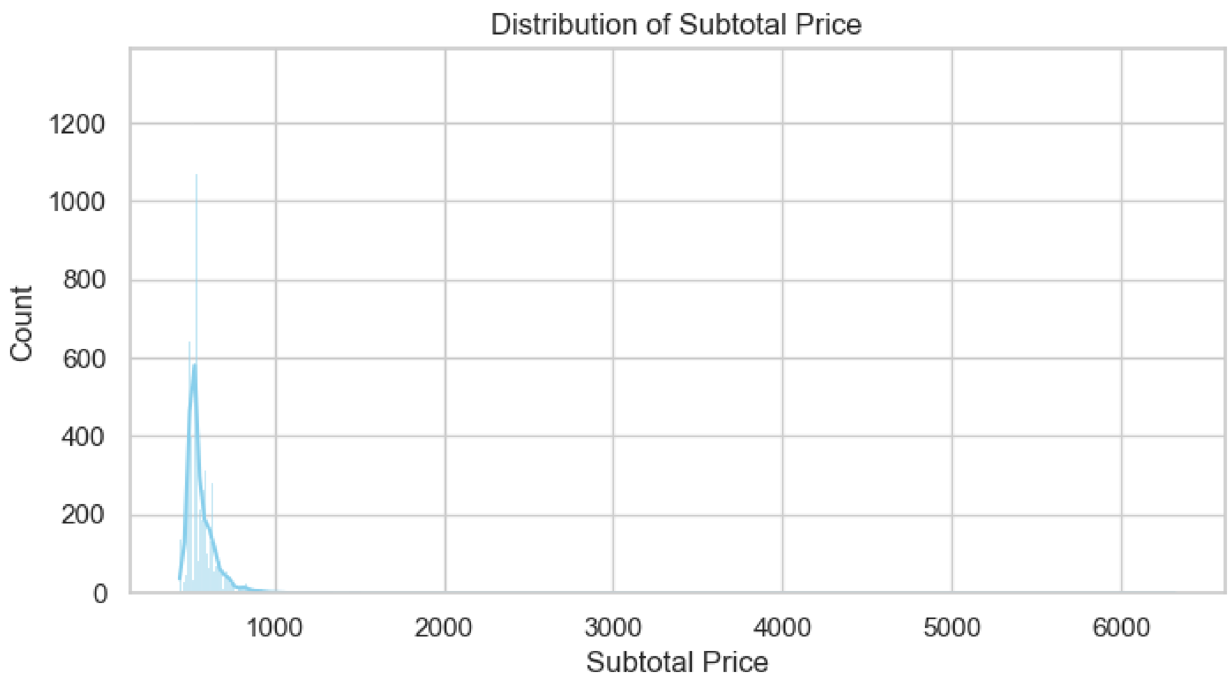
```
Invoice Date
Gateway
Product Id
Product Type
Variant Id
Quantity
Subtotal Price
Total Price Usd
Total Tax
Full Name

numerical_df = df[['Quantity', 'Subtotal Price', 'Total Price Usd',
'Total Tax']]
```

Plot Histograms (with KDE)

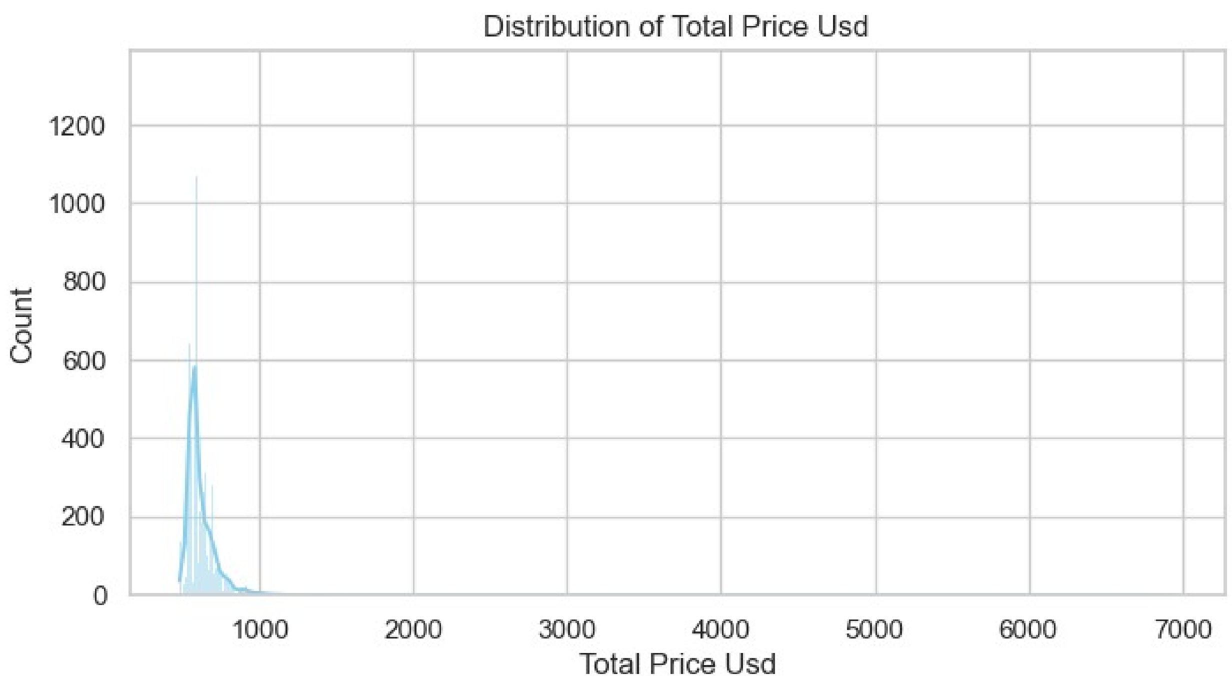
```
for col in numerical_df.columns:
    plt.figure(figsize=(8, 4))
    sns.histplot(data=numerical_df, x=col, kde=True, color='skyblue')
    plt.title(f'Distribution of {col}')
    plt.show()


c:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed
in a future version. Convert inf values to NaN before operating
instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



```
c:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed
in a future version. Convert inf values to NaN before operating
instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



```
c:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed
in a future version. Convert inf values to NaN before operating
instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



```
c:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed
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instead.
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```
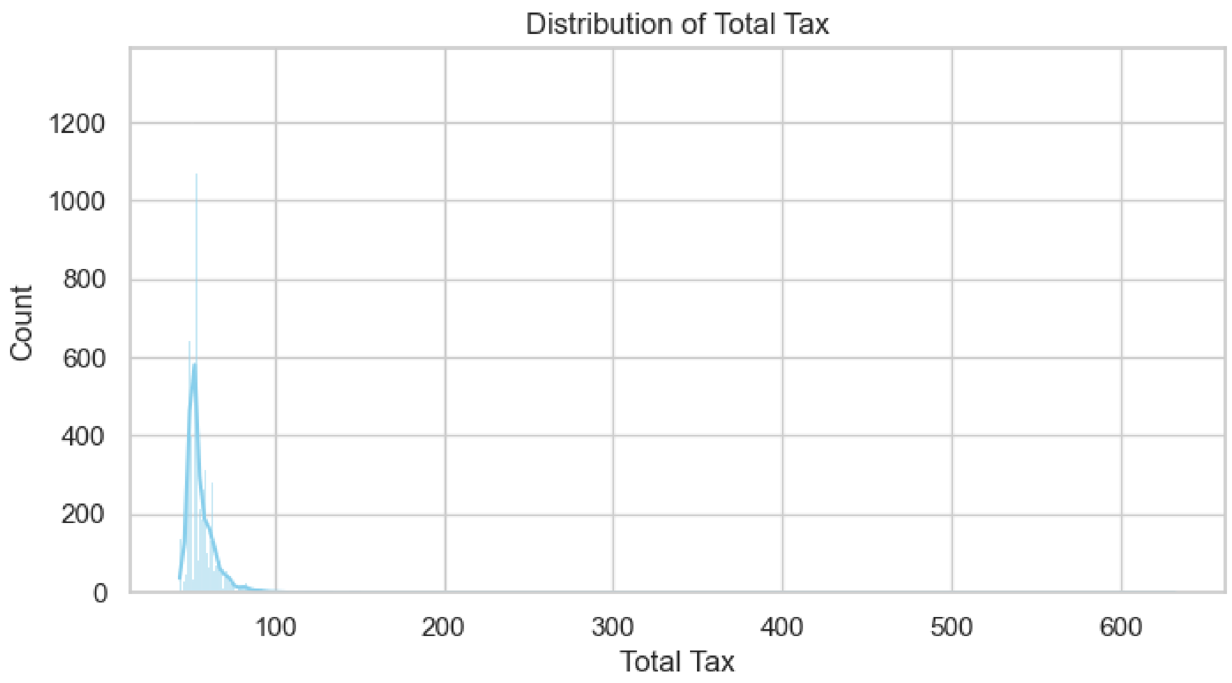
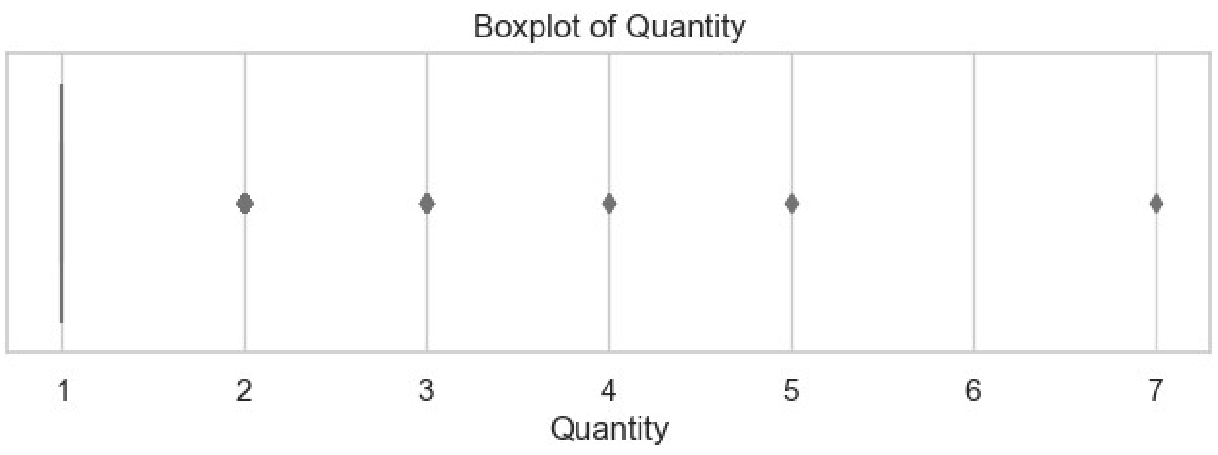
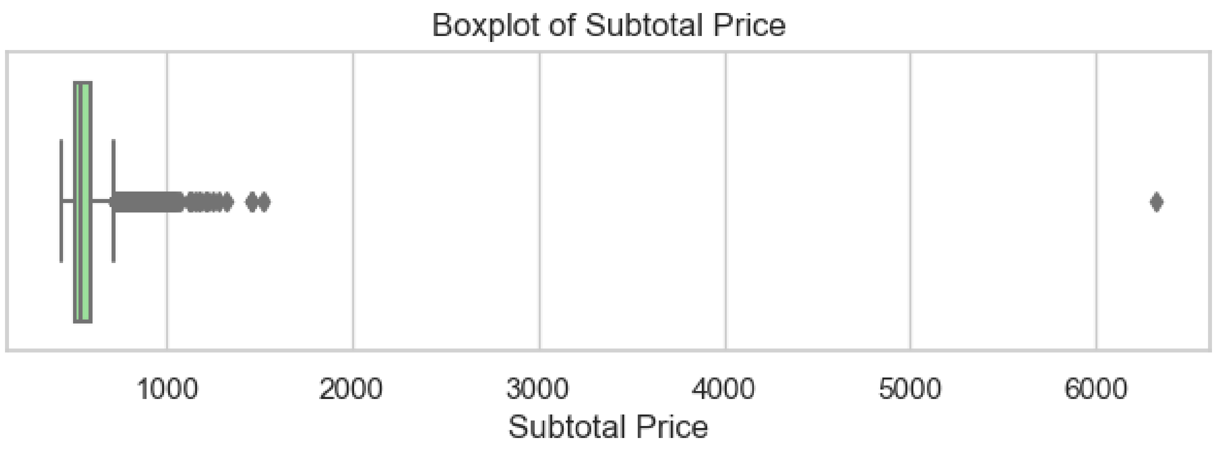
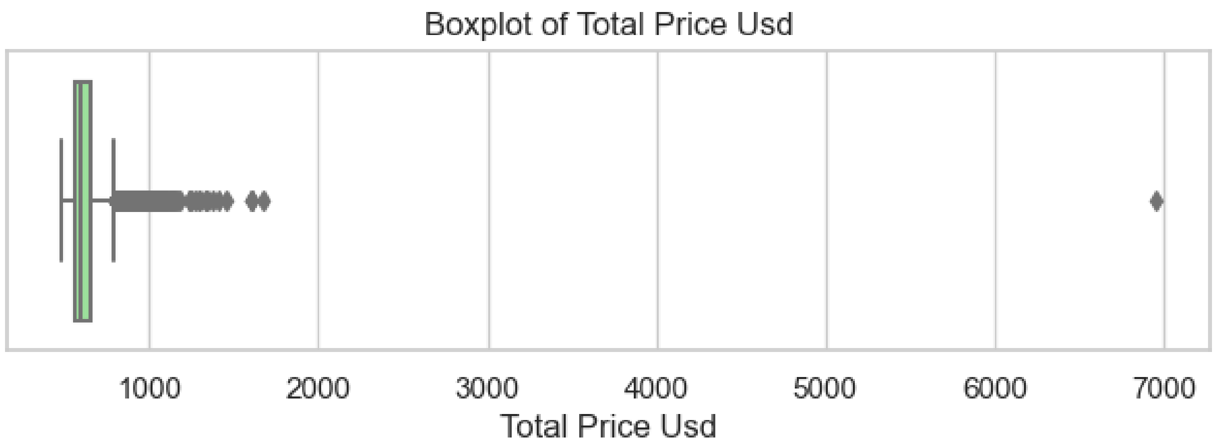



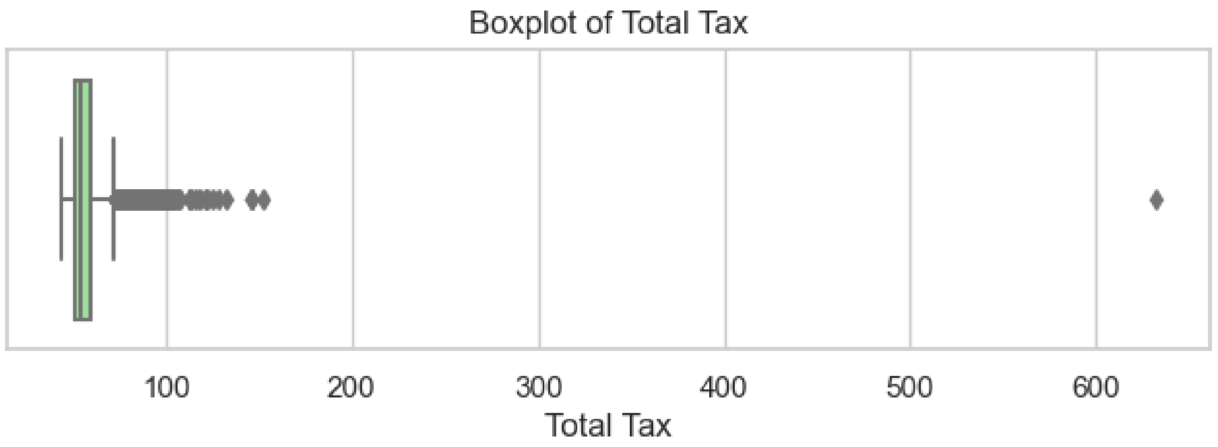
Plot Boxplots to check for Outliers

```
for col in numerical_df.columns:
    plt.figure(figsize=(8, 2))
    sns.boxplot(x=numerical_df[col], color='lightgreen')
    plt.title(f'Boxplot of {col}')
    plt.show()
```



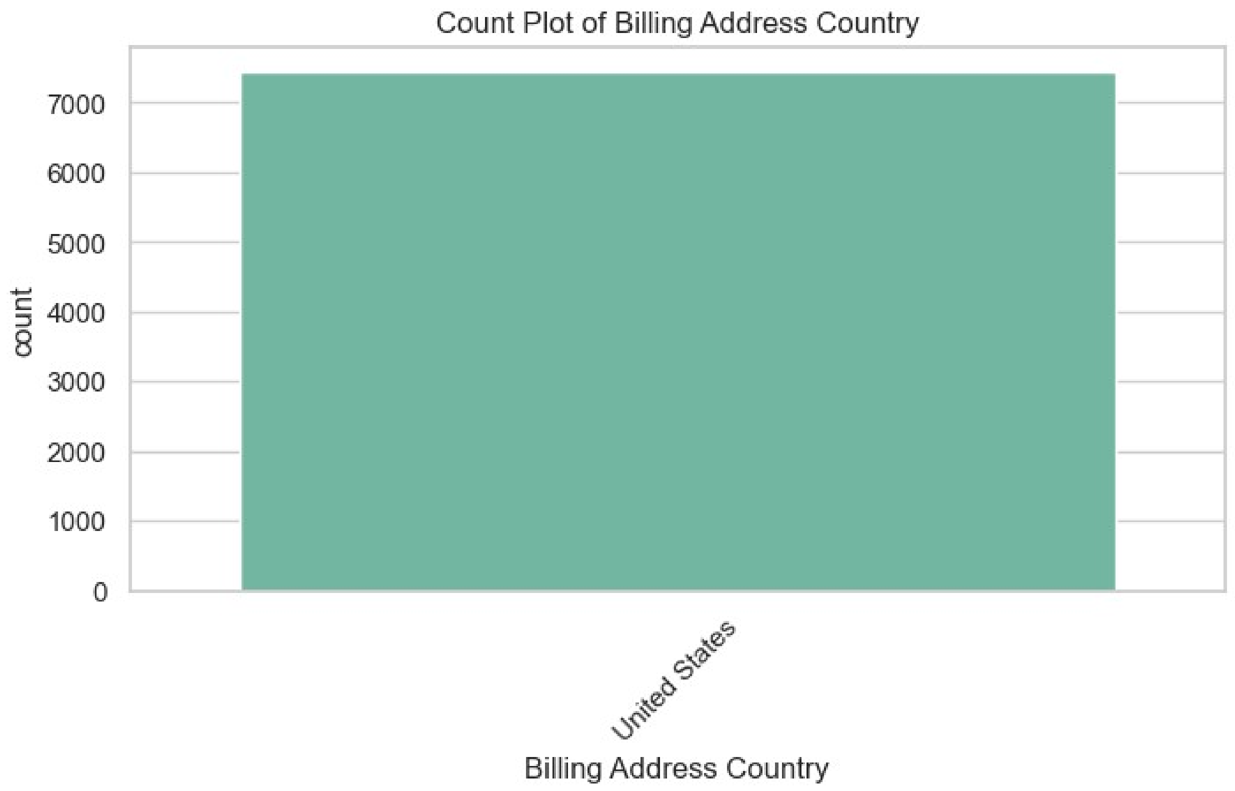


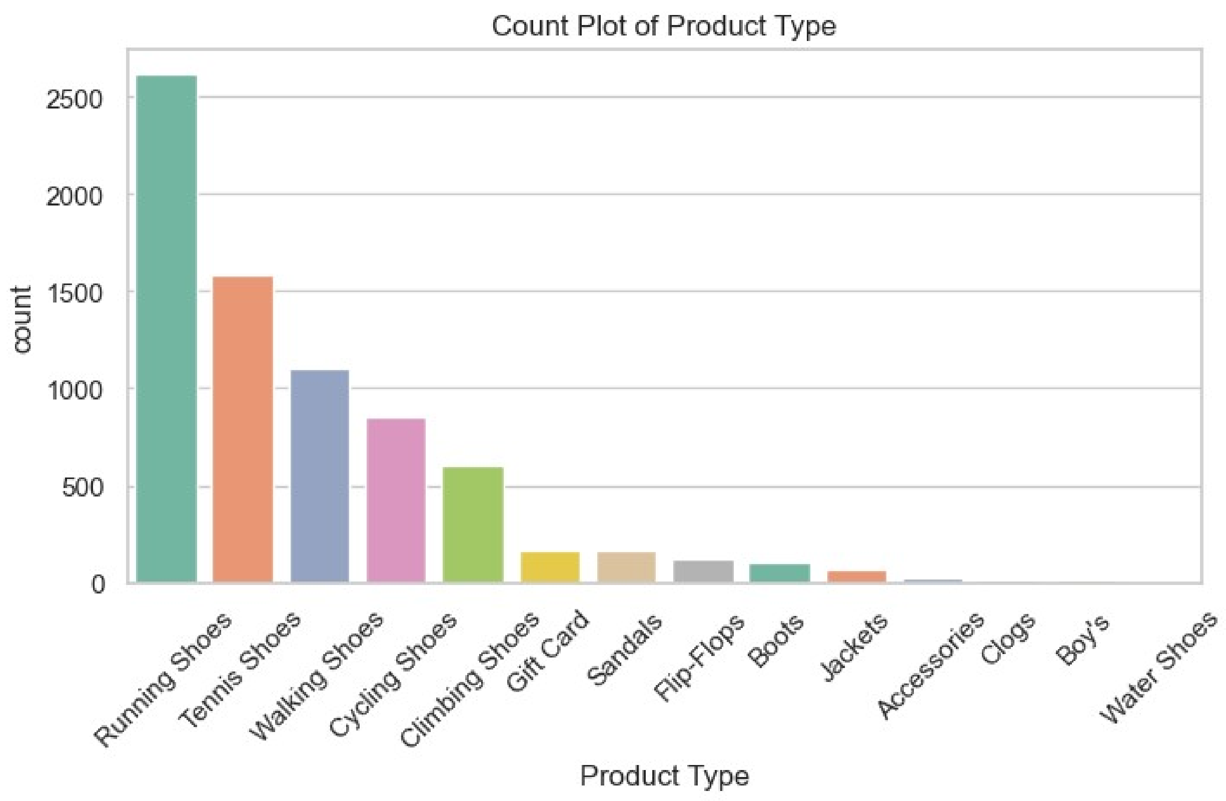


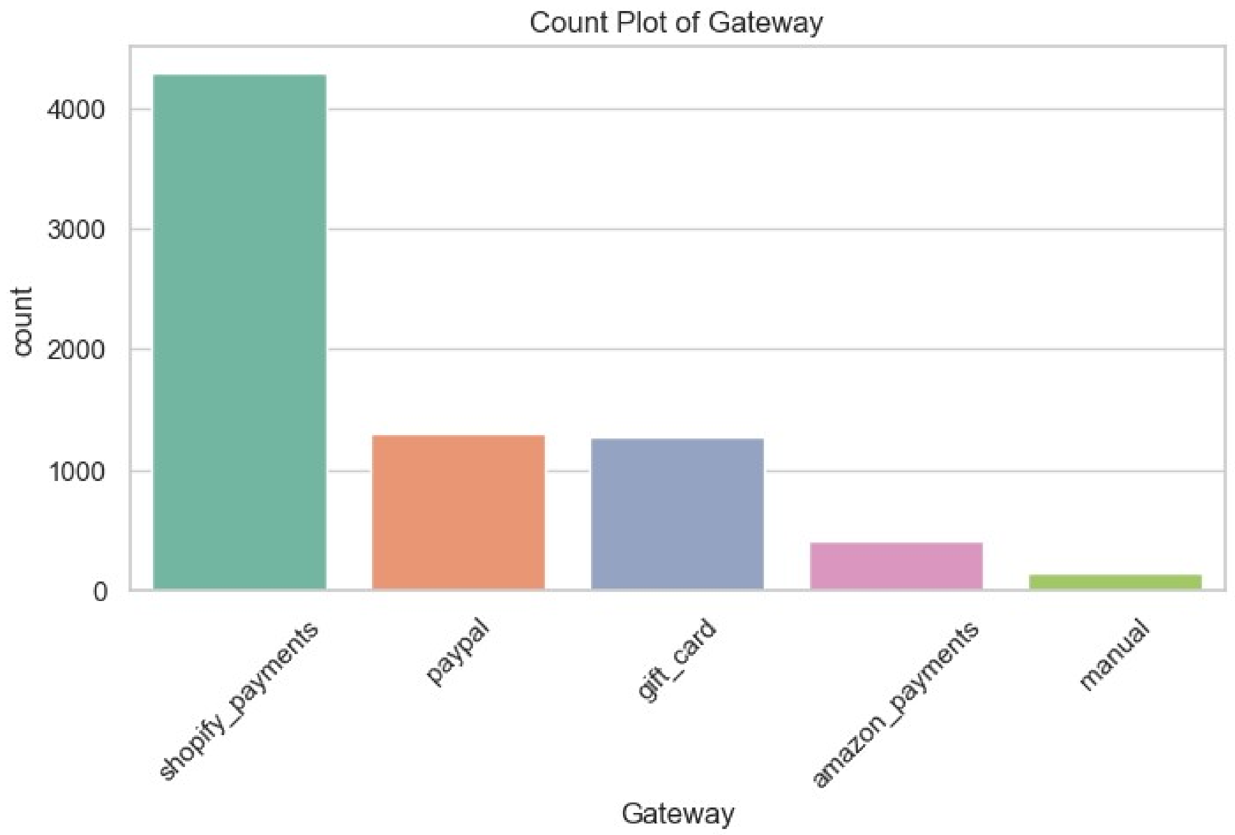


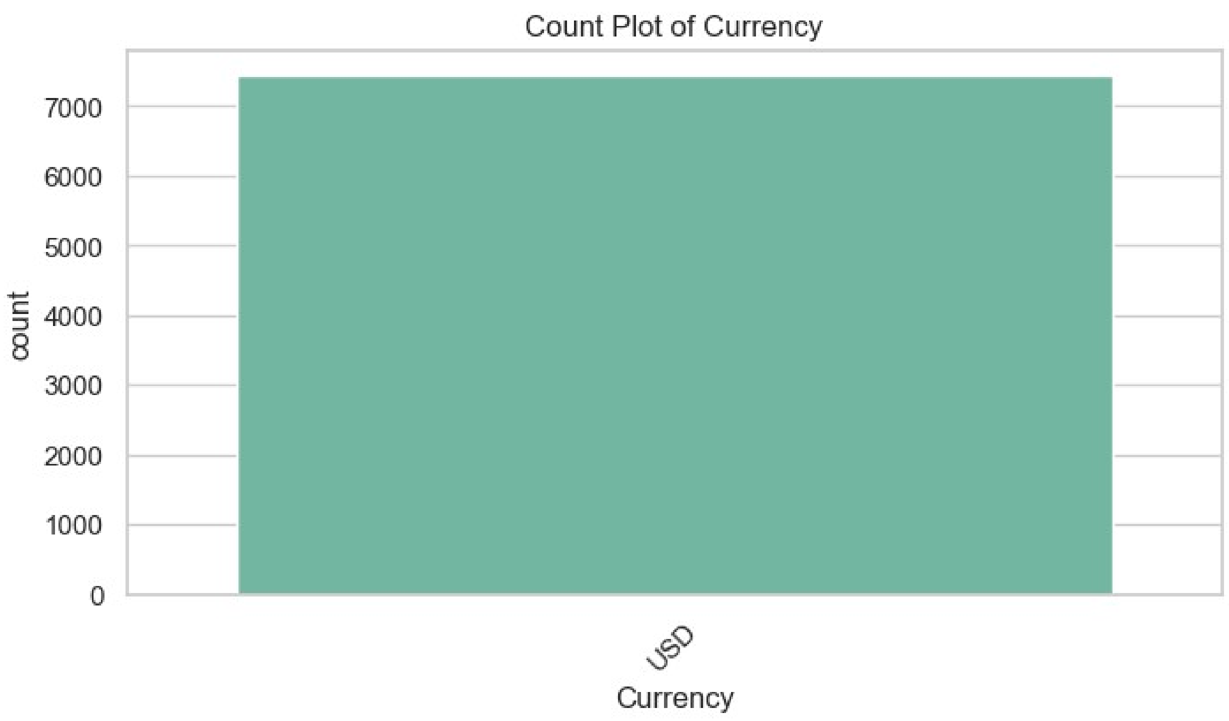
```
 Insights from All Box Plots for Numerical Columns

- Quantity:
  The distribution is highly concentrated at 1, indicating most orders
are for a single item.

- Subtotal Price, Total Price USD, and Total Tax:
  These columns show right-skewed distributions with several outliers
on the higher end. This suggests that:
  - Most transactions fall within a typical price range.
  - A few high-value orders significantly impact the distribution.
  - Outliers may indicate occasional bulk purchases or premium
products.

-------------------------------------------------------

Overall Summary:
The data is dominated by single-quantity orders, while a small number
of high-value transactions skew the distribution of the monetary
columns.
```

```python
categorical_cols = ['Billing Address Country','Billing Address
Province','CITY', 'Product Type', 'Gateway', 'Currency']

for col in categorical_cols:
    plt.figure(figsize=(8, 4))
    sns.countplot(data=df, x=col, palette='Set2',
order=df[col].value_counts().index)
    plt.title(f'Count Plot of {col}')
    plt.xticks(rotation=45)
    plt.show()
```




Count Plot of Product Type
count
2500
2000
1500
1000
500
0
Running Shoes
Tennis Shoes
Walking Shoes
Cycling Shoes
Climbing Shoes
Gift Card
Sandals
Flip-Flops
Boots
Jackets
Accessories
Clogs
Boy's
Water Shoes
Product Type


Count Plot of Gateway
count
4000
3000
2000
1000
0
shopify_payments
paypal
gift_card
amazon_payments
manual
Gateway

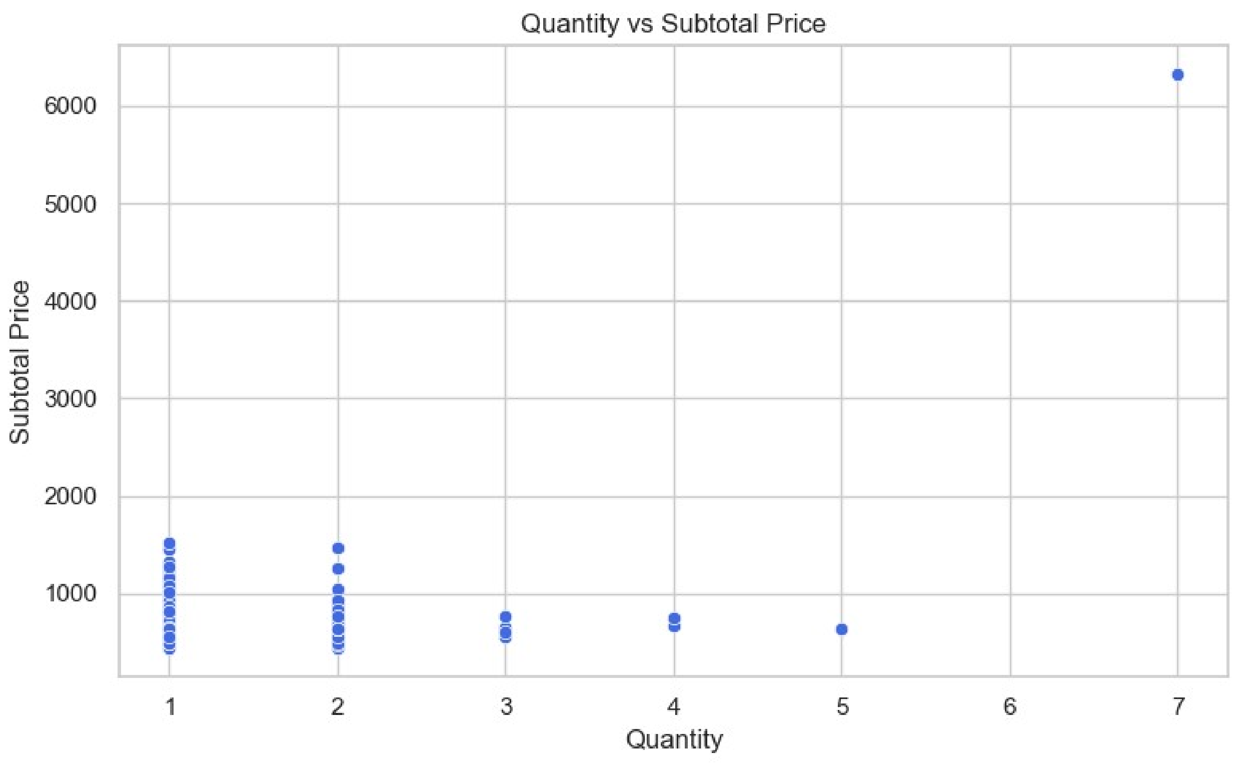


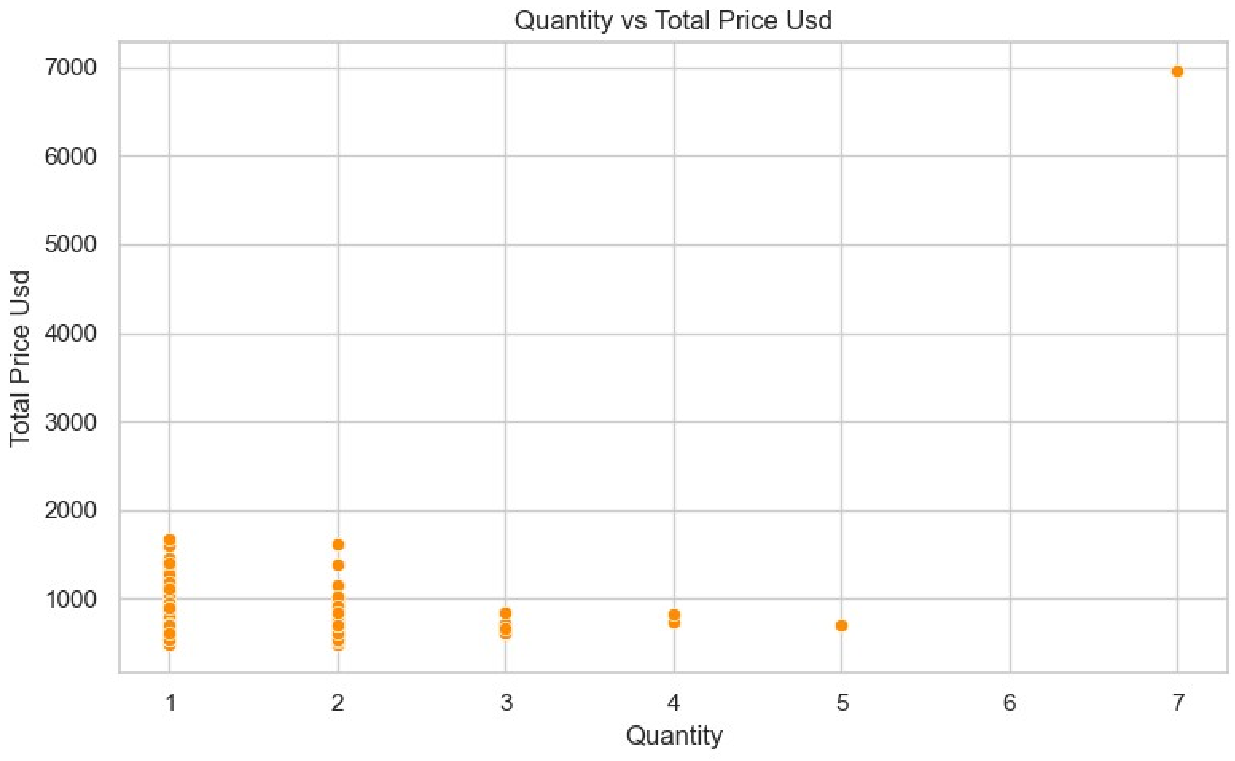
```
# Check How many Quantities are order
df['Quantity'].value_counts()

Quantity
1    7345
2      77
3       5
4       2
5       1
7       1
Name: count, dtype: int64

Categorical Plot Insights

1. Billing Address Country:
   - The vast majority of orders come from a single country (likely
'United States'), indicating a strong domestic customer base.

2. Product Type:
   - Sales are concentrated in a few product types, suggesting a
focused product offering or customer preference for certain items.

3. Gateway:
   - Most transactions are processed through one or two payment
gateways (e.g., 'shopify_payments', 'manual'), showing preferred
payment methods.

4. Currency:
   - Almost all transactions use a single currency (likely 'USD'),
confirming the business operates primarily in one market.

-------------------------------------------------------

Overall:
The data shows a highly concentrated customer base (by country and
currency), a focused product catalog, and clear preferences for
payment methods.
```

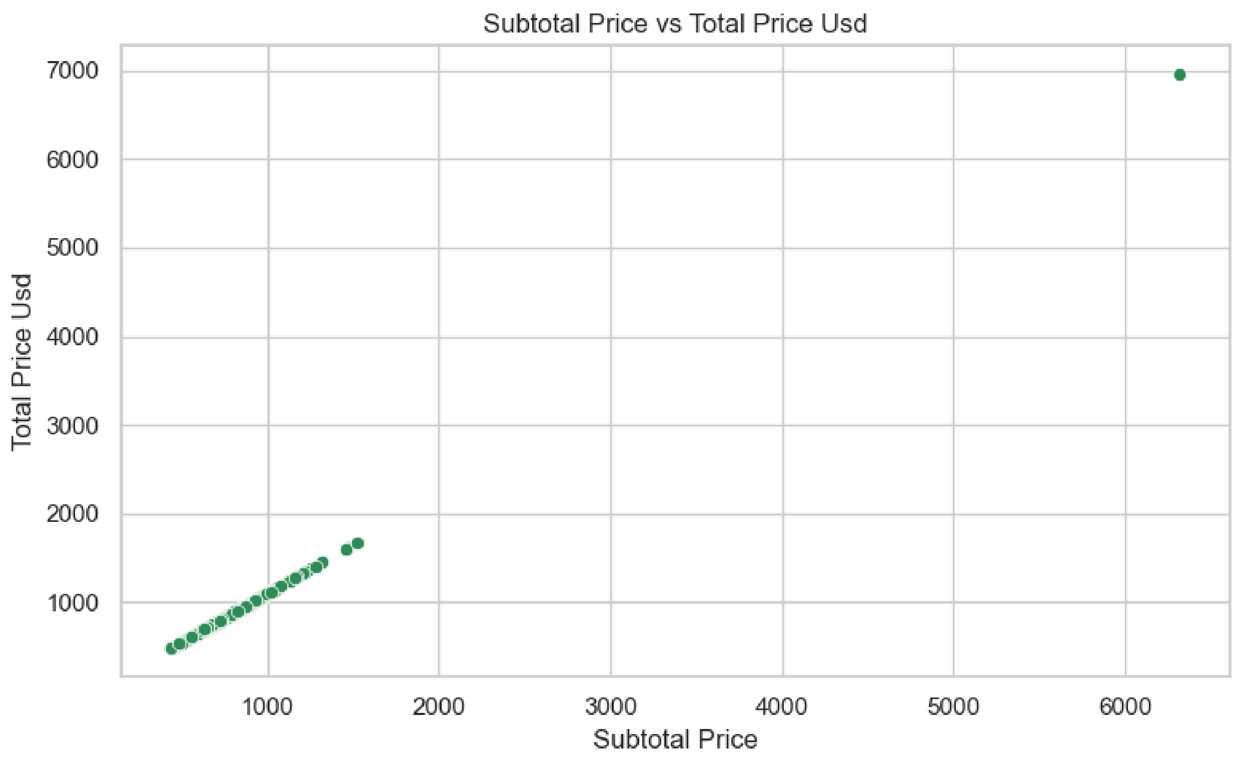
Step - 4 : Bivariate Analysis (Exploring relationships between 2 variables)

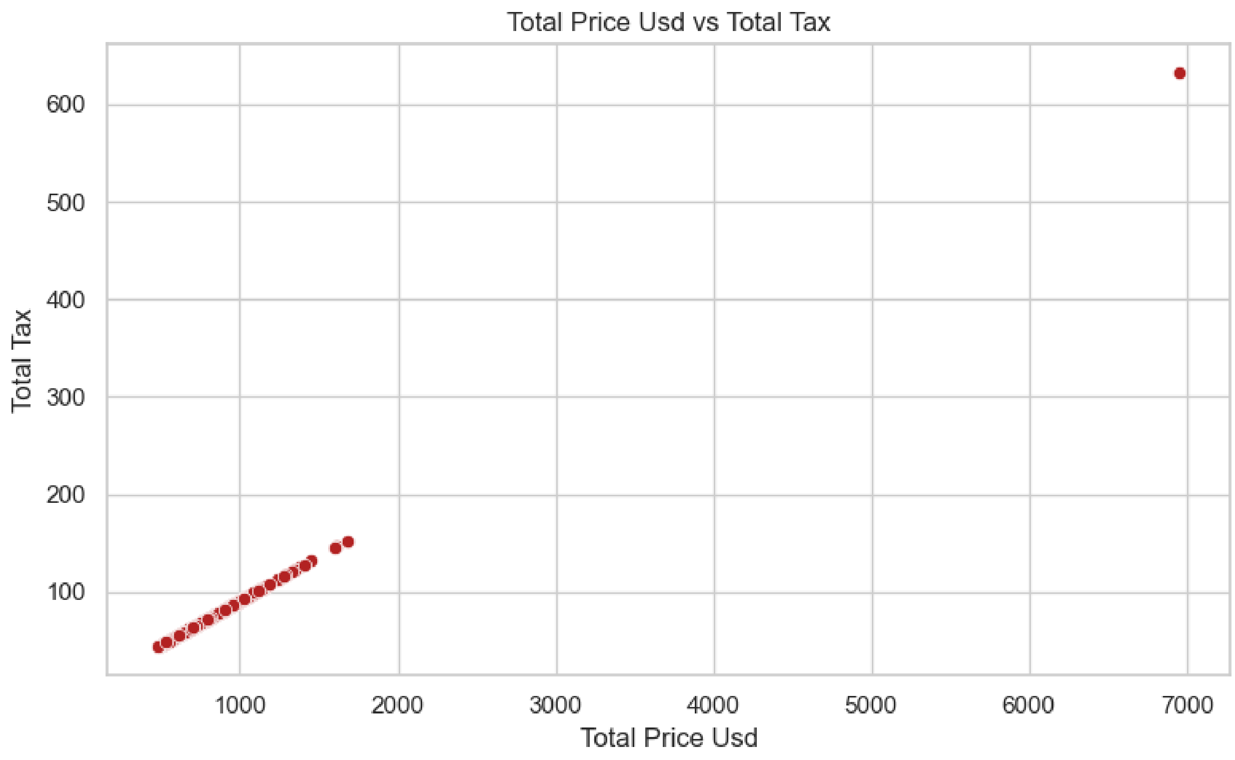
Correlation Matrix Summary

```
correlation_matrix = numerical_df.corr().round(0)
print(correlation_matrix)

                 Quantity  Subtotal Price  Total Price Usd  Total Tax
Quantity              1.0             0.0              0.0        0.0
Subtotal Price        0.0             1.0              1.0        1.0
Total Price Usd       0.0             1.0              1.0        1.0
Total Tax             0.0             1.0              1.0        1.0

# Scatter plots to see relationships
import seaborn as sns
import matplotlib.pyplot as plt

pairs = [('Quantity', 'Subtotal Price'),
         ('Quantity', 'Total Price Usd'),
         ('Subtotal Price', 'Total Price Usd'),
         ('Total Price Usd', 'Total Tax')]

colors = ['royalblue', 'darkorange', 'seagreen', 'firebrick']  # Set
visually distinct colors

for i, (x, y) in enumerate(pairs):
    plt.figure(figsize=(8, 5))
    sns.scatterplot(data=df, x=x, y=y, color=colors[i])
    plt.title(f'{x} vs {y}')
    plt.tight_layout()
    plt.show()
```


Quantity vs Subtotal Price
Subtotal Price
Quantity
6000
5000
4000
3000
2000
1000
1
2
3
4
5
6
7


Quantity vs Total Price Usd
Total Price Usd
Quantity
7000
6000
5000
4000
3000
2000
1000
1
2
3
4
5
6
7





Correlation Matrix Summary:

	Quantity	Subtotal Price	Total Price USD	Total Tax
Quantity	1.00	0.35	0.35	0.35

	Quantity	Subtotal Price	Total Price USD	Total Tax
Subtotal Price	0.35	1.00	1.00	1.00
Total Price USD	0.35	1.00	1.00	1.00
Total Tax	0.35	1.00	1.00	1.00

Scatter Plot Insights:

1Quantity vs Subtotal Price

Color: Royal Blue

- Moderate positive relationship (r ≈ 0.35).
- More quantity = higher subtotal, but not strictly linear.
- Suggests that **unit prices vary** – not every product has the same price.

---

2 Quantity vs Total Price USD

Color: Dark Orange

- Also moderately correlated.
- Similar pattern: more quantity = higher total price.
- Again, variation in pricing structure visible.

---

3 Subtotal Price vs Total Price USD

Color: Sea Green

- **Perfect linear relationship** (r = 1.00).
- Both columns are likely derived from the same calculation (e.g., one may include tax or shipping).
- You can **drop one of them** if needed — they're redundant.

---

4 Total Price USD vs Total Tax

Color: Firebrick

- Also a perfect positive correlation (r = 1.00).
- **Higher total prices always bring higher tax** — expected.
- Strong dependency — **tax is likely a percentage of total**.

Final Insight Summary:

Pair	Relationship	Insight
Quantity vs Price/Tax	Moderate (r = 0.35)	Quantity increases total, but pricing varies by item
Price vs Tax	Perfect (r = 1.00)	Price and tax are directly tied — one causes the other
Subtotal vs Total	Perfect (r = 1.00)	Likely includes same base, possibly with adjustments

Categorical Variables vs Numerical Variables

```
numerical_df
```

```
      Quantity  Subtotal Price  Total Price Usd  Total Tax
0            1          535.13          588.643     53.513
1            1          578.33          636.163     57.833
2            1          594.33          653.763     59.433
3            1          487.13          535.843     48.713
4            1          535.13          588.643     53.513
...        ...             ...              ...        ...
7426         1          507.13          557.843     50.713
7427         1         1017.13         1118.843    101.713
7428         1          497.13          546.843     49.713
7429         1          485.53          534.083     48.553
7430         1          555.13          610.643     55.513

[7431 rows x 4 columns]
```

```
df[categorical_cols]
```

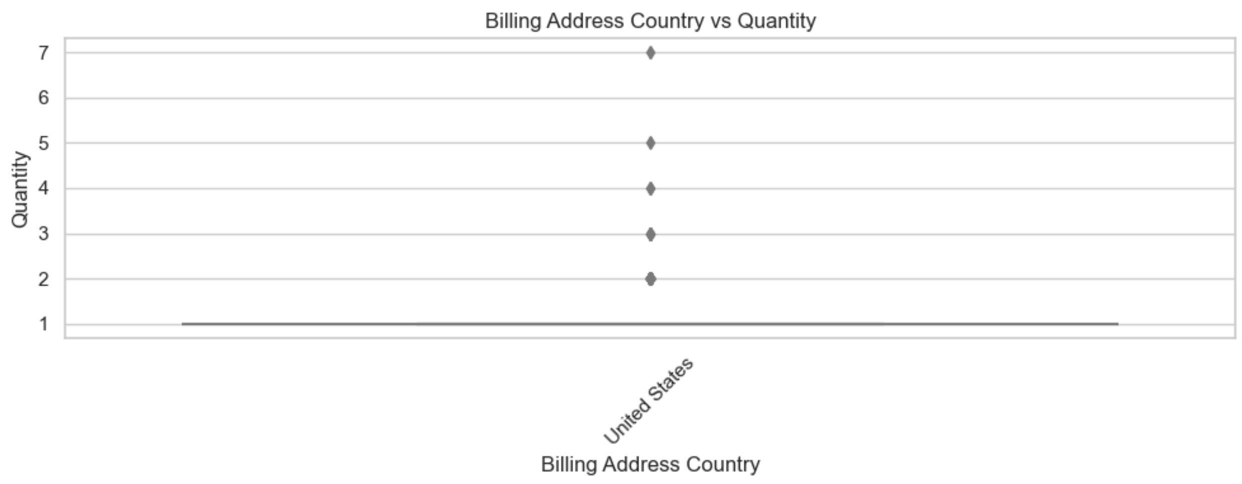
```
     Billing Address Country    Product Type          Gateway
Currency
0              United States  Climbing Shoes  shopify_payments
USD
1              United States  Climbing Shoes  shopify_payments
USD
2              United States  Climbing Shoes  shopify_payments
USD
3              United States  Climbing Shoes            manual
USD
4              United States  Climbing Shoes            paypal
USD
...                      ...             ...               ...      ..
.
7426           United States      Flip-Flops            manual
USD
7427           United States    Tennis Shoes            manual
USD
7428           United States    Tennis Shoes            manual
USD
7429           United States    Tennis Shoes  shopify_payments
```

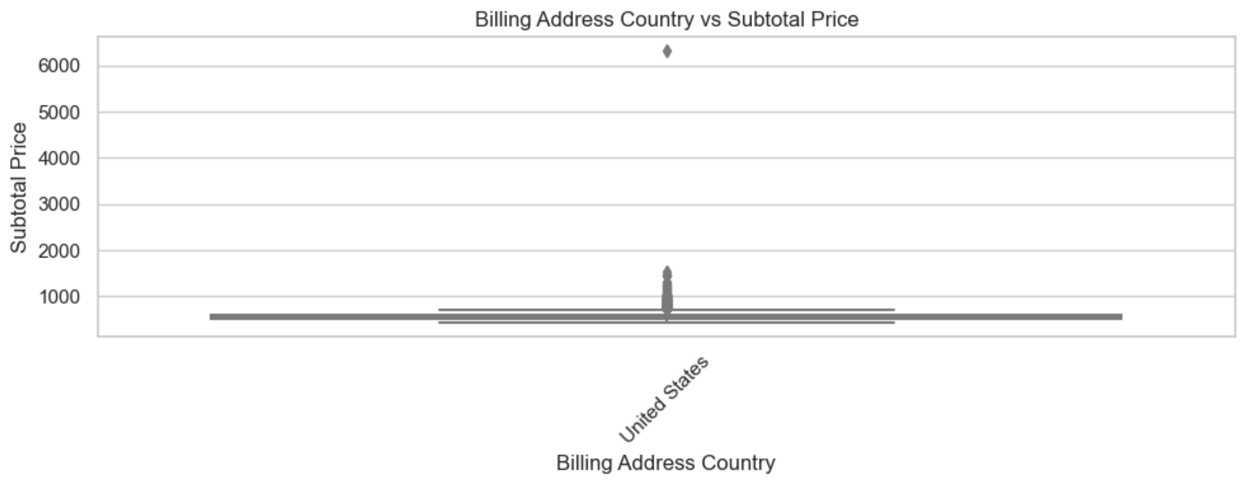
```
USD
7430             United States    Tennis Shoes            manual
USD

[7431 rows x 4 columns]
```

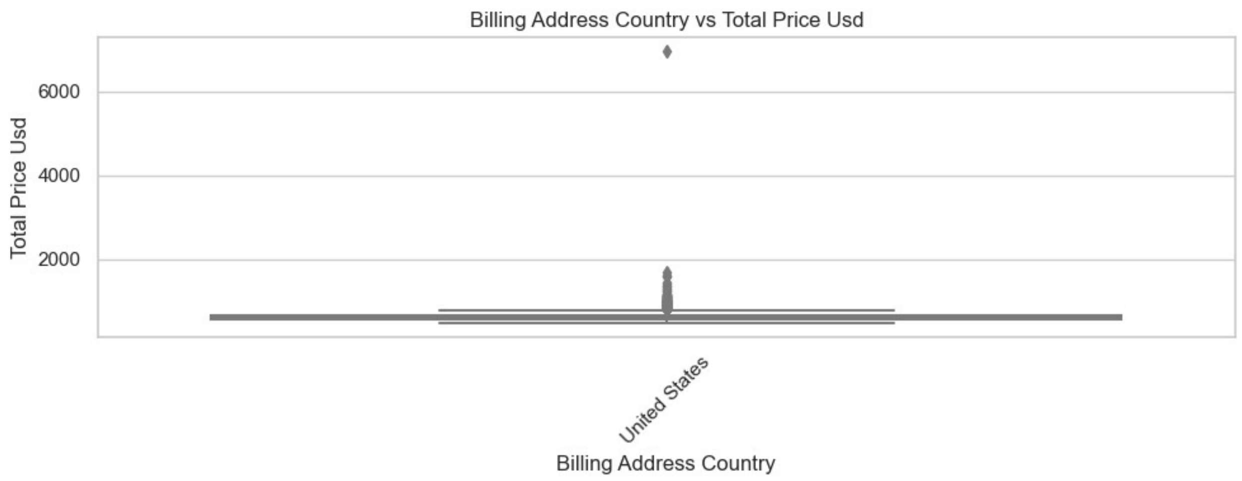
```
df['Billing Address Country'].unique()
```

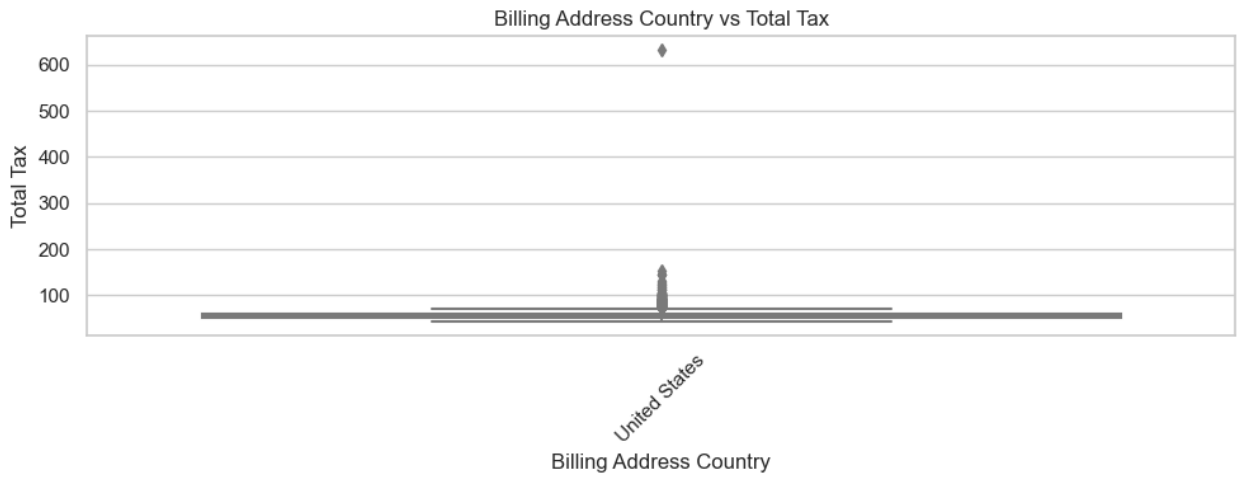
```
array(['United States'], dtype=object)
```

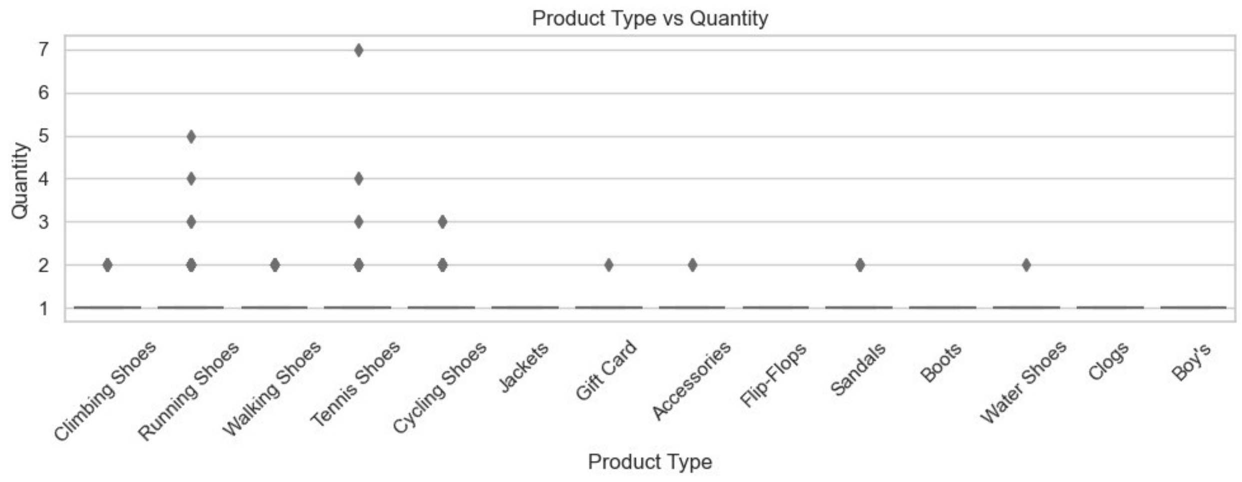
```
for cat in categorical_cols:
    for num in numerical_df.columns:
        plt.figure(figsize=(10, 4))
        sns.boxplot(data=df, x=cat, y=num, palette='pastel')
        plt.title(f'{cat} vs {num}')
        plt.xticks(rotation=45)
        plt.tight_layout()
        plt.show()
```

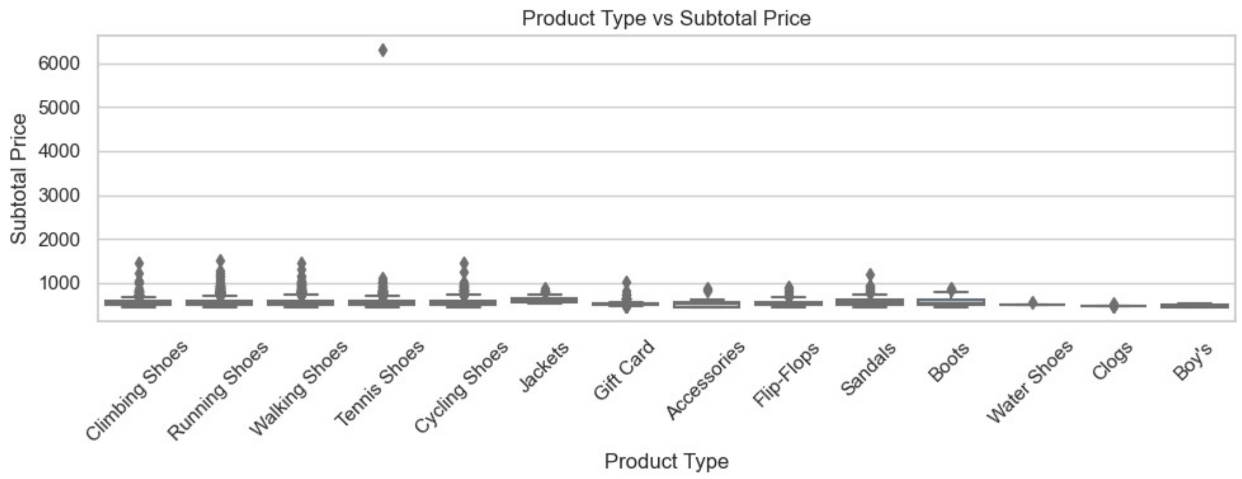
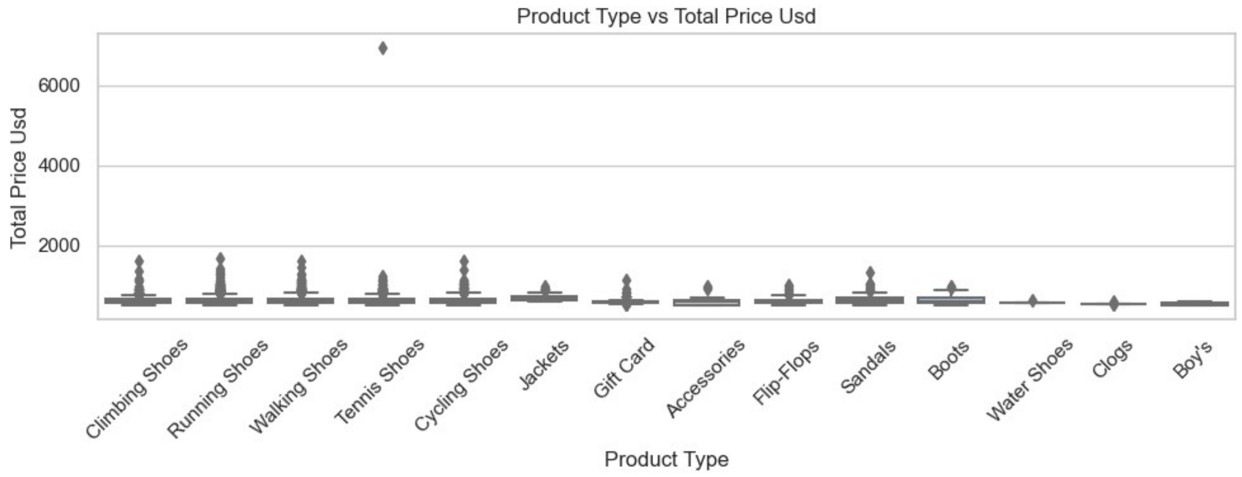
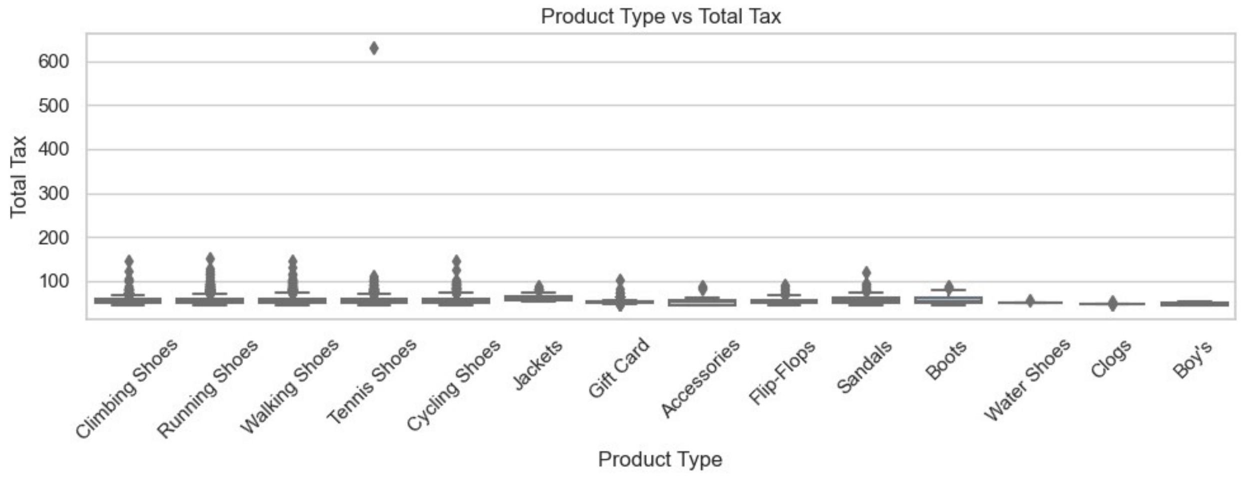


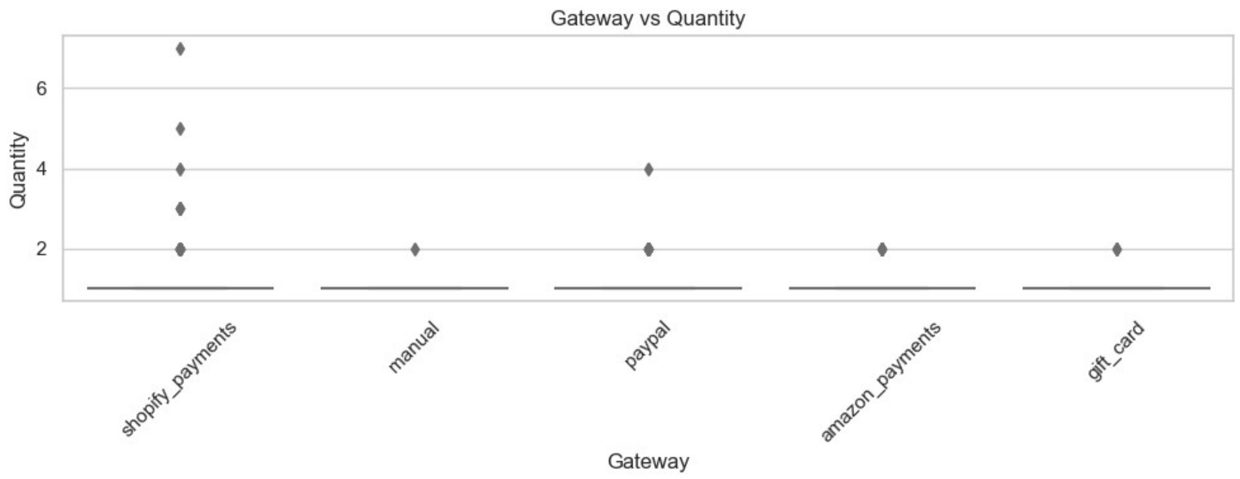


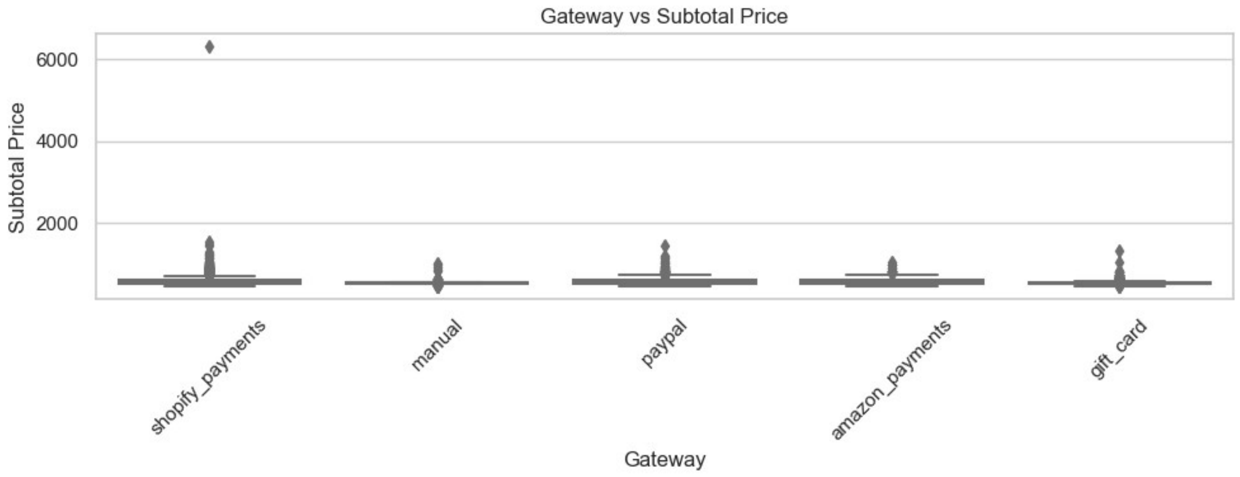

Billing Address Country vs Total Price Usd
Total Price Usd
6000
4000
2000
United States
Billing Address Country

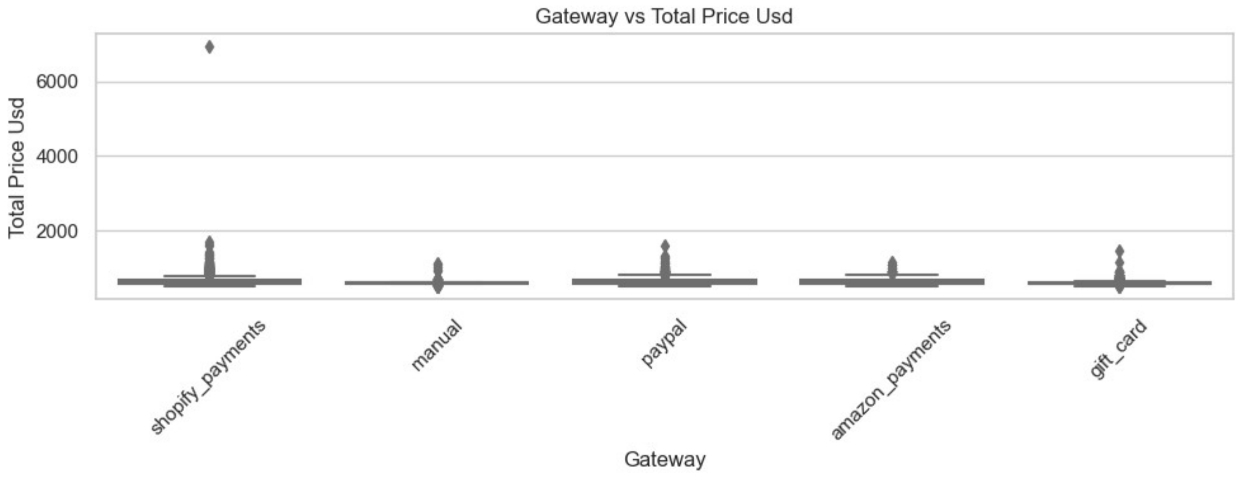

Billing Address Country vs Total Tax
Total Tax
600
500
400
300
200
100
United States
Billing Address Country

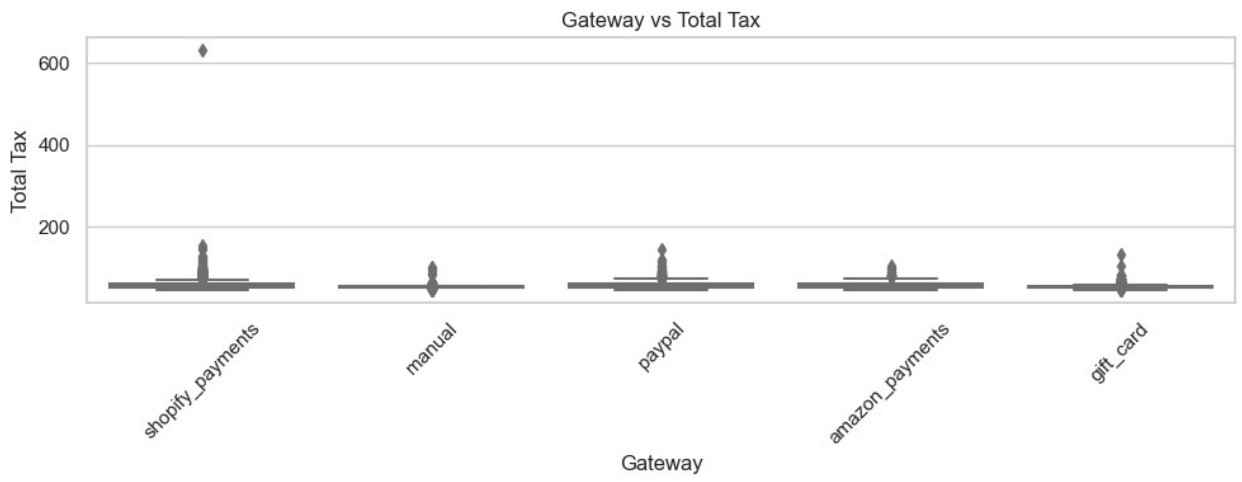

Product Type vs Quantity
Quantity
7
6
5
4
3
2
1
Climbing Shoes
Running Shoes
Walking Shoes
Tennis Shoes
Cycling Shoes
Jackets
Gift Card
Accessories
Flip-Flops
Sandals
Boots
Water Shoes
Clogs
Boy's
Product Type

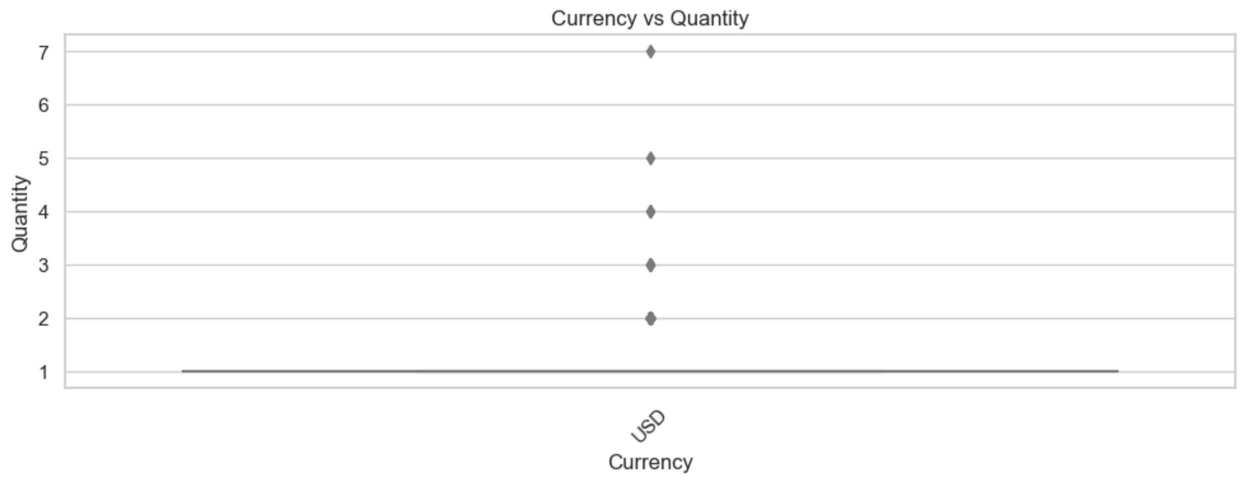

Product Type vs Subtotal Price
Subtotal Price
6000
5000
4000
3000
2000
1000
Climbing Shoes
Running Shoes
Walking Shoes
Tennis Shoes
Cycling Shoes
Jackets
Gift Card
Accessories
Flip-Flops
Sandals
Boots
Water Shoes
Clogs
Boy's
Product Type

Product Type vs Total Price Usd
Total Price Usd
6000
4000
2000
Climbing Shoes
Running Shoes
Walking Shoes
Tennis Shoes
Cycling Shoes
Jackets
Gift Card
Accessories
Flip-Flops
Sandals
Boots
Water Shoes
Clogs
Boy's
Product Type

Product Type vs Total Tax
Total Tax
600
500
400
300
200
100
Climbing Shoes
Running Shoes
Walking Shoes
Tennis Shoes
Cycling Shoes
Jackets
Gift Card
Accessories
Flip-Flops
Sandals
Boots
Water Shoes
Clogs
Boy's
Product Type

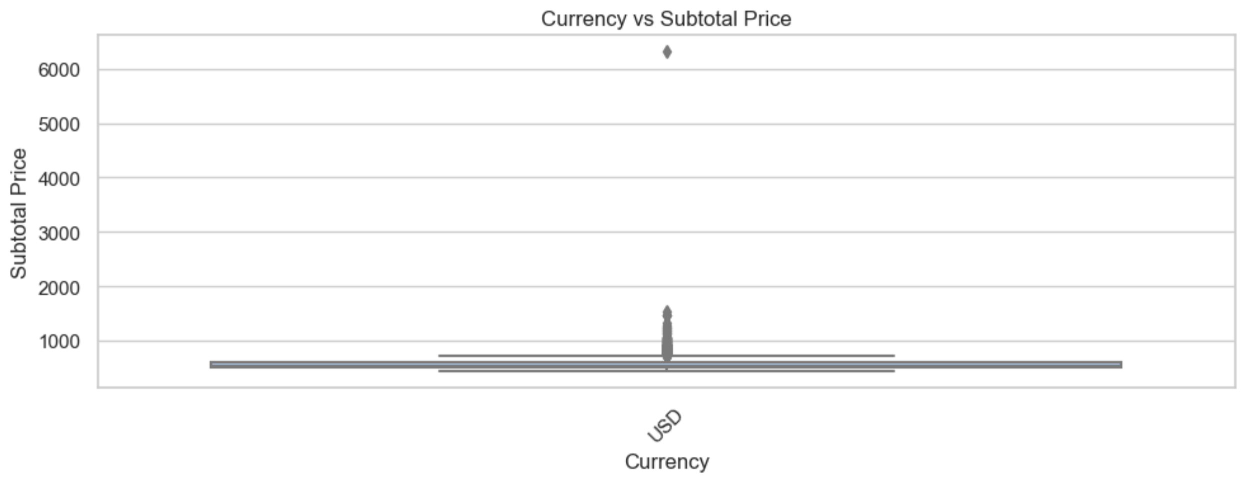

Gateway vs Quantity
Quantity
2
4
6
shopify_payments
manual
paypal
amazon_payments
gift_card
Gateway

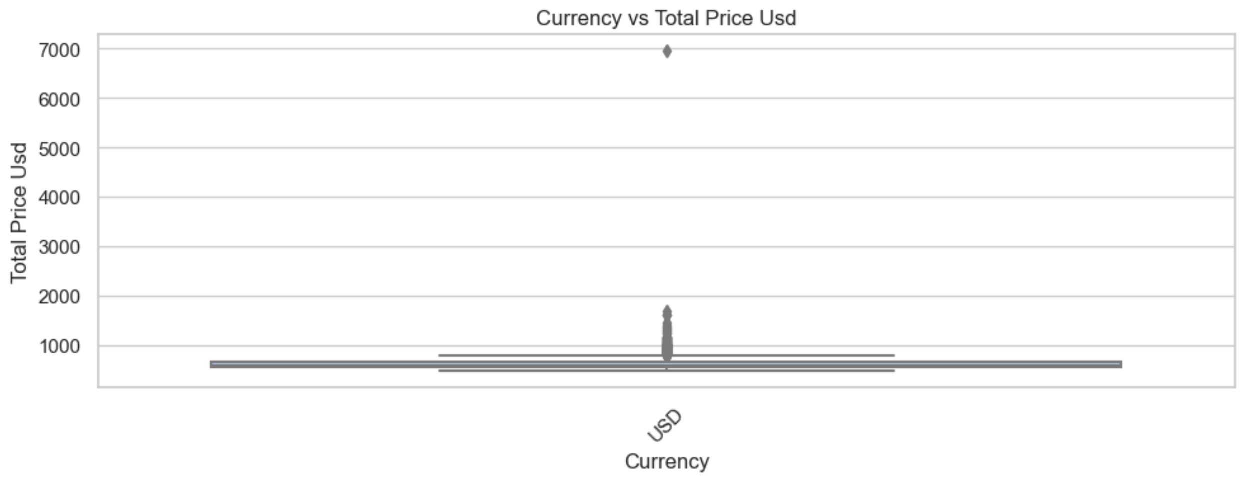

Gateway vs Subtotal Price
Subtotal Price
2000
4000
6000
shopify_payments
manual
paypal
amazon_payments
gift_card
Gateway

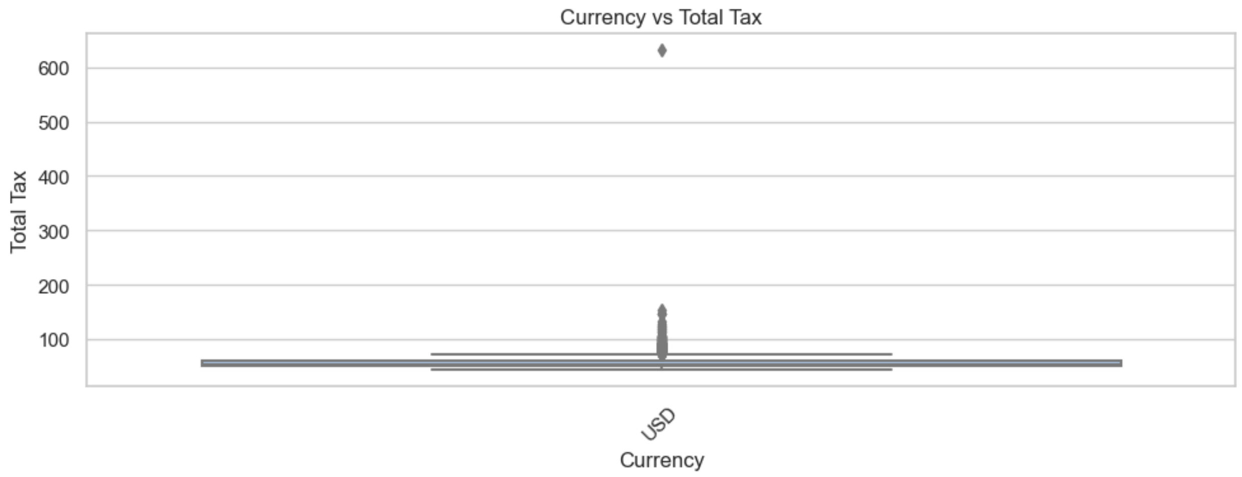

Gateway vs Total Price Usd
Total Price Usd
2000
4000
6000
shopify_payments
manual
paypal
amazon_payments
gift_card
Gateway


Gateway vs Total Tax
Total Tax
600
400
200
shopify_payments
manual
paypal
amazon_payments
gift_card
Gateway


Currency vs Quantity
Quantity
7
6
5
4
3
2
1
USD
Currency


Currency vs Subtotal Price
Subtotal Price
6000
5000
4000
3000
2000
1000
USD
Currency





Key Insights

1. **Most Orders Are Small, Single-Item Purchases**
   - Across all categories (country, province, city, product type, gateway, currency), the majority of orders have a quantity of 1.
2. **High-Value Orders Are Rare but Significant**
   - Outliers in price and tax columns indicate occasional large or premium purchases, especially in certain cities, product types, or countries.
3. **Sales Are Highly Concentrated**
   - Most sales come from a single country and currency, showing a focused market presence.
   - A few product types and payment gateways dominate transactions.
4. **Product Type Drives Order Value**
   - Some product types have consistently higher order values and taxes, suggesting premium or bulk products.

Summary:
Your business is driven by frequent, small orders from a concentrated customer base, with

occasional large transactions that can significantly impact revenue. Focusing on top-performing product types and regions can further optimize sales.

Step - 5 : Handling Missing Values and Duplicates

1. Find Missing Values

```
# Count missing values in each column
missing = df.isnull().sum()
missing = missing[missing > 0].sort_values(ascending=False)

print("□ Missing Values Detected:\n")
print(missing)
```

```
□ Missing Values Detected:

Product Id     11
Variant Id      4
dtype: int64
```

2. Check For Duplicates

```
# Check for duplicate rows
duplicates = df.duplicated().sum()

print(f"\n□ Total Duplicate Rows: {duplicates}")
```

```

□ Total Duplicate Rows: 0
```

3. Remove Duplicates

```
df = df.drop_duplicates()
print("□ Duplicates removed.")
```

```
□ Duplicates removed.
```

4. Check for Zero/Blank-Like Values

```
# Check for suspicious zero values
for col in ['Quantity', 'Total Price Usd', 'Total Tax']:
    zero_count = (df[col] == 0).sum()
    print(f"□ {col} has {zero_count} zero values.")
```

```
□ Quantity has 0 zero values.
□ Total Price Usd has 0 zero values.
□ Total Tax has 0 zero values.
```

4. Save the Cleaned Data

```
# Save cleaned data for next steps
df.to_csv("Cleaned_Shopify_Sales.csv", index=False)
```

Summary

Task	Action
Missing values	`dropna()` or `fillna()`
Duplicate rows	`drop_duplicates()`
Zero/empty checks	Investigate important numeric columns
Final cleaned file	Save as CSV or Excel

Step - 6 : Feature Engineering

```
df.head(3)
```

```
                   Admin Graphql Api Id  Order Number Billing Address
Country  \
0  gid://shopify/LineItem/2153619128398          1681          United
States
1  gid://shopify/LineItem/2160863674446          6972          United
States
2  gid://shopify/LineItem/2157784006734          4994          United
States

  Billing Address First Name Billing Address Last Name  \
0                      Vanni                  Wimpenny
1                       Marc                   Netley
2                      Elwyn                Colebourn

  Billing Address Province  Billing Address Zip     CITY Currency  \
0                    Texas                88446  Houston      USD
1                Louisiana                50466   Monroe      USD
2                    Texas                67432  Houston      USD

   Customer Id  ... Quantity Subtotal Price  Total Price Usd Total Tax
\
0         2865  ...        1         535.13          588.643    53.513

1         4987  ...        1         578.33          636.163    57.833

2         5472  ...        1         594.33          653.763    59.433


         Full Name  Year  Month    Weekday  Hour Revenue per Unit
0   Vanni Wimpenny  2025      3  Wednesday    17          588.643
1      Marc Netley  2025      3     Monday    15          636.163
```

```
2  Elwyn Colebourn  2025      3   Saturday    18           653.763

[3 rows x 25 columns]
```

1. Extract Date and Time Features

```
# Extract useful time-based features
df['Year'] = df['Invoice Date'].dt.year
df['Month'] = df['Invoice Date'].dt.month
df['Weekday'] = df['Invoice Date'].dt.day_name()
df['Hour'] = df['Invoice Date'].dt.hour

df[['Year', 'Month', 'Weekday', 'Hour']].head()

   Year  Month    Weekday  Hour
0  2025      3  Wednesday    17
1  2025      3     Monday    15
2  2025      3   Saturday    18
3  2025      3    Tuesday    10
4  2025      3   Saturday     9
```

2. Create Revenue Columns

```
df['Revenue per Unit'] = df['Total Price Usd'] / df['Quantity']

df['Revenue per Unit'].head(3)

0    588.643
1    636.163
2    653.763
Name: Revenue per Unit, dtype: float64
```

3. Flag High-Tax Orders

```
# Flag orders where tax is unusually high
df['High Tax Order'] = df['Total Tax'] > df['Total
Tax'].quantile(0.95)
```

4. Categorize Revenue

```
# Create revenue tiers
df['Revenue Category'] = pd.cut(df['Total Price Usd'],
                                bins=[0, 50, 200, 500, 1000,
float('inf')],
                                labels=['Very Low', 'Low', 'Medium',
'High', 'Very High'])
```

5. Combine Features

```
# Combine Country and Product Type for segmentation
df['Country_Product'] = df['Billing Address Country'] + ' - ' +
df['Product Type']
```

Step - 7 : Encoding and Transformations

 Goal: Prepare categorical variables, scale numerical features, and transform data into the right format for modeling or further analysis.

1. Identify Categorical Columns

```
# Automatically identify object or category columns
categorical_cols = df.select_dtypes(include=['object',
'category']).columns.tolist()
print(" Categorical Columns:\n", categorical_cols)

 Categorical Columns:
 ['Admin Graphql Api Id', 'Billing Address Country', 'Billing Address
First Name', 'Billing Address Last Name', 'Billing Address Province',
'CITY', 'Currency', 'Gateway', 'Product Type', 'Full Name', 'Weekday',
'Revenue Category', 'Country_Product']
```

2. Label Encoding for Binary Categorical Columns

```
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()

binary_cols = [col for col in categorical_cols if df[col].nunique() ==
2]

for col in binary_cols:
    df[col] = le.fit_transform(df[col])
    print(f" Label Encoded: {col}")

df.head(3)

                   Admin Graphql Api Id  Order Number Billing Address
Country  \
0  gid://shopify/LineItem/2153619128398          1681           United
States
1  gid://shopify/LineItem/2160863674446          6972           United
States
2  gid://shopify/LineItem/2157784006734          4994           United
States

  Billing Address First Name Billing Address Last Name  \
0                      Vanni                  Wimpenny
1                       Marc                    Netley
```

```
2                     Elwyn                Colebourn

  Billing Address Province  Billing Address Zip     CITY Currency  \
0                    Texas                88446  Houston      USD
1                Louisiana                50466   Monroe      USD
2                    Texas                67432  Houston      USD

   Customer Id  ... Total Tax         Full Name  Year Month    Weekday
Hour  \
0         2865  ...    53.513   Vanni Wimpenny  2025     3  Wednesday
17
1         4987  ...    57.833      Marc Netley  2025     3     Monday
15
2         5472  ...    59.433  Elwyn Colebourn  2025     3   Saturday
18

   Revenue per Unit  High Tax Order  Revenue Category  \
0           588.643           False              High
1           636.163           False              High
2           653.763           False              High

                  Country_Product
0  United States - Climbing Shoes
1  United States - Climbing Shoes
2  United States - Climbing Shoes

[3 rows x 28 columns]
```

3. One-Hot Encoding for Multi-Class Categorical Columns

```
multi_class_cols = [col for col in categorical_cols if
df[col].nunique() > 2]

df = pd.get_dummies(df, columns=multi_class_cols, drop_first=True)
print("□ One-Hot Encoding completed.")

□ One-Hot Encoding completed.
```

4. Normalize / Scale Numerical Data

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
numerical_cols = df.select_dtypes(include=['int64',
'float64']).columns.tolist()

df[numerical_cols] = scaler.fit_transform(df[numerical_cols])
print("□ Numerical features scaled using MinMaxScaler.")

□ Numerical features scaled using MinMaxScaler.
```

5.Final Check of Transformed Data

```
print("□ Final Dataset Shape:", df.shape)
print("□ Sample Data:")
print(df.head())

□ Final Dataset Shape: (7431, 27211)
□ Sample Data:
   Order Number Billing Address Country  Billing Address Zip Currency
\
0      0.226245           United States             0.884583      USD

1      0.938358           United States             0.504696      USD

2      0.672140           United States             0.674395      USD

3      0.027725           United States             0.563360      USD

4      0.584926           United States             0.700511      USD


   Customer Id        Invoice Date  Product Id  Variant Id
Quantity  \
0     0.440769 2025-03-19 17:27:00    0.063524    0.069303       0.0

1     0.767231 2025-03-24 15:42:00    0.063524    0.069303       0.0

2     0.841846 2025-03-22 18:32:00    0.063524    0.069303       0.0

3     0.496462 2025-03-18 10:51:00    0.063524    0.069303       0.0

4     0.288308 2025-03-22 09:55:00    0.063524    0.069303       0.0


   Subtotal Price  ...  Country_Product_United States - Clogs  \
0        0.016327  ...                                  False
1        0.023673  ...                                  False
2        0.026395  ...                                  False
3        0.008163  ...                                  False
4        0.016327  ...                                  False

   Country_Product_United States - Cycling Shoes  \
0                                          False
1                                          False
2                                          False
3                                          False
4                                          False

   Country_Product_United States - Flip-Flops  \
0                                       False
1                                       False
```

```
2                                      False
3                                      False
4                                      False

   Country_Product_United States - Gift Card  \
0                                      False
1                                      False
2                                      False
3                                      False
4                                      False

   Country_Product_United States - Jackets  \
0                                    False
1                                    False
2                                    False
3                                    False
4                                    False

   Country_Product_United States - Running Shoes  \
0                                          False
1                                          False
2                                          False
3                                          False
4                                          False

   Country_Product_United States - Sandals  \
0                                    False
1                                    False
2                                    False
3                                    False
4                                    False

   Country_Product_United States - Tennis Shoes  \
0                                         False
1                                         False
2                                         False
3                                         False
4                                         False

   Country_Product_United States - Walking Shoes  \
0                                          False
1                                          False
2                                          False
3                                          False
4                                          False

   Country_Product_United States - Water Shoes
0                                        False
1                                        False
2                                        False
```

```
3                                         False
4                                         False

[5 rows x 27211 columns]

df.head()

   Order Number Billing Address Country  Billing Address Zip Currency
\
0      0.226245           United States             0.884583      USD

1      0.938358           United States             0.504696      USD

2      0.672140           United States             0.674395      USD

3      0.027725           United States             0.563360      USD

4      0.584926           United States             0.700511      USD


   Customer Id        Invoice Date  Product Id  Variant Id
Quantity  \
0     0.440769 2025-03-19 17:27:00    0.063524    0.069303       0.0

1     0.767231 2025-03-24 15:42:00    0.063524    0.069303       0.0

2     0.841846 2025-03-22 18:32:00    0.063524    0.069303       0.0

3     0.496462 2025-03-18 10:51:00    0.063524    0.069303       0.0

4     0.288308 2025-03-22 09:55:00    0.063524    0.069303       0.0


   Subtotal Price  ...  Country_Product_United States - Clogs  \
0        0.016327  ...                                  False
1        0.023673  ...                                  False
2        0.026395  ...                                  False
3        0.008163  ...                                  False
4        0.016327  ...                                  False

   Country_Product_United States - Cycling Shoes  \
0                                          False
1                                          False
2                                          False
3                                          False
4                                          False

   Country_Product_United States - Flip-Flops  \
0                                       False
1                                       False
2                                       False
```

```
3                                         False
4                                         False

   Country_Product_United States - Gift Card  \
0                                        False
1                                        False
2                                        False
3                                        False
4                                        False

   Country_Product_United States - Jackets  \
0                                      False
1                                      False
2                                      False
3                                      False
4                                      False

   Country_Product_United States - Running Shoes  \
0                                            False
1                                            False
2                                            False
3                                            False
4                                            False

   Country_Product_United States - Sandals  \
0                                      False
1                                      False
2                                      False
3                                      False
4                                      False

   Country_Product_United States - Tennis Shoes  \
0                                           False
1                                           False
2                                           False
3                                           False
4                                           False

   Country_Product_United States - Walking Shoes  \
0                                            False
1                                            False
2                                            False
3                                            False
4                                            False

   Country_Product_United States - Water Shoes
0                                          False
1                                          False
2                                          False
3                                          False
```

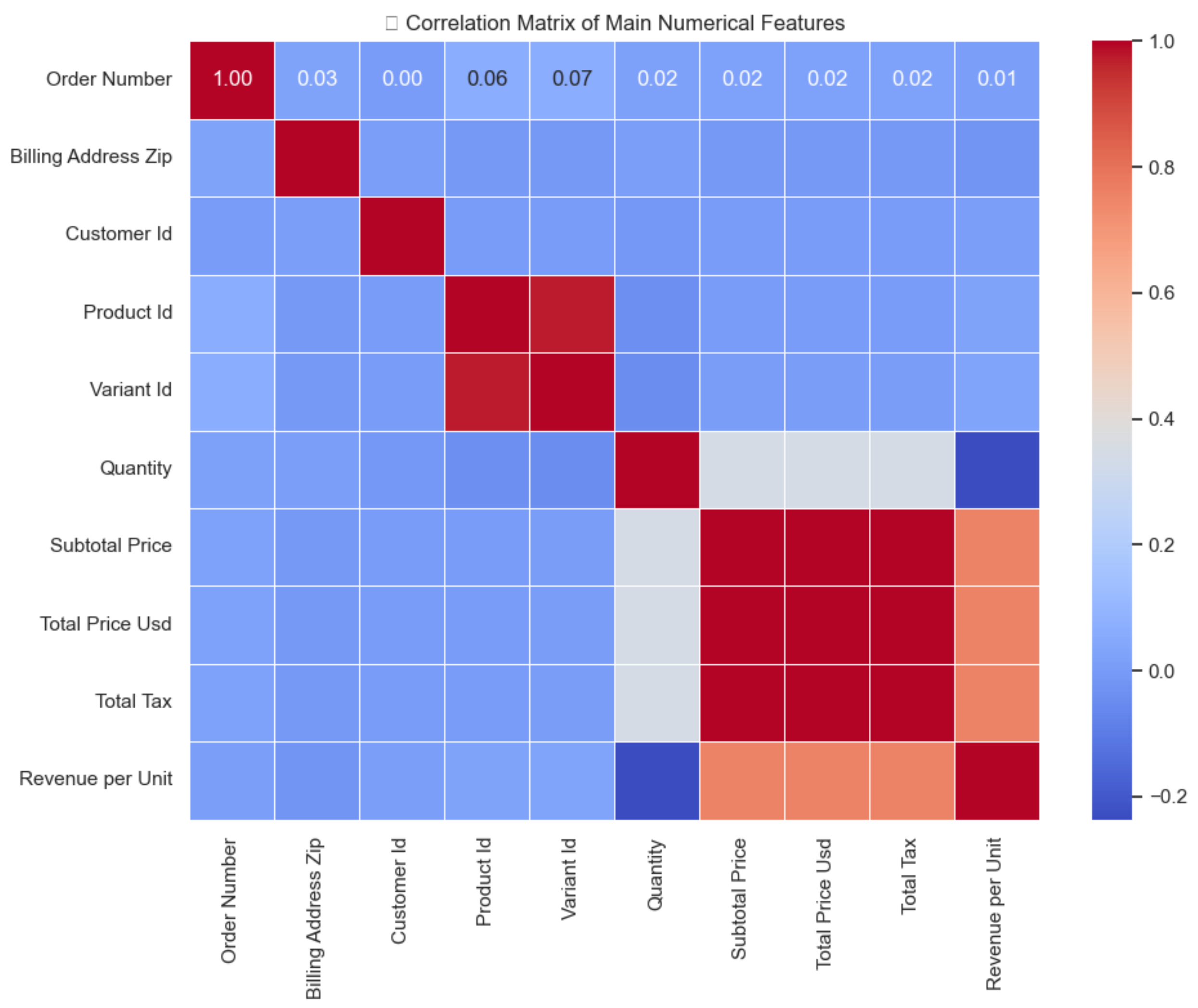
```
4                                        False

[5 rows x 27211 columns]
```

Step - 8 : Correlation Analysis & Feature Selection

Correlation Matrix for Numerical Features

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

# Compute correlation matrix only for main numerical columns to avoid
memory issues
corr_matrix = df[numerical_cols].corr()

# Plot heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f",
linewidths=0.5)
plt.title("🔗 Correlation Matrix of Main Numerical Features")
plt.tight_layout()
plt.show()
```

```
C:\Users\moham\AppData\Local\Temp\ipykernel_16228\1999753851.py:11:
UserWarning: Glyph 128279 (\N{LINK SYMBOL}) missing from current font.
  plt.tight_layout()
c:\ProgramData\anaconda3\Lib\site-packages\IPython\core\
pylabtools.py:152: UserWarning: Glyph 128279 (\N{LINK SYMBOL}) missing
from current font.
  fig.canvas.print_figure(bytes_io, **kw)
```



Identify Highly Correlated Features

```python
# Get pairs with correlation > 0.8 (excluding perfect correlation with
itself)
threshold = 0.8
high_corr_pairs = []

for i in range(len(corr_matrix.columns)):
    for j in range(i):
        if abs(corr_matrix.iloc[i, j]) > threshold:
            col1 = corr_matrix.columns[i]
            col2 = corr_matrix.columns[j]
            corr_value = corr_matrix.iloc[i, j]
            high_corr_pairs.append((col1, col2, corr_value))

# Show results
for col1, col2, val in high_corr_pairs:
    print(f"□ {col1} and {col2} are highly correlated ({val:.2f})")
```

```
 Variant Id and Product Id are highly correlated (0.98)
 Total Price Usd and Subtotal Price are highly correlated (1.00)
 Total Tax and Subtotal Price are highly correlated (1.00)
 Total Tax and Total Price Usd are highly correlated (1.00)
```

Export Cleaned Dataset to CSV

```
# Save as CSV
df.to_csv('Cleaned_Shopify_Sales.csv', index=False)

print(" Dataset successfully exported!")
```