Supermarket Sales - End-to-End EDA

This notebook explores the supermarket sales dataset using **Pandas** for data handling and **Seaborn**, **matplotlib** for charts.

Steps included:

1. Load the data
2. Inspect structure (.info, .describe, .isnull)
3. Parse dates & create time features
4. Visualize distributions (histplot, boxplot)
5. Category analysis (countplot, barplot)
6. Correlation heatmap & pairplot
7. Groupby aggregations for insights
8. Outliers & skewness (IQR, skew)

Import all required libraries:

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

plt.style.use('seaborn-v0_8-whitegrid')
sns.set_palette('Set2')
```

In [2]:
```
# Load dataset
path = r"C:\Users\hp\Downloads\Internship Task\Task-2\supermarket_sales.csv"
df = pd.read_csv(path)
```

In [3]:
```
df.head()
```

Out[3]:

	invoice_id	branch	city	customer_type	gender_customer	product_line	unit_cost	quantity	5pct_markup	revenue	
0	750-67-8428	A	Yangon	Member	Female	Health and beauty	74.69	7	26.1415	548.9715	01/(
1	226-31-3081	C	Naypyitaw	Normal	Female	Electronic accessories	15.28	5	3.8200	80.2200	03/(
2	631-41-3108	A	Yangon	Normal	Male	Home and lifestyle	46.33	7	16.2155	340.5255	03/(
3	123-19-1176	A	Yangon	Member	Male	Health and beauty	58.22	8	23.2880	489.0480	1/27/
4	373-73-7910	A	Yangon	Normal	Male	Sports and travel	86.31	7	30.2085	634.3785	02/(

In [4]:
```
# summary
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 17 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   invoice_id       1000 non-null   object 
 1   branch           1000 non-null   object 
 2   city             1000 non-null   object 
 3   customer_type    1000 non-null   object 
 4   gender_customer  1000 non-null   object 
 5   product_line     1000 non-null   object 
 6   unit_cost        1000 non-null   float64
 7   quantity         1000 non-null   int64  
 8   5pct_markup      1000 non-null   float64
 9   revenue          1000 non-null   float64
 10  date             1000 non-null   object 
 11  time             1000 non-null   object 
 12  payment_method   1000 non-null   object 
 13  cogs             1000 non-null   float64
 14  gm_pct           1000 non-null   float64
 15  gross_income     1000 non-null   float64
 16  rating           1000 non-null   float64
dtypes: float64(7), int64(1), object(9)
memory usage: 132.9+ KB
```

In [5]:
```
# Structure
print("\nShape:", df.shape)
```

```
Shape: (1000, 17)
```

In [6]:
```
# Statistical analysis for numeric columns
print("\nNumeric summary:\n", df.describe(include=[np.number]))
```

```
Numeric summary:
          unit_cost     quantity  5pct_markup      revenue        cogs  \
count  1000.000000  1000.000000  1000.000000  1000.000000  1000.00000   
mean     55.672130     5.510000    15.379369   322.966749   307.58738   
std      26.494628     2.923431    11.708825   245.885335   234.17651   
min      10.080000     1.000000     0.508500    10.678500    10.17000   
25%      32.875000     3.000000     5.924875   124.422375   118.49750   
50%      55.230000     5.000000    12.088000   253.848000   241.76000   
75%      77.935000     8.000000    22.445250   471.350250   448.90500   
max      99.960000    10.000000    49.650000  1042.650000   993.00000   

             gm_pct  gross_income      rating  
count  1.000000e+03   1000.000000  1000.00000  
mean   4.761905e+00     15.379369     6.97270  
std    6.131498e-14     11.708825     1.71858  
min    4.761905e+00      0.508500     4.00000  
25%    4.761905e+00      5.924875     5.50000  
50%    4.761905e+00     12.088000     7.00000  
75%    4.761905e+00     22.445250     8.50000  
max    4.761905e+00     49.650000    10.00000  
```

In [7]:
```
# Statistical analysis for categorical columns
print("\nCategorical summary:\n", df.describe(include=['object']))
```

```
Categorical summary:
          invoice_id branch    city customer_type gender_customer  \
count          1000   1000    1000          1000            1000   
unique         1000      3       3             2               2   
top     750-67-8428      A  Yangon        Member          Female   
freq              1    340     340           501             501   

                  product_line      date   time payment_method  
count                     1000      1000   1000           1000  
unique                       6        89    506              3  
top     Fashion accessories  02/07/19  19:48        Ewallet  
freq                       178        20      7            345  
```

In [8]:
```
print("\nMissing values per column:\n", df.isnull().sum())
```

```
Missing values per column:
 invoice_id         0
branch             0
city               0
customer_type      0
gender_customer    0
product_line       0
unit_cost          0
quantity           0
5pct_markup        0
revenue            0
date               0
time               0
payment_method     0
cogs               0
gm_pct             0
gross_income       0
rating             0
dtype: int64
```

In [9]:

```
# Convert 'date' column into proper date format
df['date_parsed'] = pd.to_datetime(df['date'])

# Extract year, month, day, and weekday from the date
df['year'] = df['date_parsed'].dt.year
df['month'] = df['date_parsed'].dt.month
df['day'] = df['date_parsed'].dt.day
df['weekday'] = df['date_parsed'].dt.day_name()

# Convert 'time' column and extract hour
df['hour'] = pd.to_datetime(df['time'], format='%H:%M').dt.hour

# Check the new columns
df.head()
```

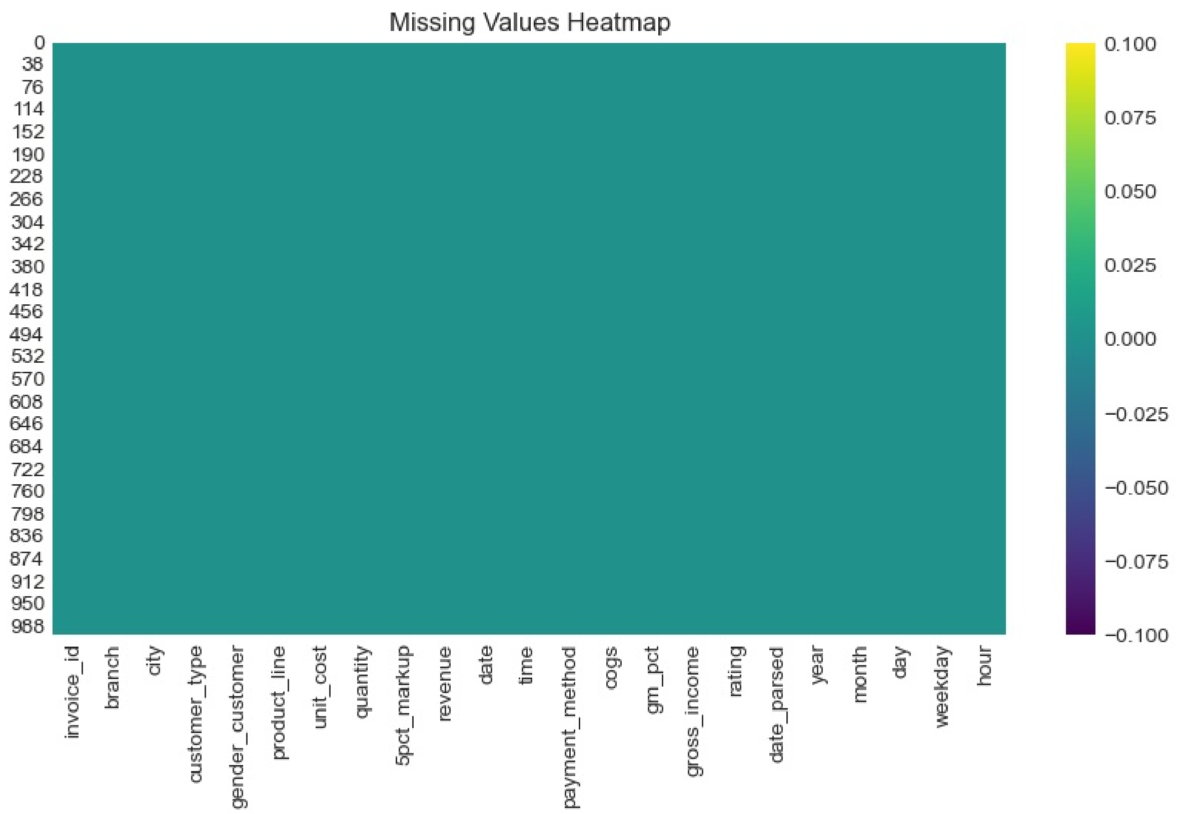
Out[9]:

	invoice_id	branch	city	customer_type	gender_customer	product_line	unit_cost	quantity	5pct_markup	revenue	...
0	750-67-8428	A	Yangon	Member	Female	Health and beauty	74.69	7	26.1415	548.9715	...	5
1	226-31-3081	C	Naypyitaw	Normal	Female	Electronic accessories	15.28	5	3.8200	80.2200	...	
2	631-41-3108	A	Yangon	Normal	Male	Home and lifestyle	46.33	7	16.2155	340.5255	...	3
3	123-19-1176	A	Yangon	Member	Male	Health and beauty	58.22	8	23.2880	489.0480	...	4
4	373-73-7910	A	Yangon	Normal	Male	Sports and travel	86.31	7	30.2085	634.3785	...	6

5 rows × 23 columns

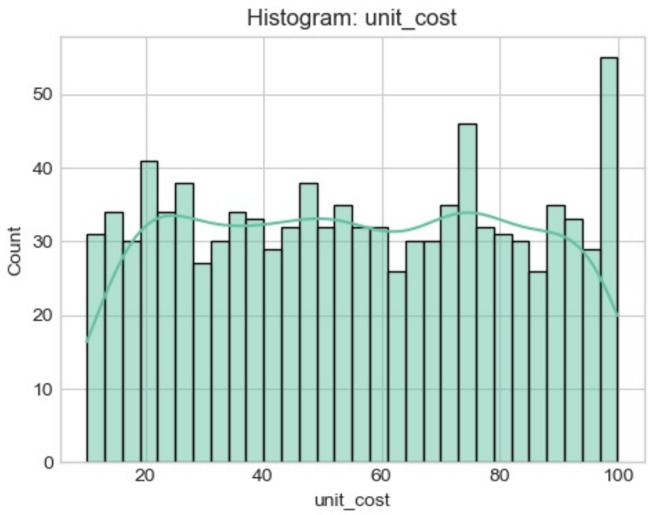
In [10]:

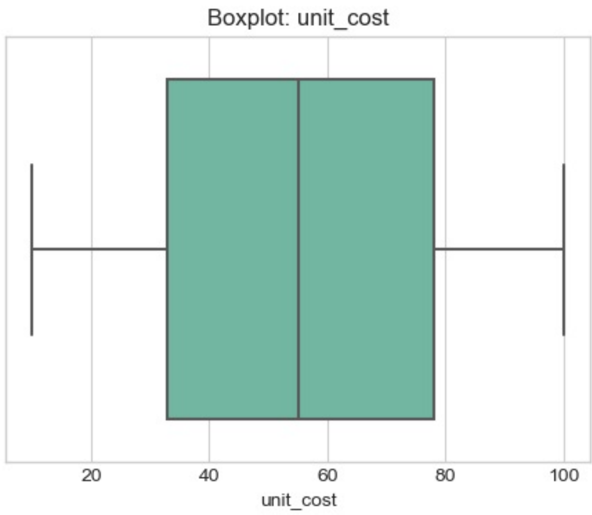
```
# Visualize missingness
plt.figure(figsize=(10,5))
sns.heatmap(df.isnull(), cbar=True, cmap='viridis')
plt.title('Missing Values Heatmap')
plt.show()
```

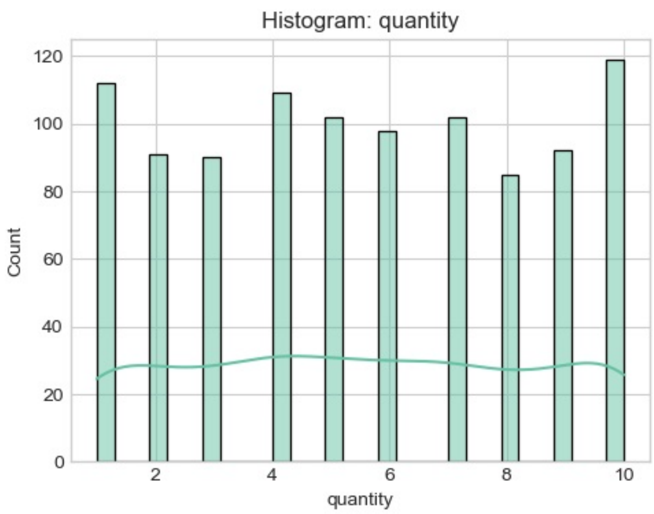


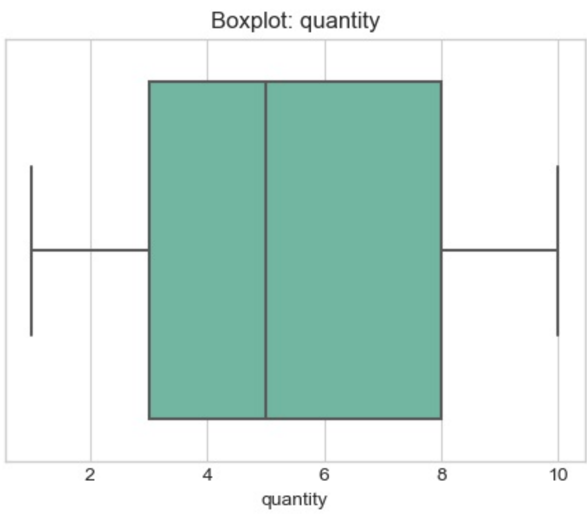
In [11]:

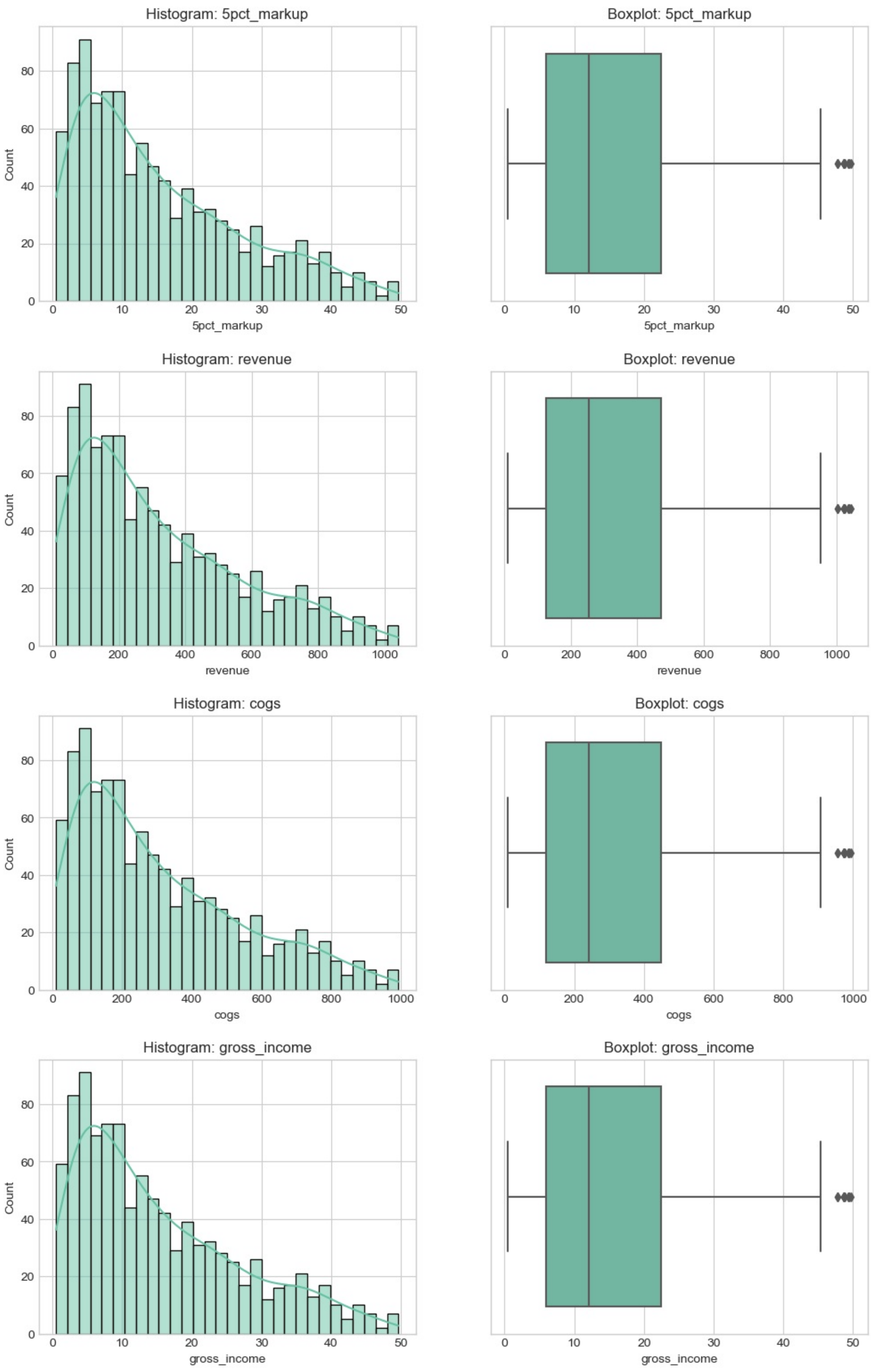
```
numeric_cols = df.select_dtypes(include=[np.number]).columns
for col in numeric_cols:
    if col != 'gm_pct':
        fig, axes = plt.subplots(1,2, figsize=(12,4))
        sns.histplot(df[col], bins=30, kde=True, ax=axes[0])
        axes[0].set_title(f'Histogram: {col}')
        sns.boxplot(x=df[col], ax=axes[1])
        axes[1].set_title(f'Boxplot: {col}')
        plt.show()
```

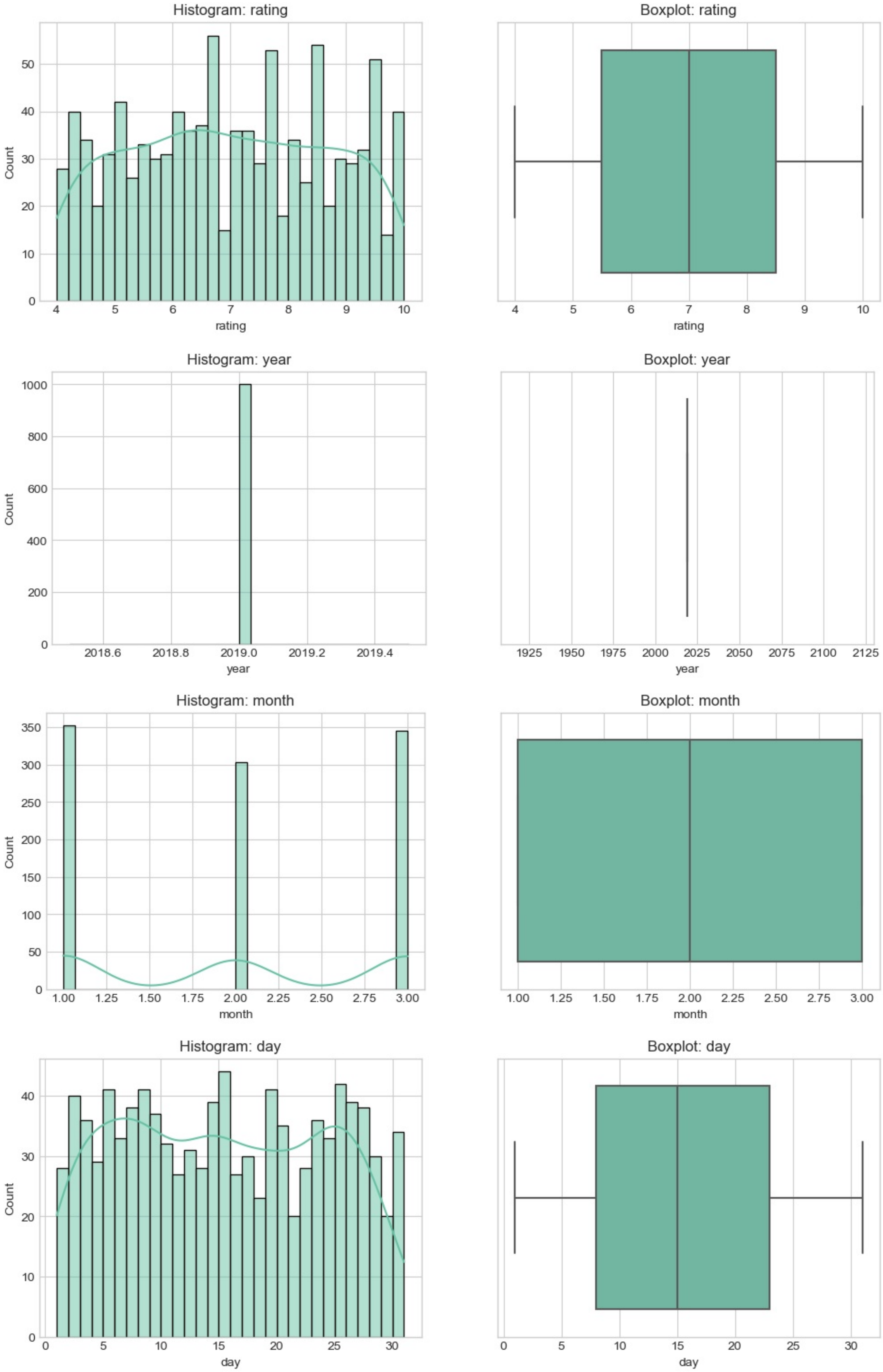




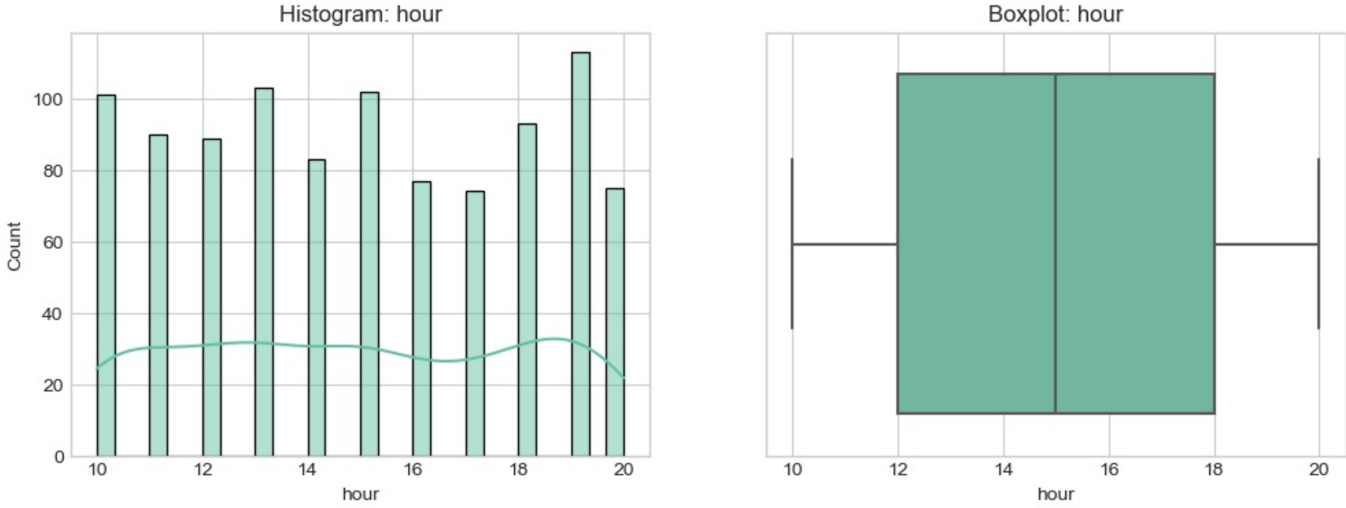





Histogram: 5pct_markup
Boxplot: 5pct_markup
Count
5pct_markup
Histogram: revenue
Boxplot: revenue
revenue
Histogram: cogs
Boxplot: cogs
cogs
Histogram: gross_income
Boxplot: gross_income
gross_income

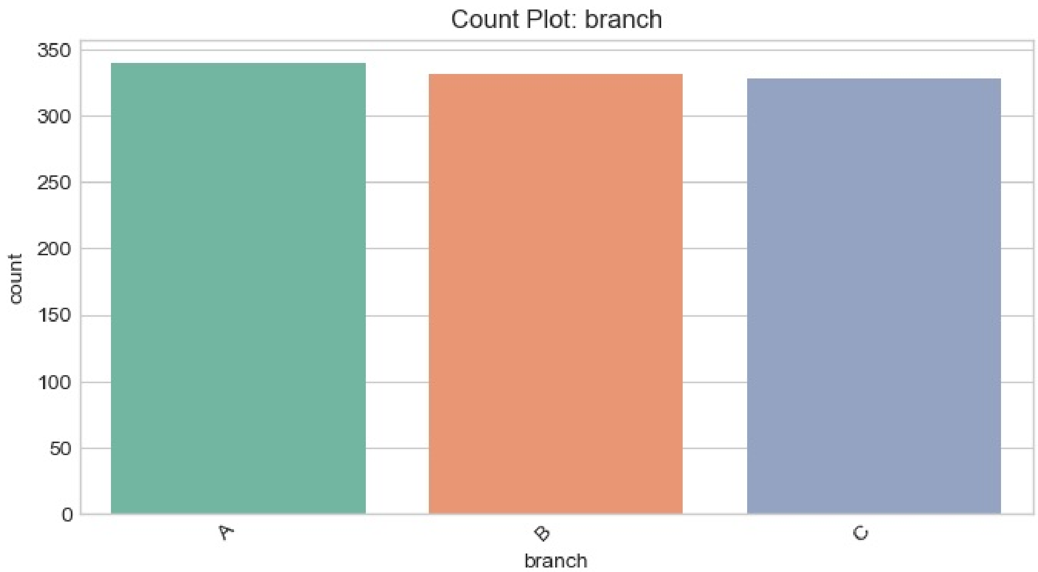


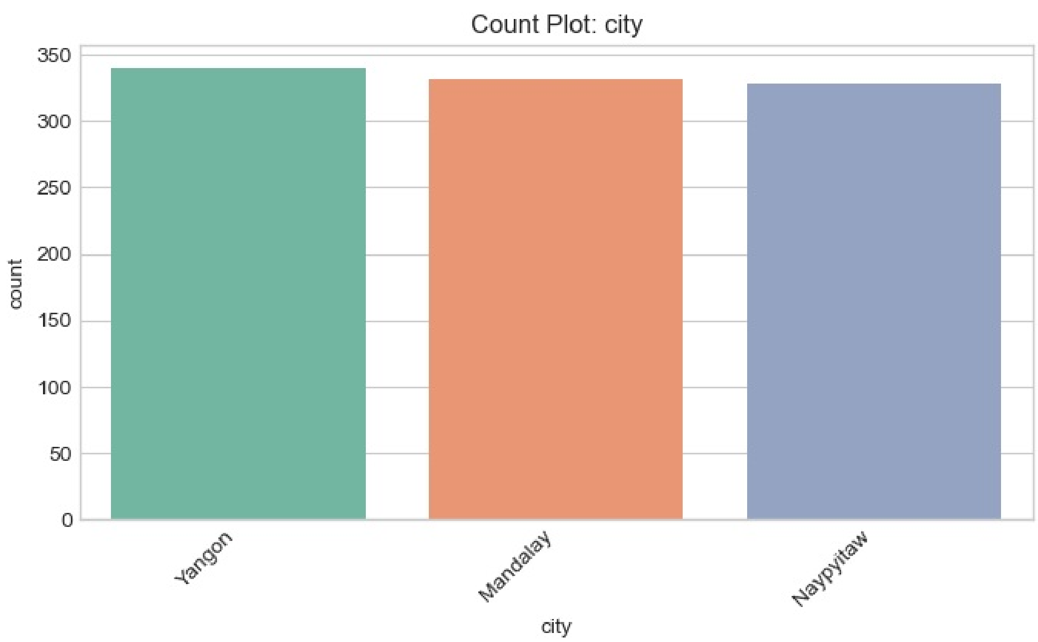
Histogram: rating
Count
0
10
20
30
40
50
4
5
6
7
8
9
10
rating
Boxplot: rating
4
5
6
7
8
9
10
rating
Histogram: year
Count
0
200
400
600
800
1000
2018.6
2018.8
2019.0
2019.2
2019.4
year
Boxplot: year
1925
1950
1975
2000
2025
2050
2075
2100
2125
year
Histogram: month
Count
0
50
100
150
200
250
300
350
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
month
Boxplot: month
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
month
Histogram: day
Count
0
10
20
30
40
0
5
10
15
20
25
30
day
Boxplot: day
0
5
10
15
20
25
30
day

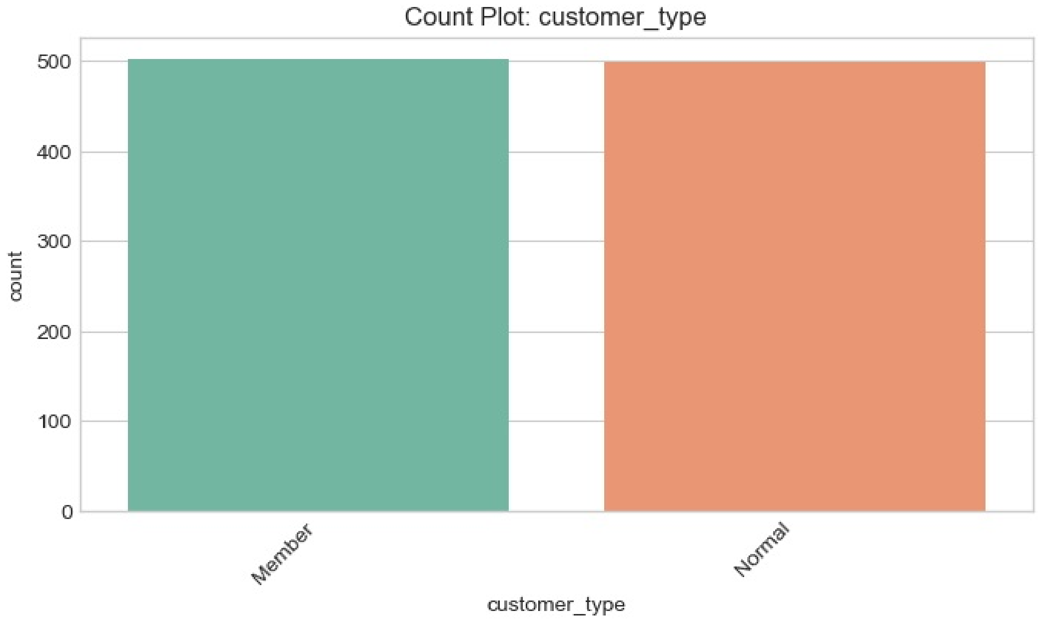


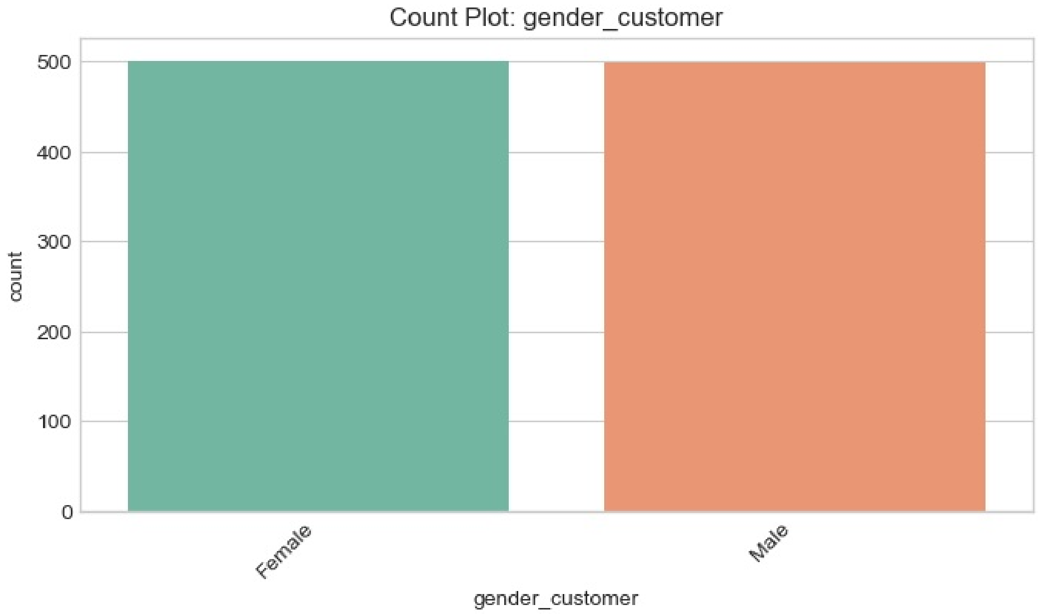
In [12]:

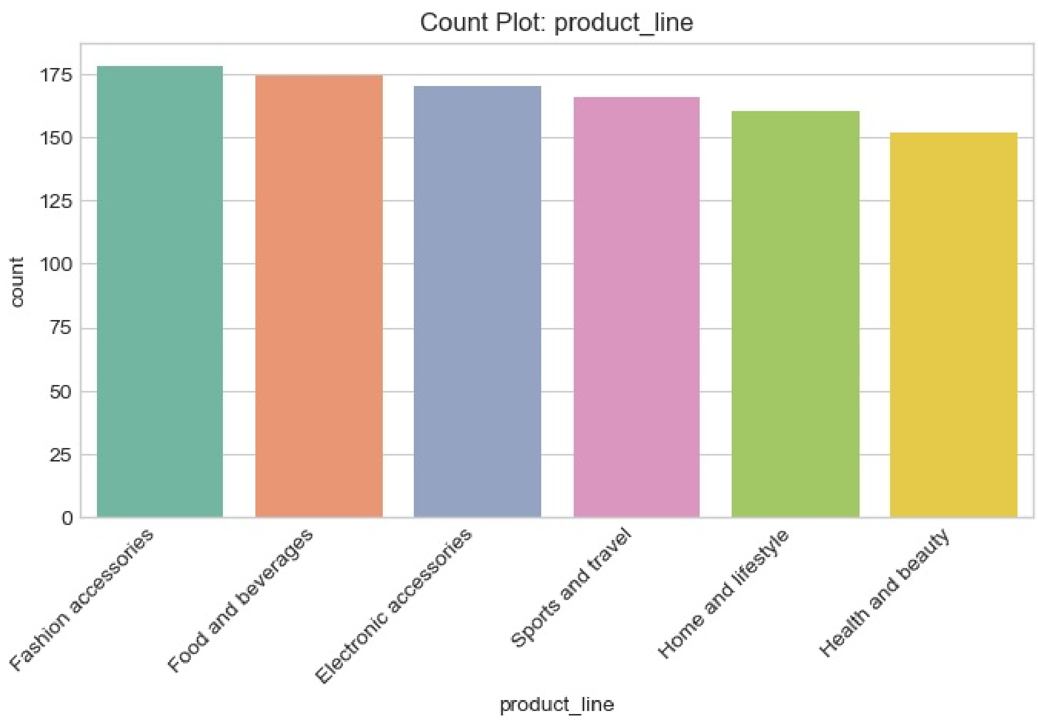
```
# Count plots for categorical features
categorical_cols = df.select_dtypes(include=['object']).columns

for col in categorical_cols:
    if col not in ['invoice_id', 'date', 'time']:   # skip unique or too detailed columns
        plt.figure(figsize=(8,4))
        sns.countplot(data=df, x=col, order=df[col].value_counts().index)
        plt.title(f'Count Plot: {col}')
        plt.xticks(rotation=45, ha='right')
        plt.show()
```

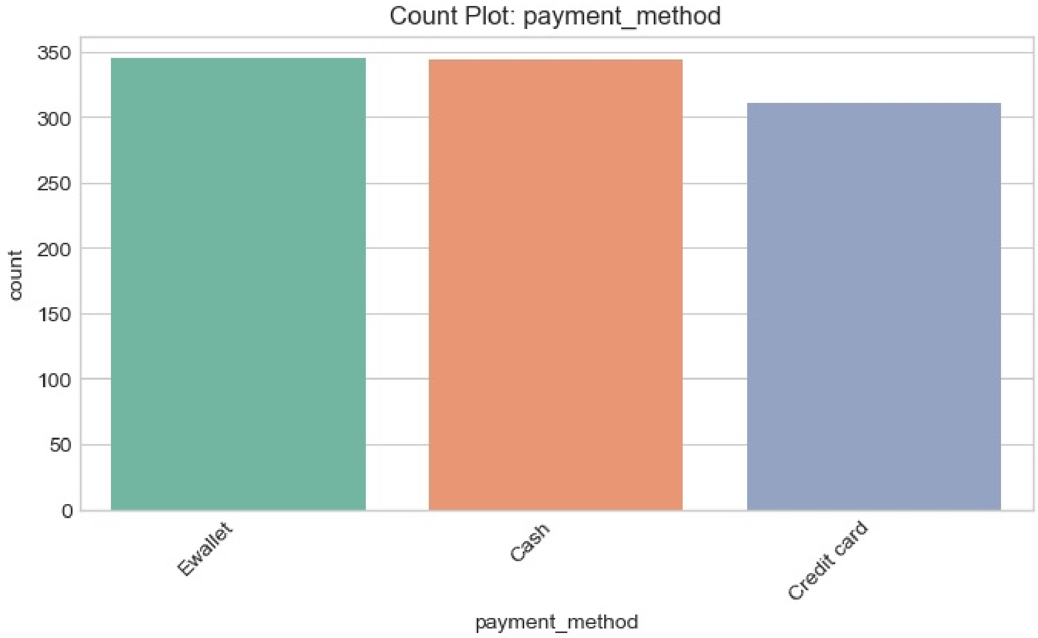


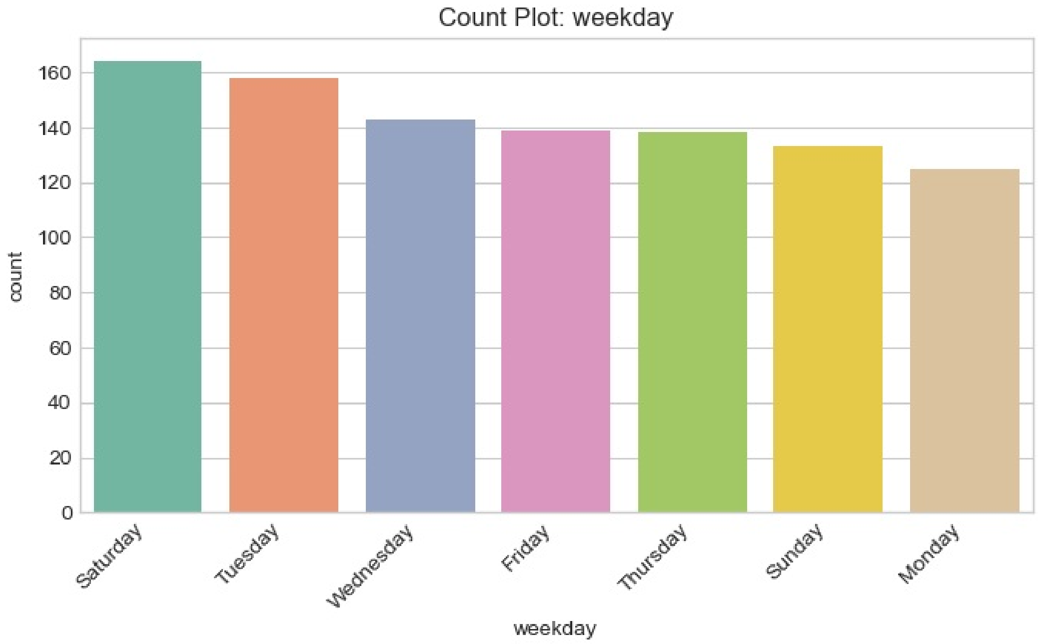



Count Plot: customer_type
count
500
400
300
200
100
0
Member
Normal
customer_type


Count Plot: gender_customer
count
500
400
300
200
100
0
Female
Male
gender_customer

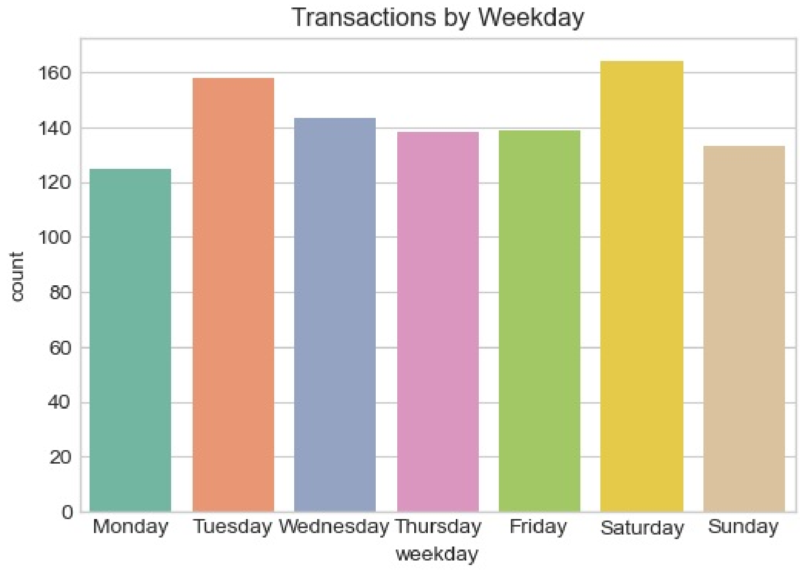

Count Plot: product_line
count
175
150
125
100
75
50
25
0
Fashion accessories
Food and beverages
Electronic accessories
Sports and travel
Home and lifestyle
Health and beauty
product_line

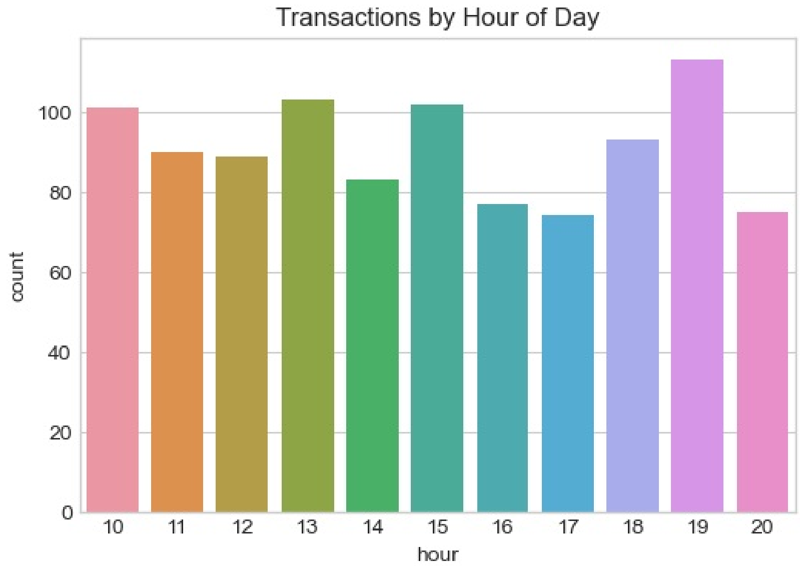




In [13]:

```
# Plot time-based features
plt.figure(figsize=(6,4))
sns.countplot(data=df, x='weekday', order=['Monday','Tuesday','Wednesday','Thursday','Friday','Saturday','Sunda
plt.title("Transactions by Weekday")
plt.show()

plt.figure(figsize=(6,4))
sns.countplot(data=df, x='hour')
plt.title("Transactions by Hour of Day")
plt.show()

plt.figure(figsize=(6,4))
sns.countplot(data=df, x='month')
plt.title("Transactions by Month")
plt.show()
```

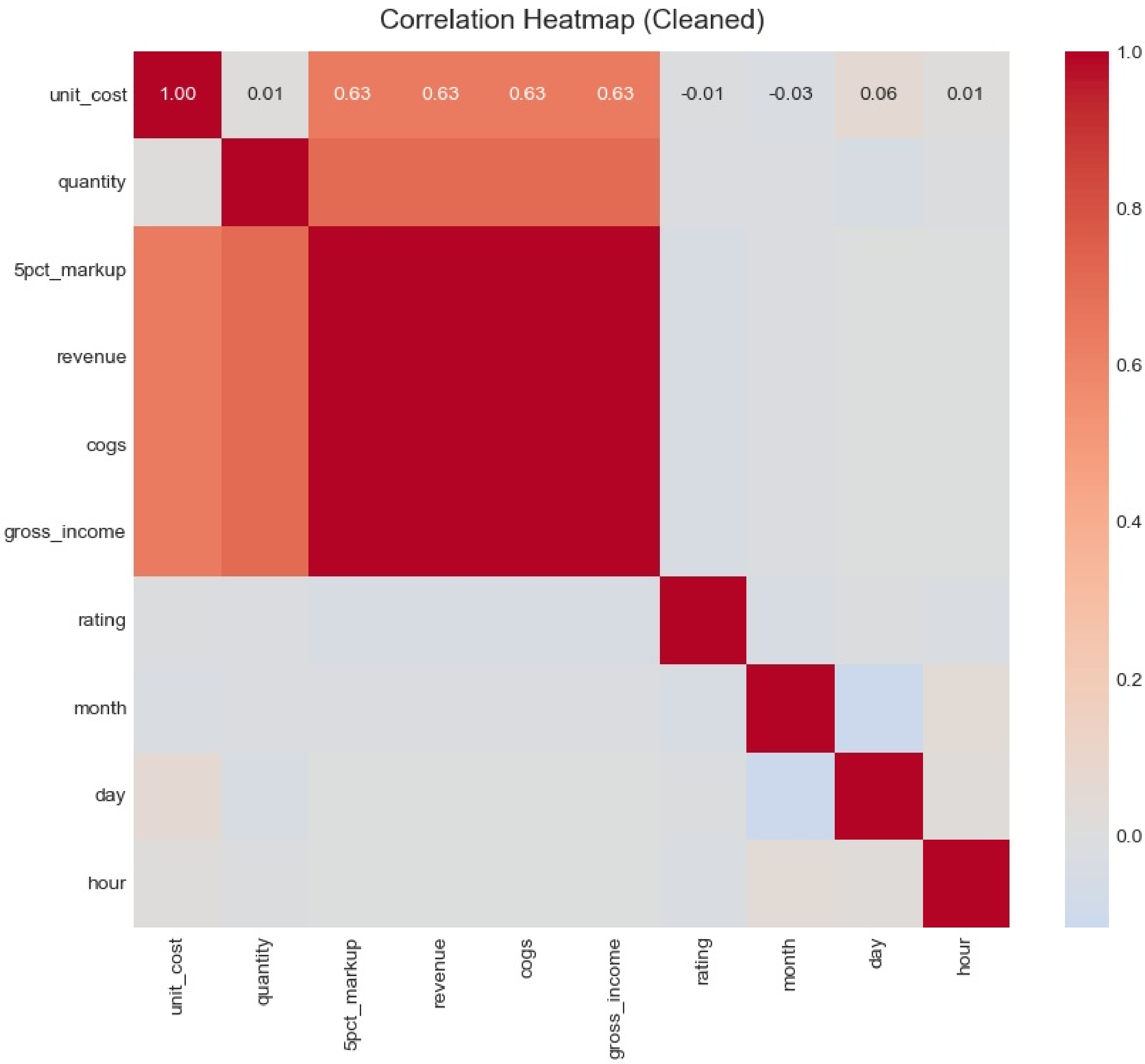


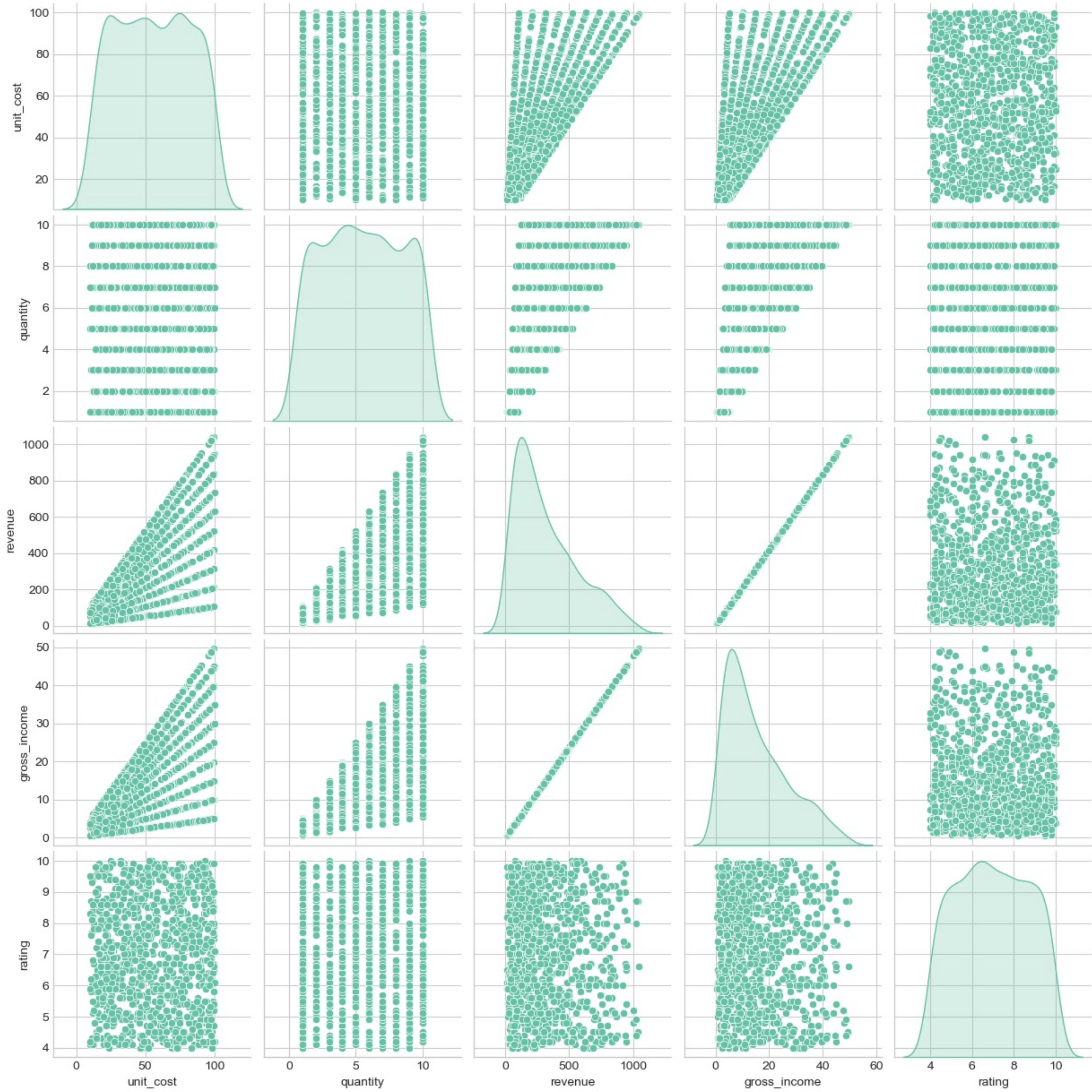


In [14]:

```
# Correlation heatmap & pairplot
# Drop useless columns
numeric_df = df.select_dtypes(include=['number']).drop(columns=['year','gm_pct'], errors='ignore')

# Compute correlation matrix
corr = numeric_df.corr()

# Plot heatmap
plt.figure(figsize=(10,8))
sns.heatmap(
    corr,
    annot=True,              # show values
    fmt=".2f",               # 2 decimal places
    cmap="coolwarm",         # better colormap
```

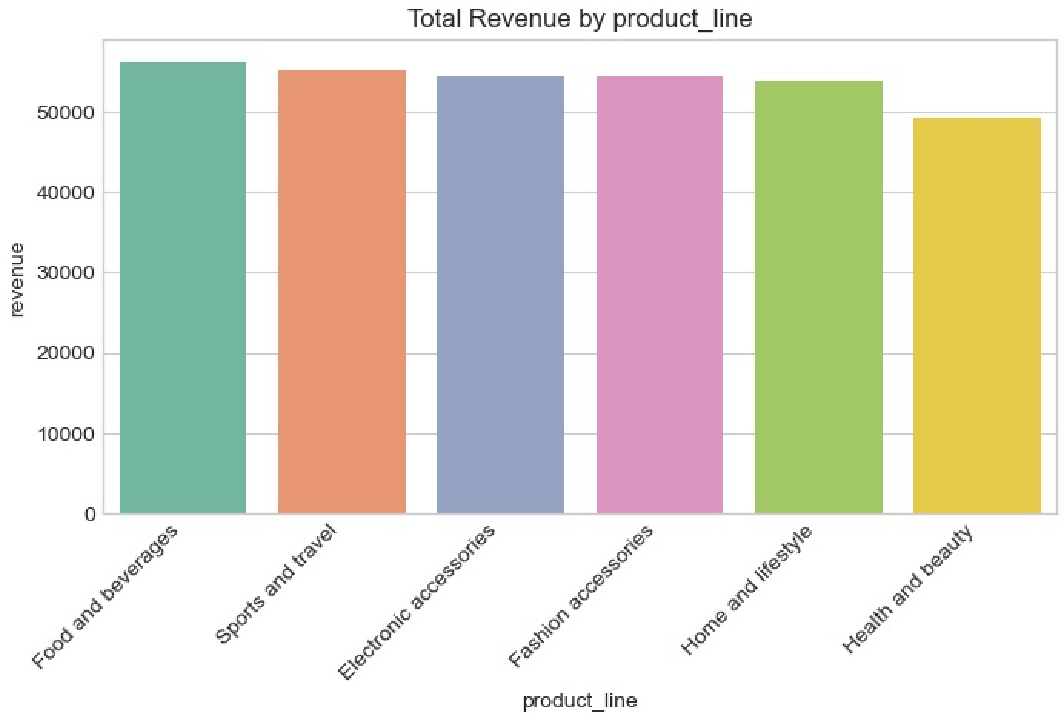
```
    center=0,                # center at 0
    square=True,             # keep square cells
)
plt.title("Correlation Heatmap (Cleaned)", fontsize=14, pad=12)
plt.show()


# Pairplot (subset to avoid clutter)
subset_cols = ['unit_cost','quantity','revenue','gross_income','rating']
sns.pairplot(df[subset_cols].dropna(), diag_kind='kde')
plt.show()
```

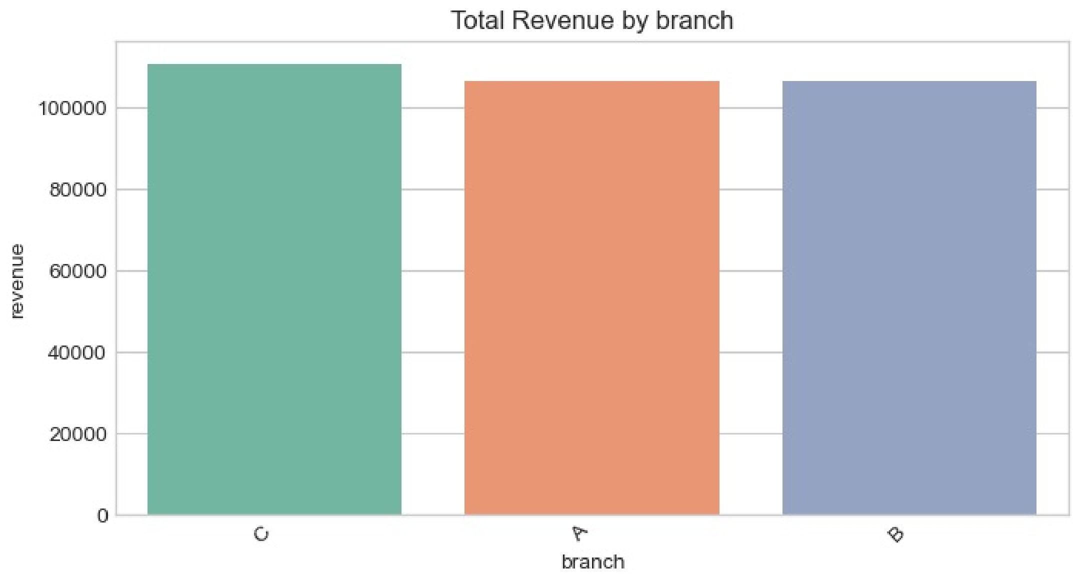


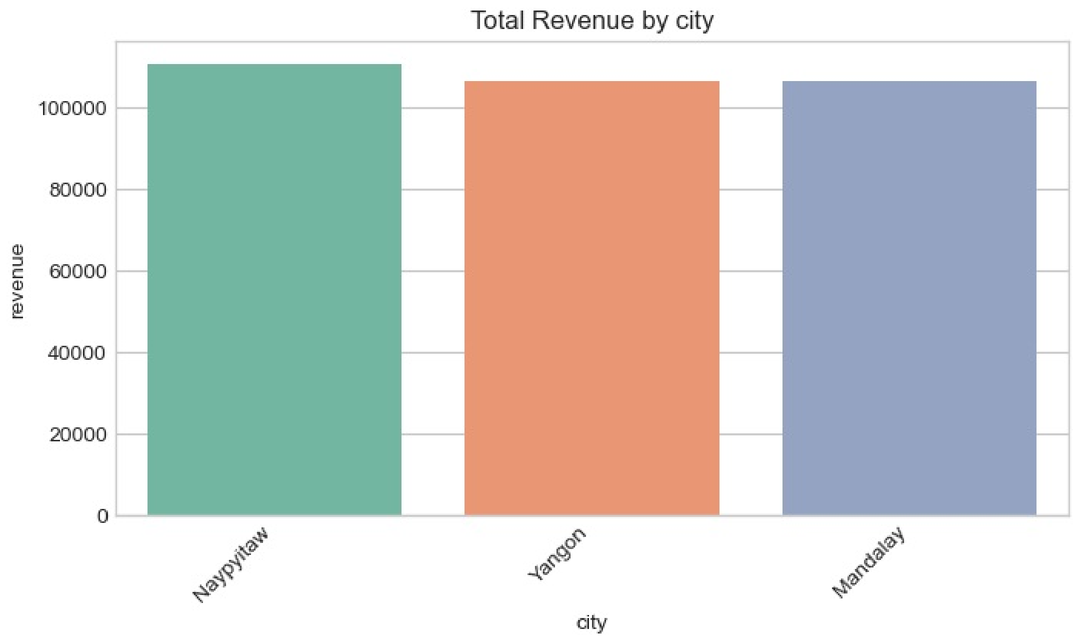


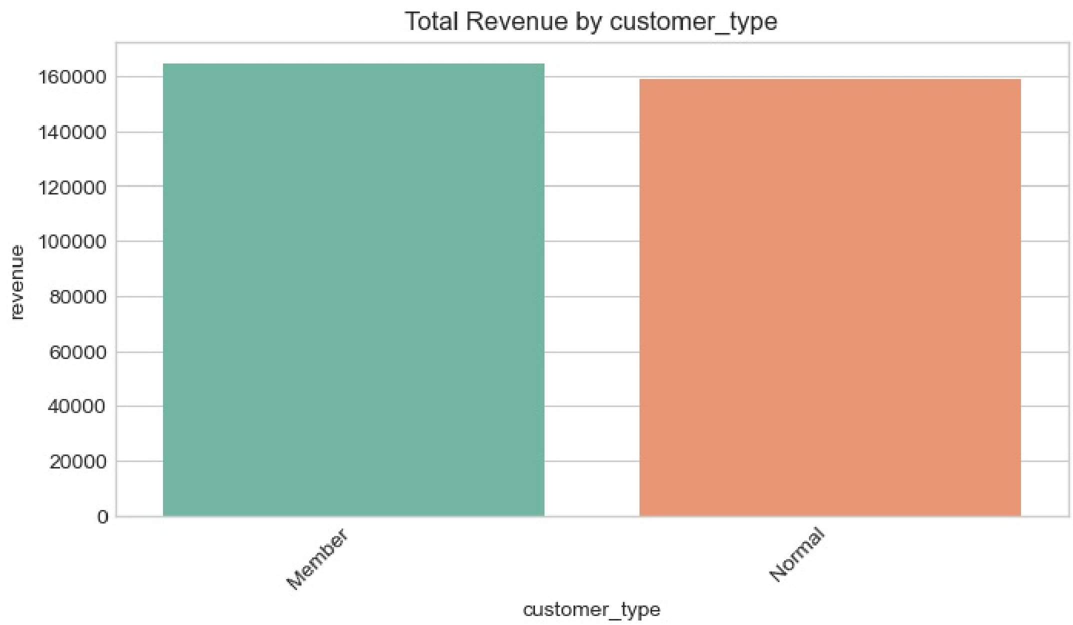
In [15]:
```
# Groupby analysis with barplots
group_cols = ['product_line', 'branch', 'city', 'customer_type', 'gender_customer', 'payment_method', 'weekday'
```

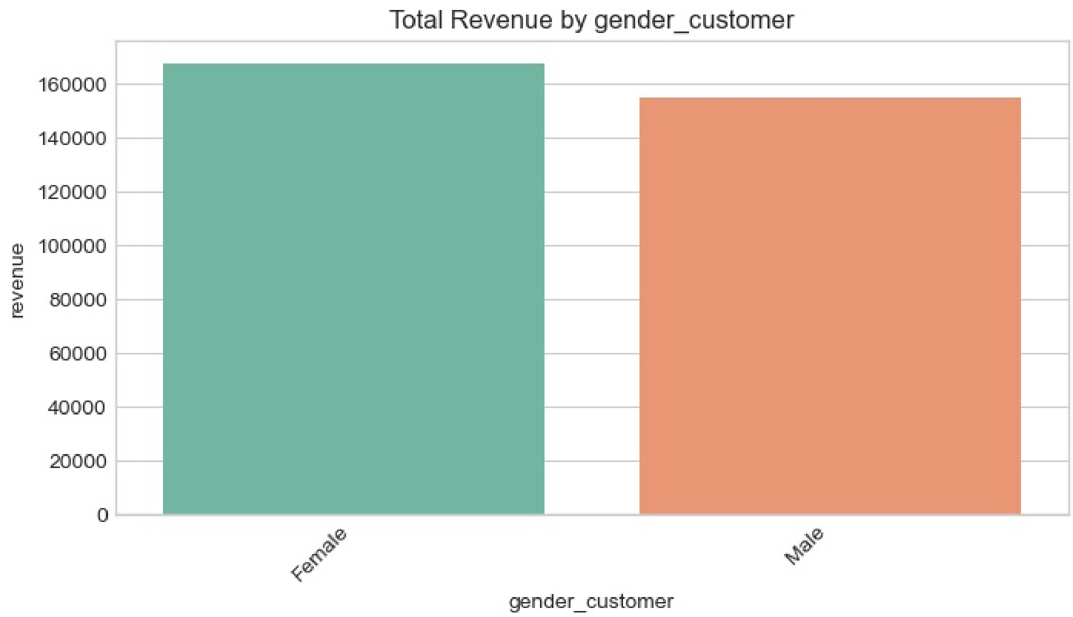
```
for gc in group_cols:
    if gc in df.columns:
        g = df.groupby(gc).agg({'revenue':'sum','gross_income':'sum','quantity':'sum','rating':'mean'}).reset_i
        plt.figure(figsize=(8,4))
        sns.barplot(data=g, x=gc, y='revenue', order=g.sort_values('revenue',ascending=False)[gc])
        plt.title(f'Total Revenue by {gc}')
        plt.xticks(rotation=45, ha='right')
        plt.show()
```

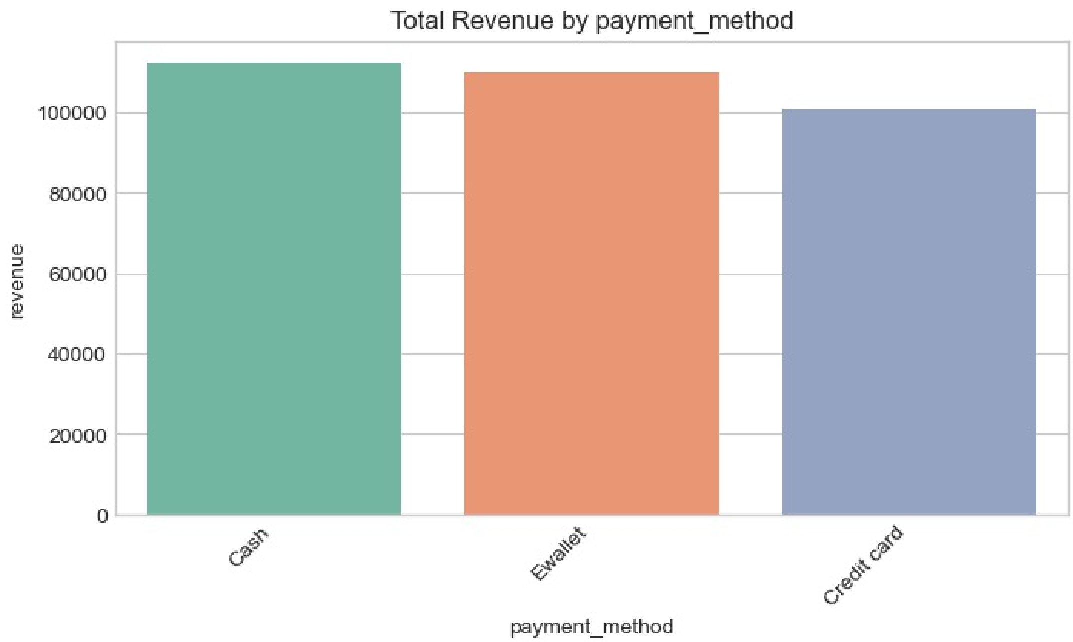


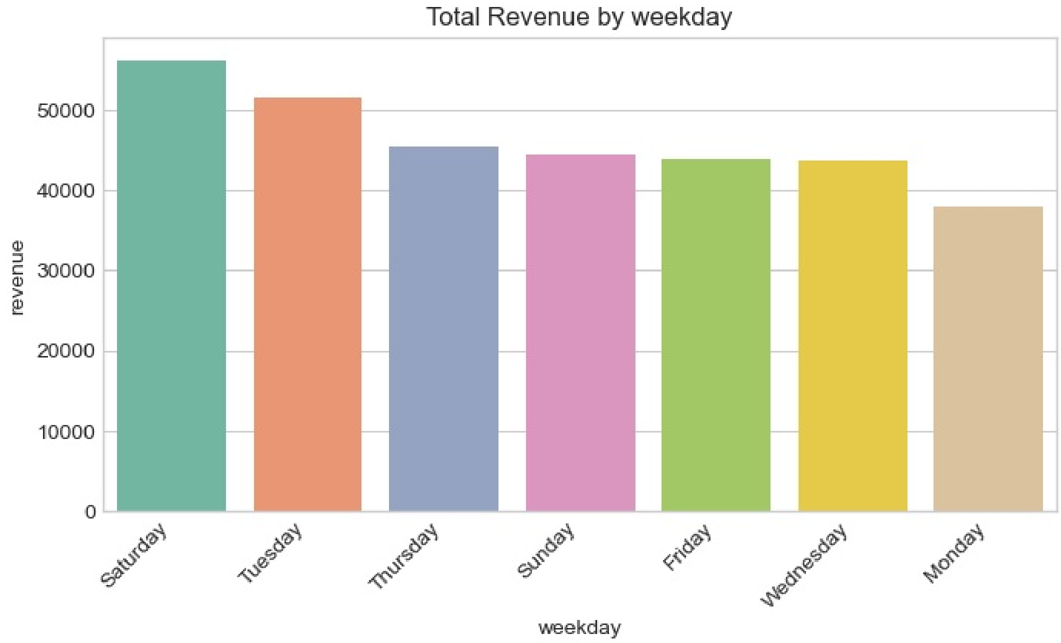


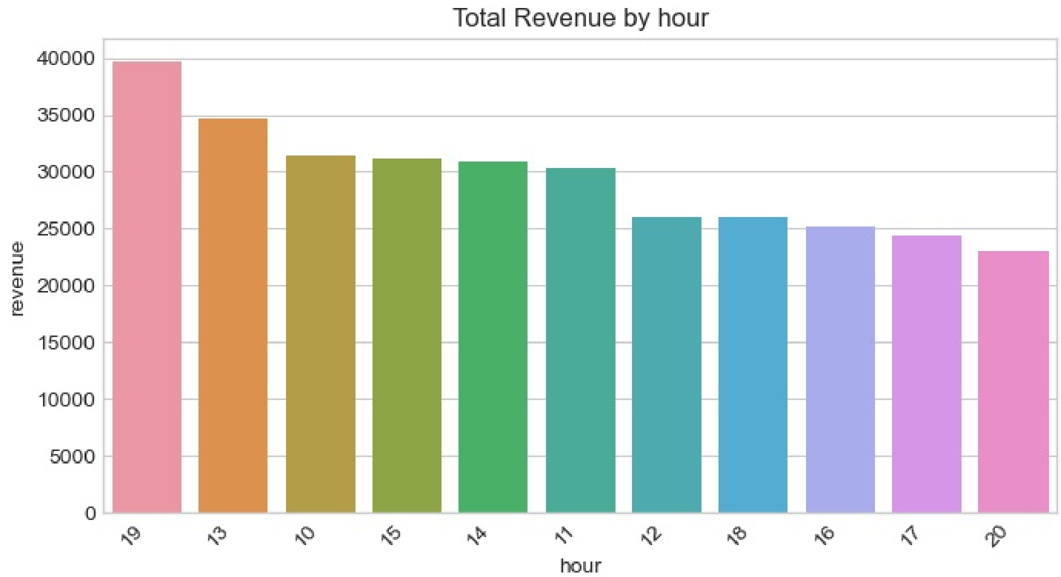

Total Revenue by city
revenue
100000
80000
60000
40000
20000
0
Naypyitaw
Yangon
Mandalay
city


Total Revenue by customer_type
revenue
160000
140000
120000
100000
80000
60000
40000
20000
0
Member
Normal
customer_type


Total Revenue by gender_customer
revenue
160000
140000
120000
100000
80000
60000
40000
20000
0
Female
Male
gender_customer


Total Revenue by payment_method
revenue
100000
80000
60000
40000
20000
0
Cash
Ewallet
Credit card
payment_method

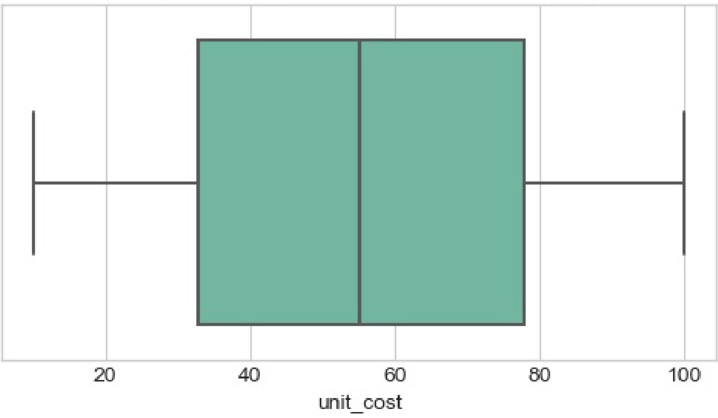




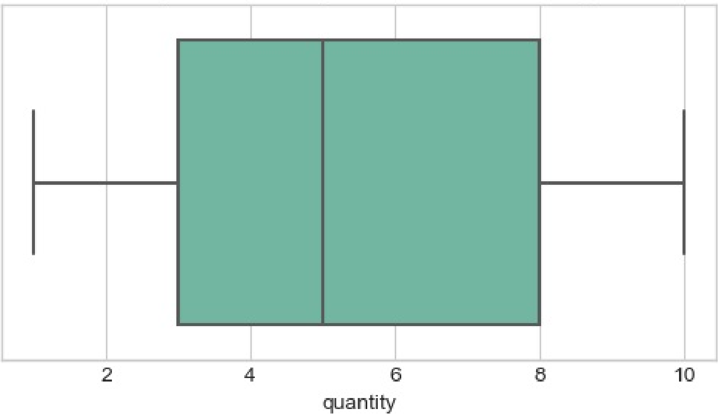
In [16]:

```
# Outlier counts & skewness
numeric_cols = df.select_dtypes(include=['number']).columns

# 3. Visualize outliers using boxplots
for col in numeric_cols:
    plt.figure(figsize=(6,3))
    sns.boxplot(x=df[col])
    plt.title(f"Boxplot of {col} before Outlier handling")
    plt.show()
```

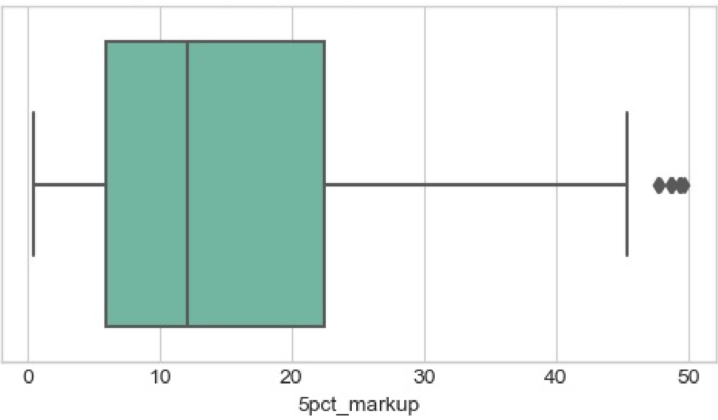
Boxplot of unit_cost before Outlier handling



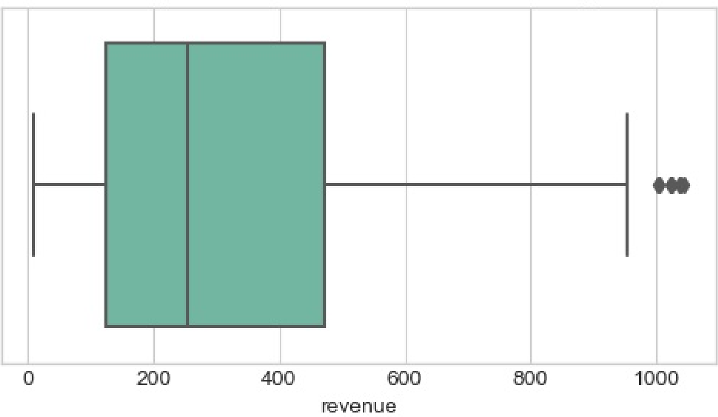
Boxplot of quantity before Outlier handling

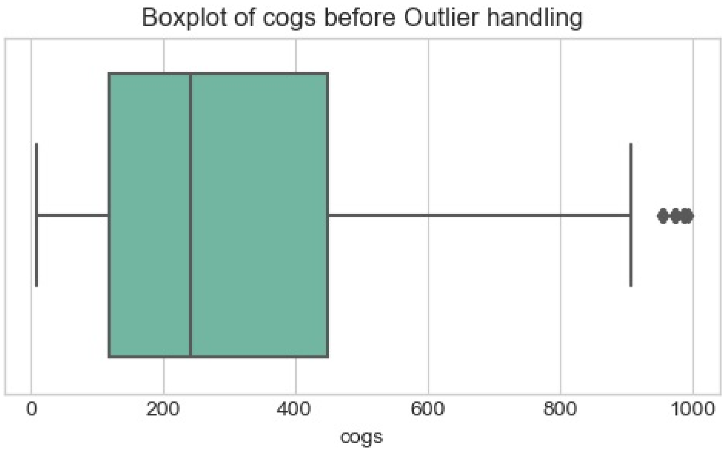


Boxplot of 5pct_markup before Outlier handling

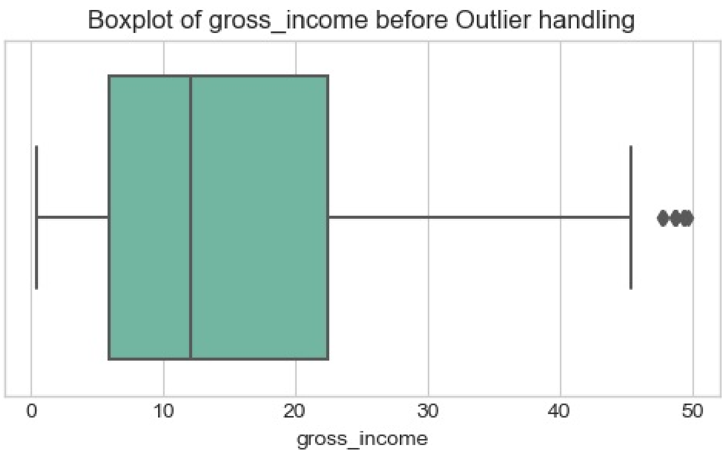


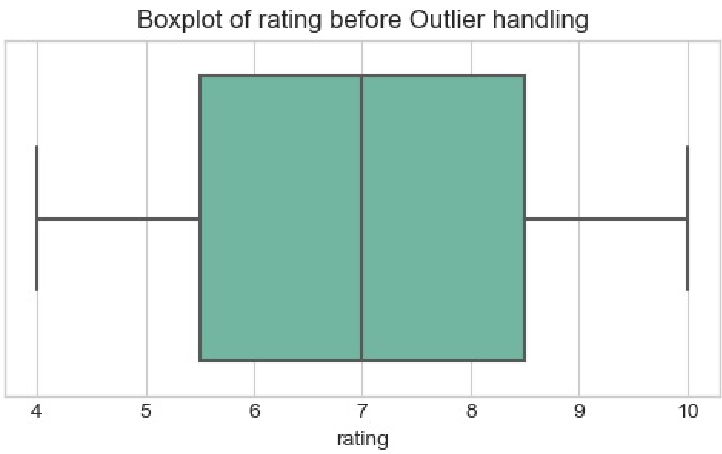
Boxplot of revenue before Outlier handling

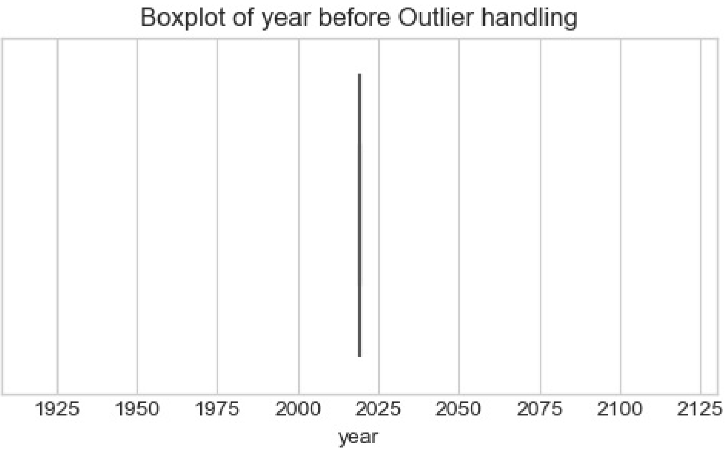


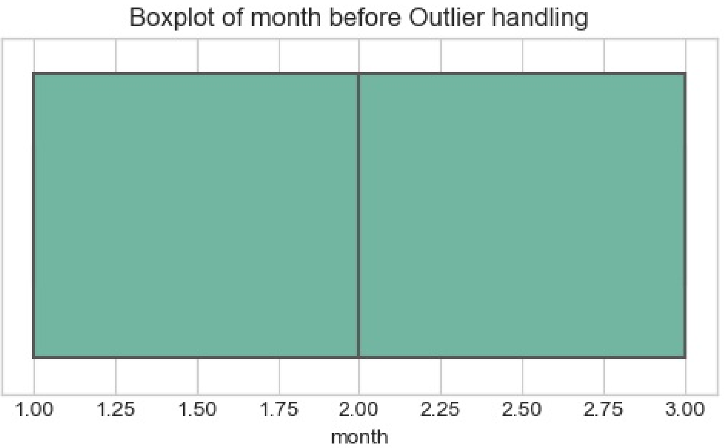

Boxplot of cogs before Outlier handling
0
200
400
600
800
1000
cogs

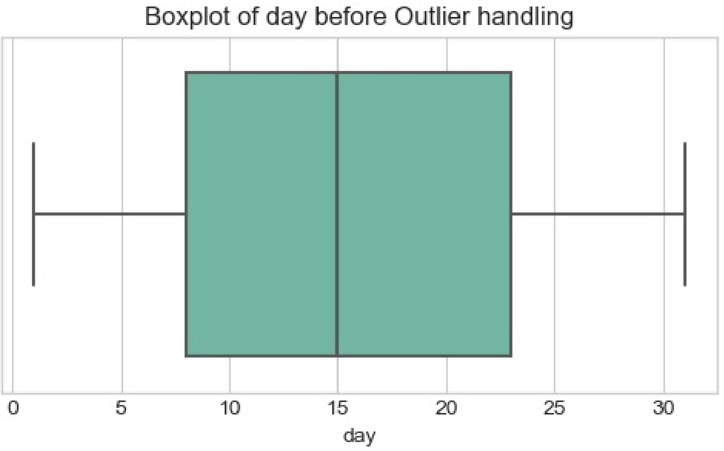

Boxplot of gm_pct before Outlier handling
4.6
4.7
4.8
4.9
5.0
gm_pct

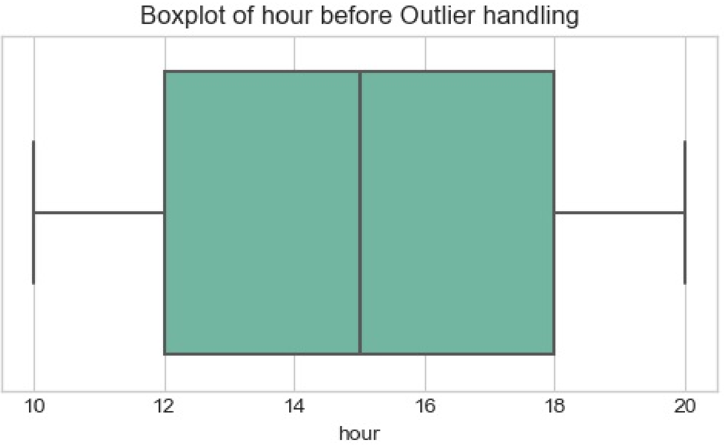

Boxplot of gross_income before Outlier handling
0
10
20
30
40
50
gross_income


Boxplot of rating before Outlier handling
4
5
6
7
8
9
10
rating







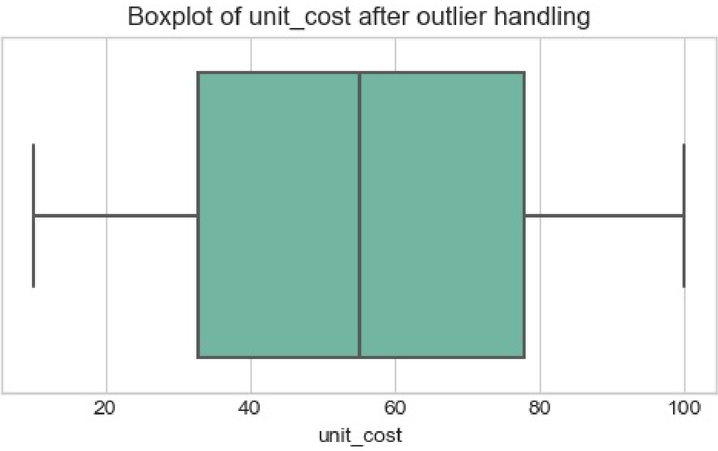


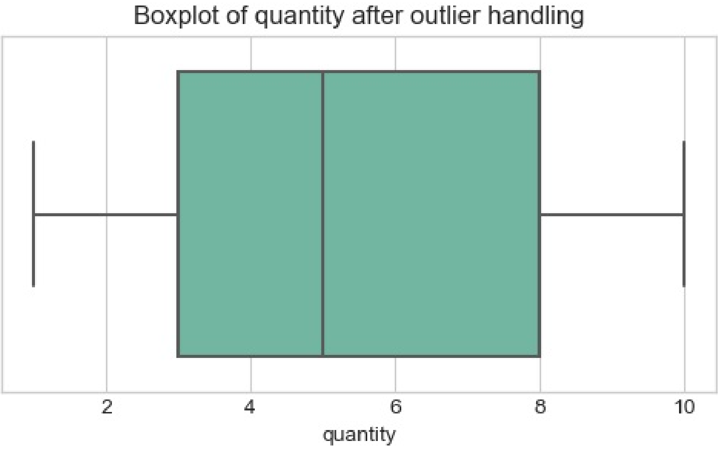
In [17]:

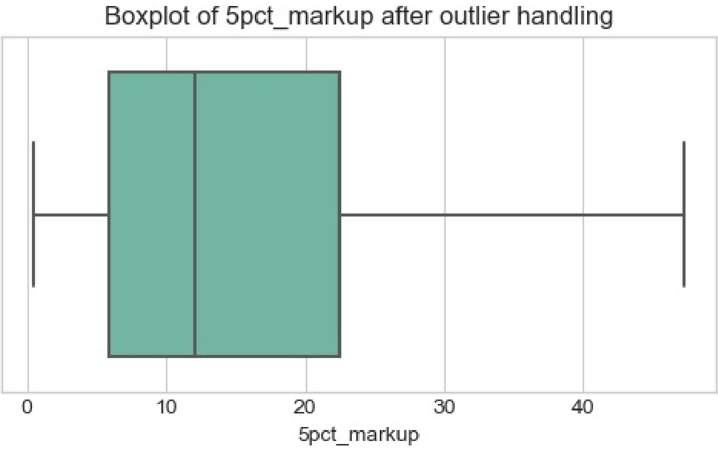
```
for col in numeric_cols:
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower = Q1 - 1.5 * IQR
    upper = Q3 + 1.5 * IQR
    df[col]=np.where(df[col] > upper, upper, df[col])
    df[col]=np.where(df[col]< lower, lower, df[col])
```

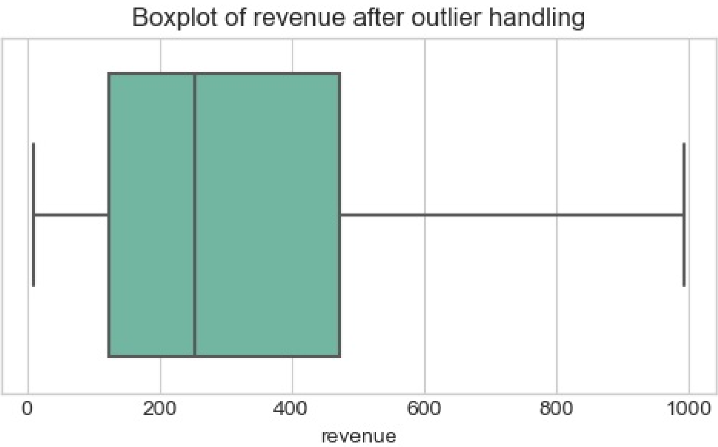
In [18]:

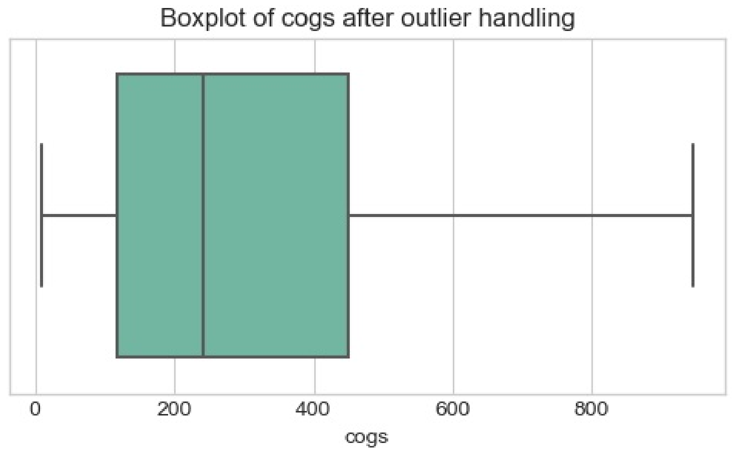
```
for col in numeric_cols:
    plt.figure(figsize=(6,3))
    sns.boxplot(x=df[col])
    plt.title(f"Boxplot of {col} after outlier handling")
    plt.show()
```

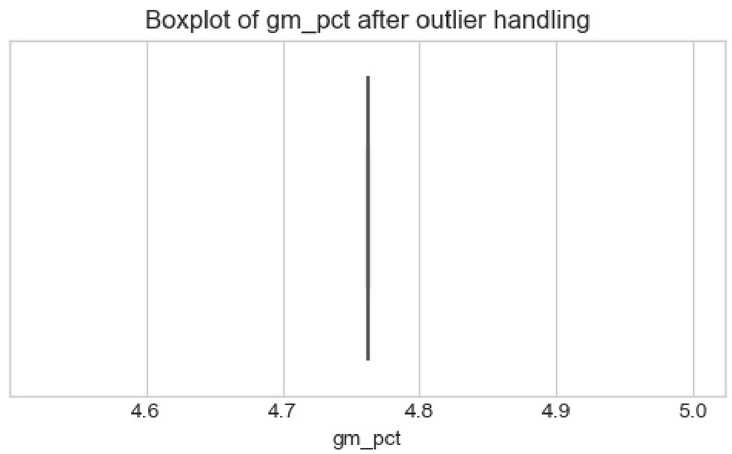


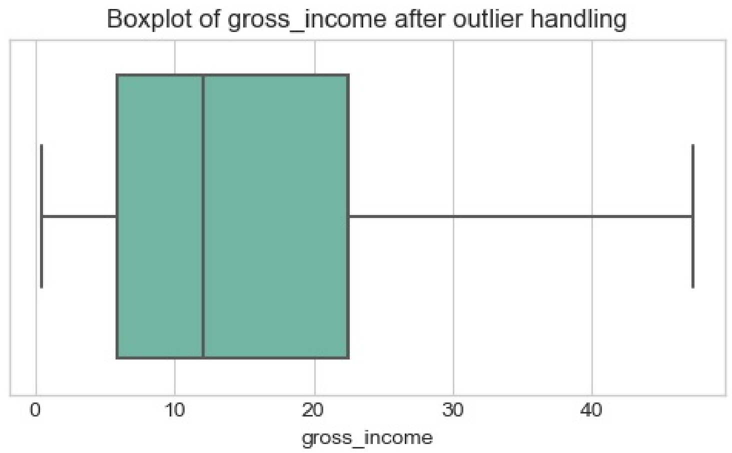


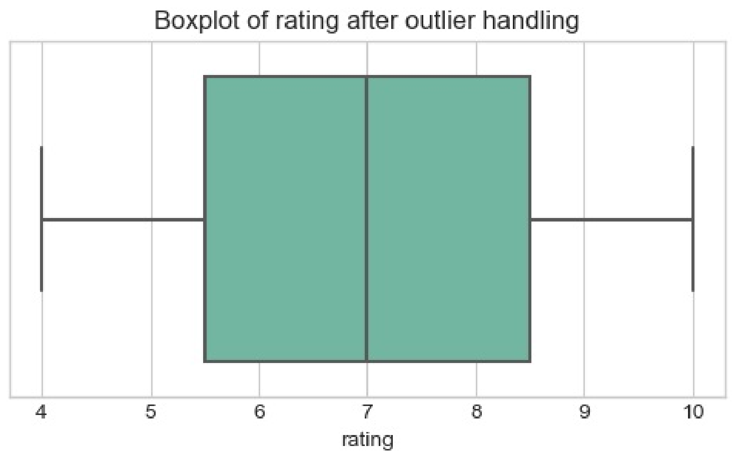


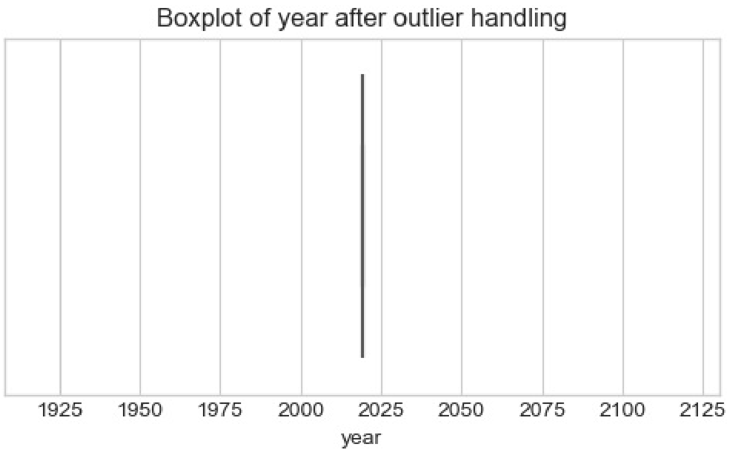


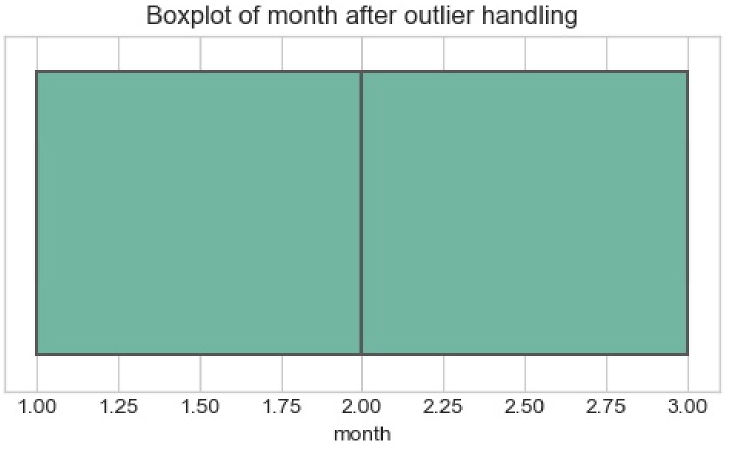

Boxplot of cogs after outlier handling
0
200
400
600
800
cogs

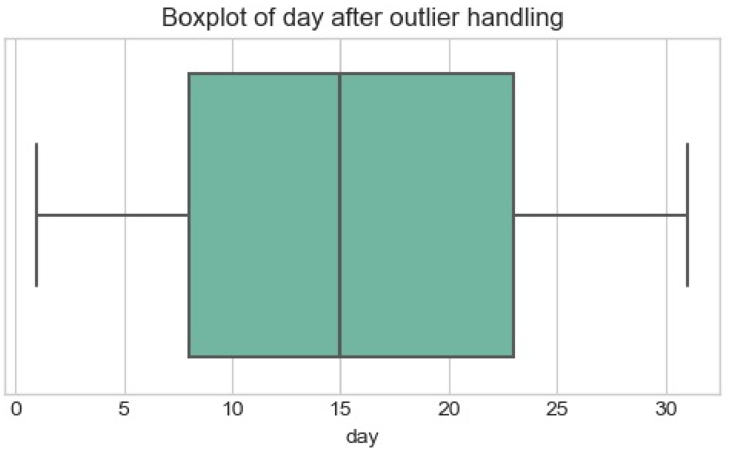

Boxplot of gm_pct after outlier handling
4.6
4.7
4.8
4.9
5.0
gm_pct

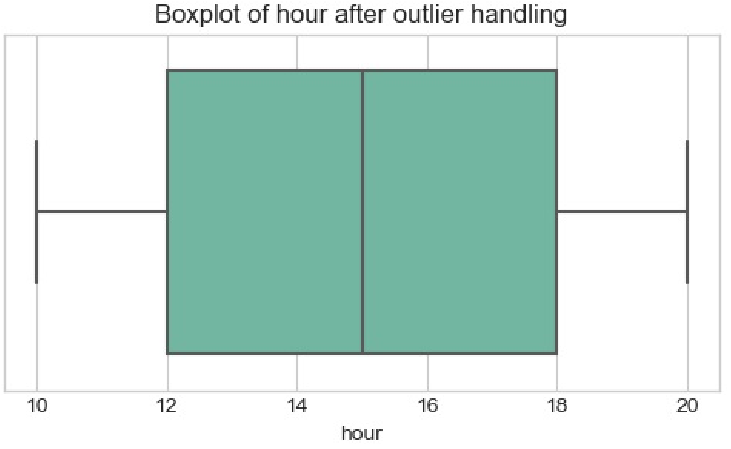

Boxplot of gross_income after outlier handling
0
10
20
30
40
gross_income


Boxplot of rating after outlier handling
4
5
6
7
8
9
10
rating







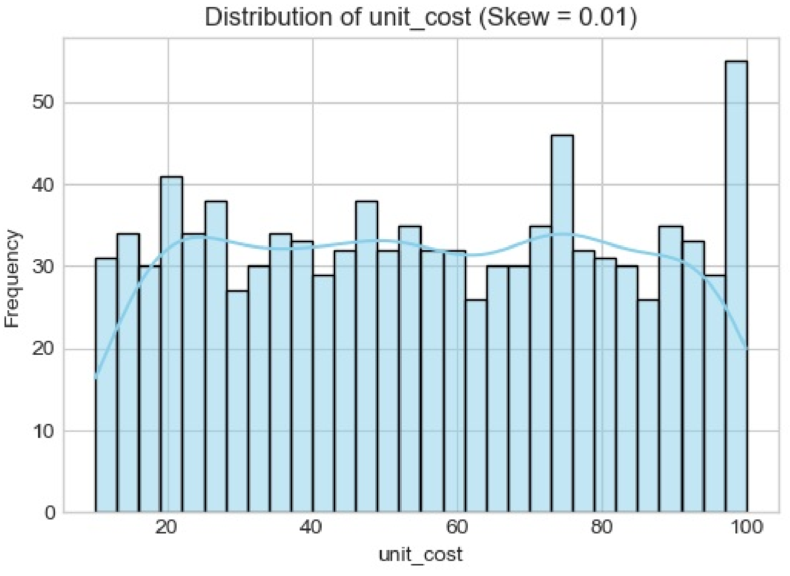


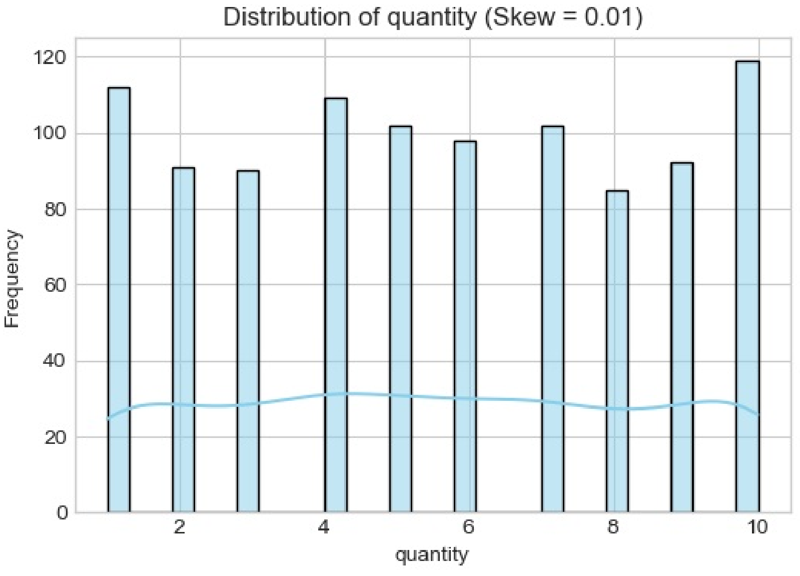
In [19]:

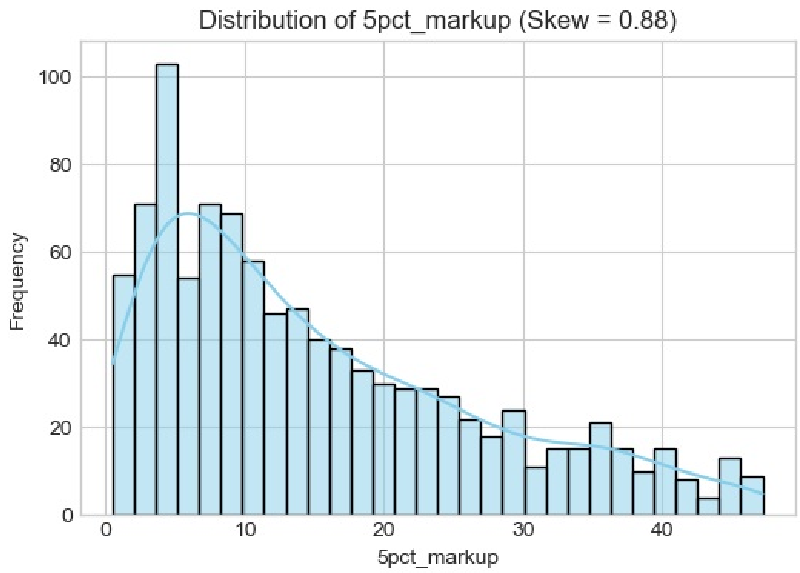
```
# 2. Check skewness of each numeric column
print("Skewness of numeric columns:")
for col in numeric_cols:
    print(f"{col}: {df[col].skew():.2f}")
```

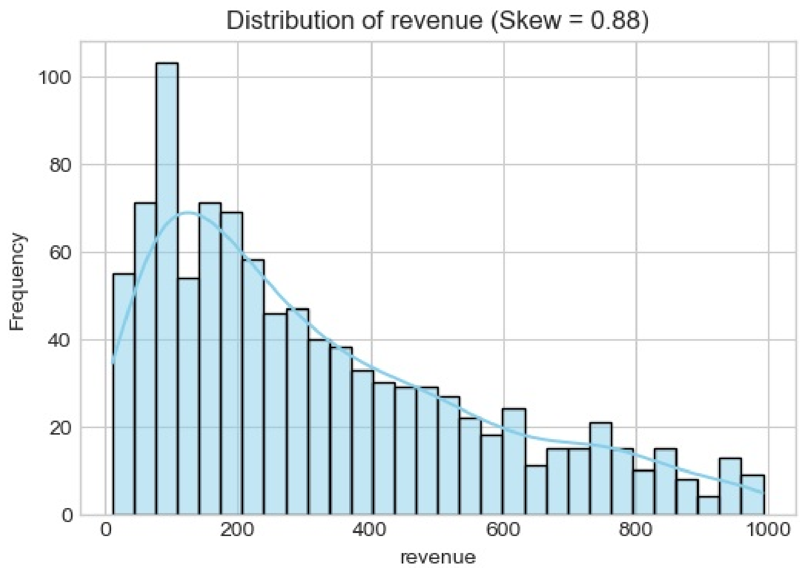
```
Skewness of numeric columns:
unit_cost: 0.01
quantity: 0.01
5pct_markup: 0.88
revenue: 0.88
cogs: 0.88
gm_pct: 0.00
gross_income: 0.88
rating: 0.01
year: 0.00
month: 0.01
day: 0.05
hour: 0.03
```

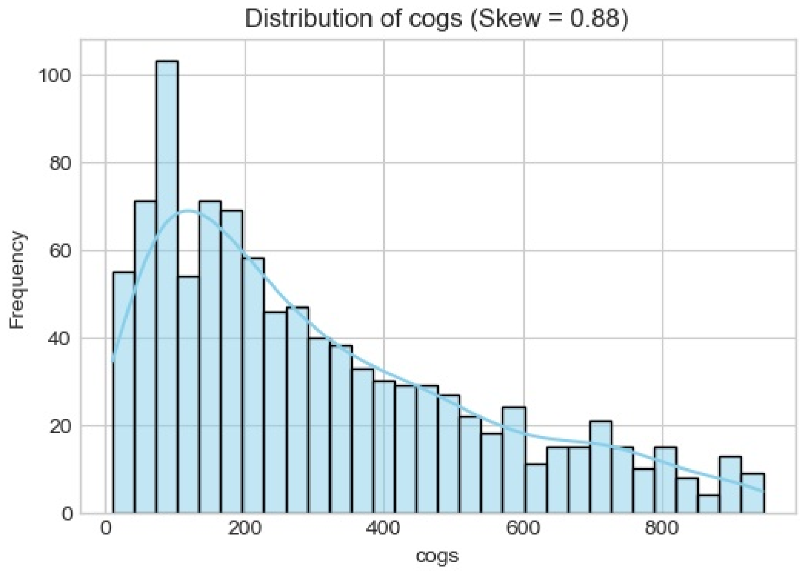
In [20]:
```
for col in numeric_cols:
    plt.figure(figsize=(6,4))
    sns.histplot(df[col], bins=30, kde=True, color="skyblue")
    plt.title(f"Distribution of {col} (Skew = {df[col].skew():.2f})")
    plt.xlabel(col)
    plt.ylabel("Frequency")
    plt.show()
```



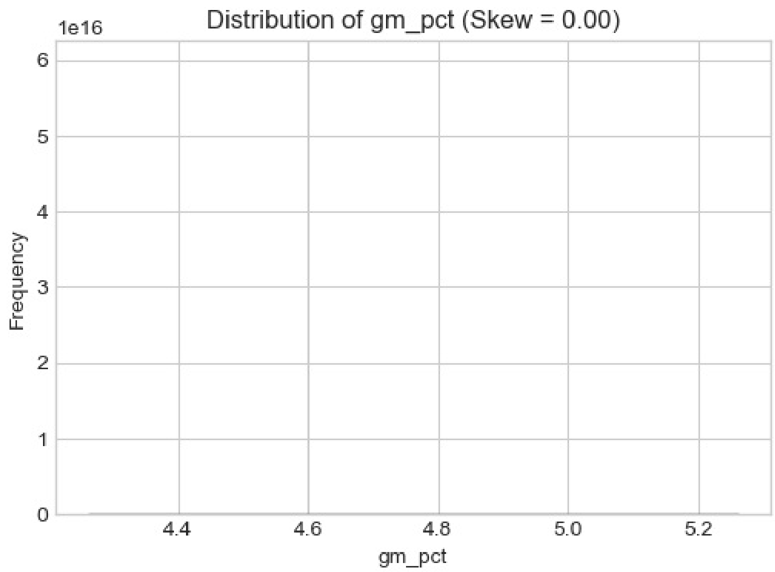



Distribution of 5pct_markup (Skew = 0.88)
Frequency
5pct_markup
0
20
40
60
80
100
0
10
20
30
40

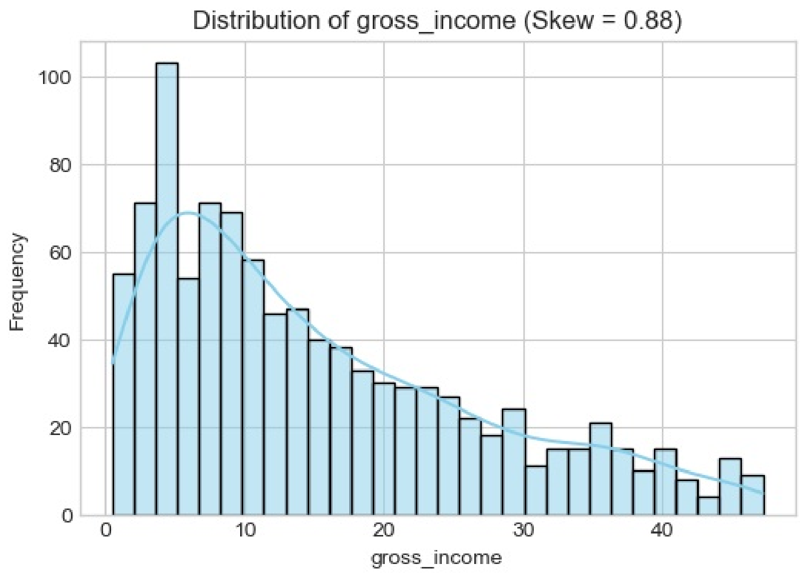

Distribution of revenue (Skew = 0.88)
Frequency
revenue
0
20
40
60
80
100
0
200
400
600
800
1000

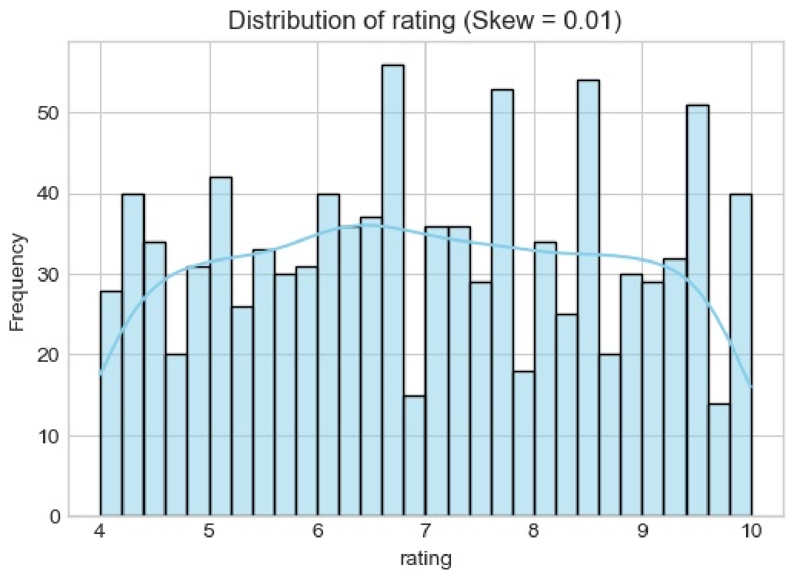


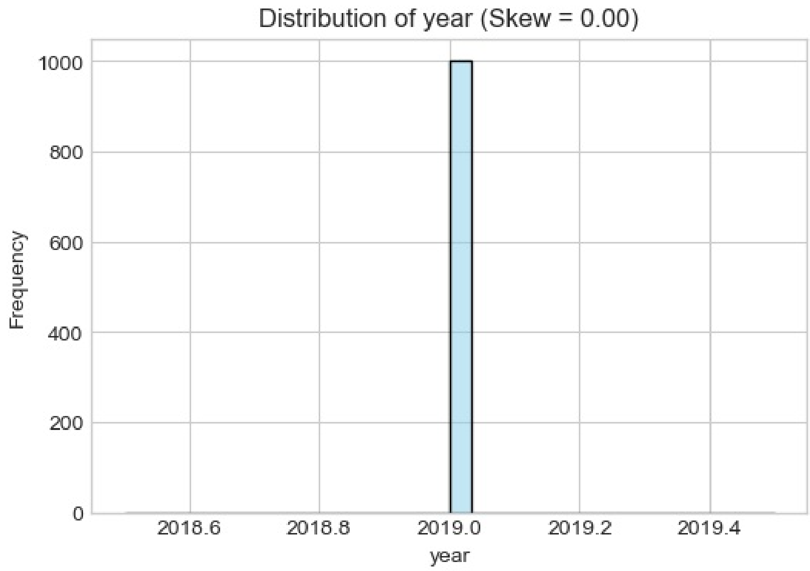
Distribution of cogs (Skew = 0.88)
Frequency
cogs
0
20
40
60
80
100
0
200
400
600
800

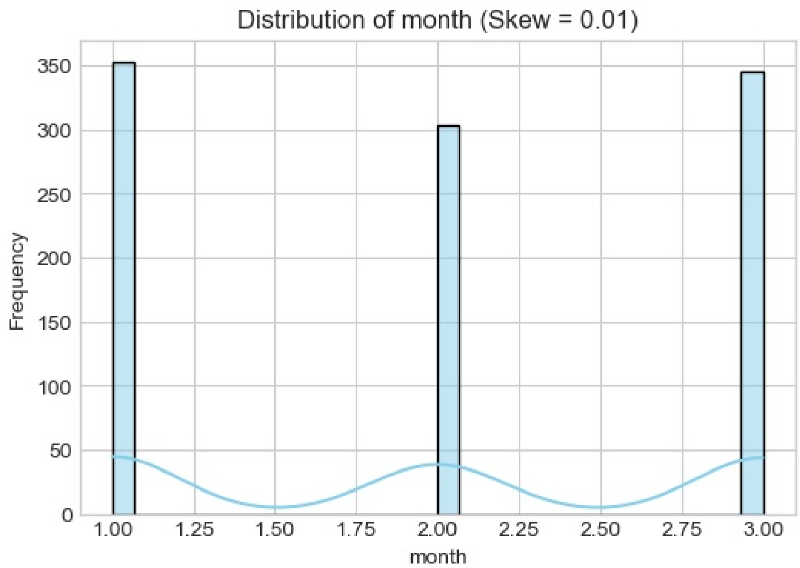


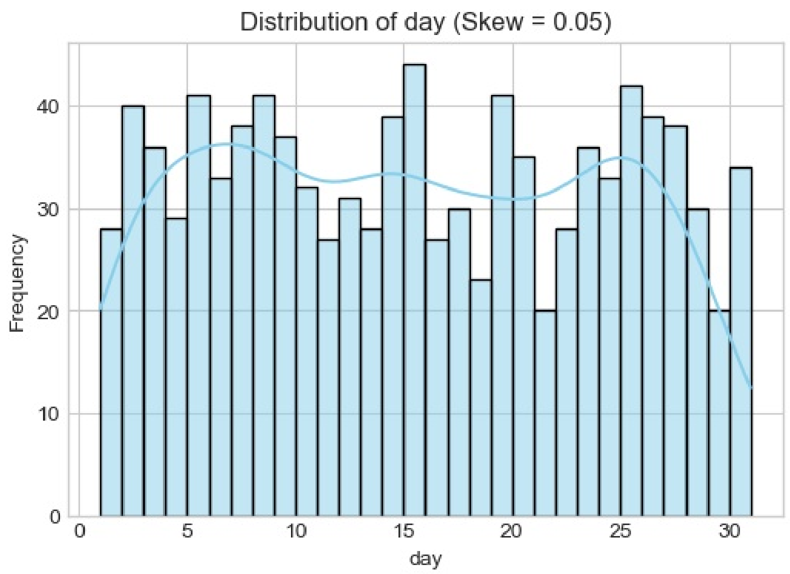
Distribution of gm_pct (Skew = 0.00)
1e16
Frequency
gm_pct
0
1
2
3
4
5
6
4.4
4.6
4.8
5.0
5.2

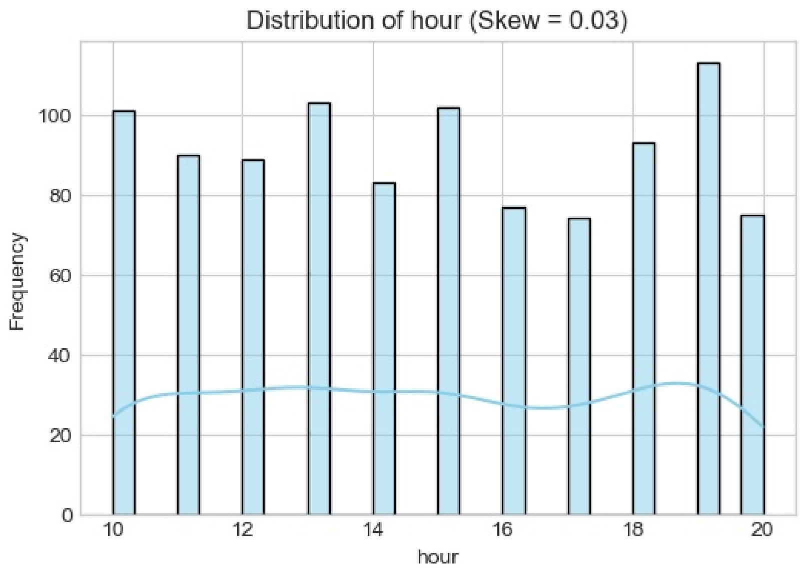

Distribution of gross_income (Skew = 0.88)
Frequency
gross_income
0
20
40
60
80
100
10
30


Distribution of rating (Skew = 0.01)
Frequency
rating
0
10
20
30
40
50
4
5
6
7
8
9
10

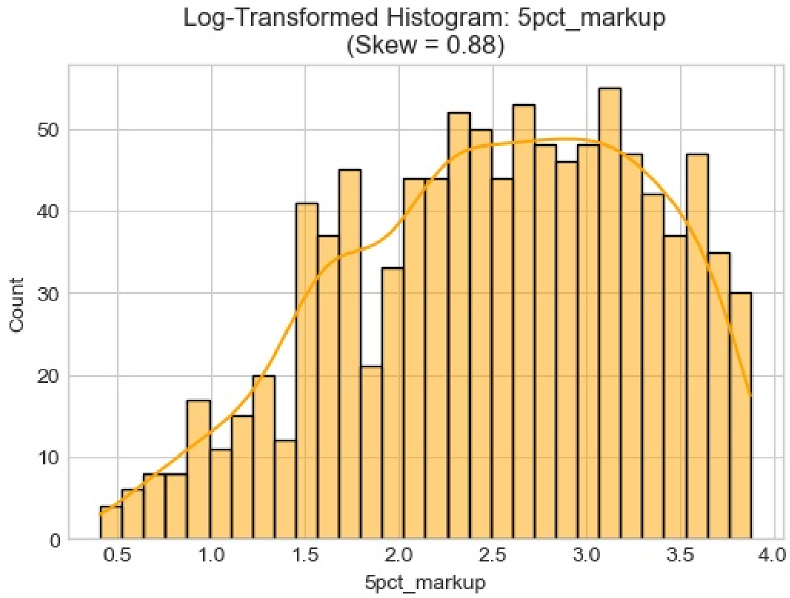

Distribution of year (Skew = 0.00)
Frequency
year
0
200
400
600
800
1000
2018.6
2018.8
2019.0
2019.2
2019.4

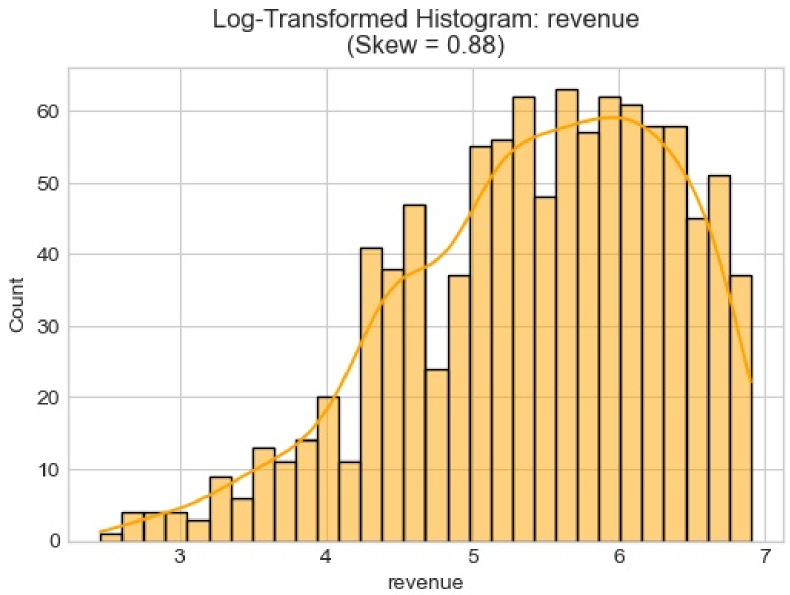

Distribution of month (Skew = 0.01)
Frequency
month
0
50
100
150
200
250
300
350
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00

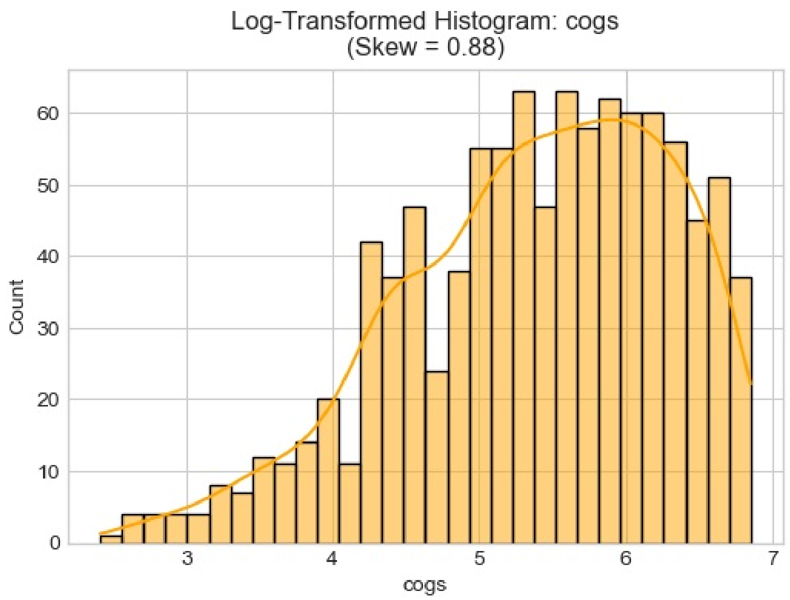


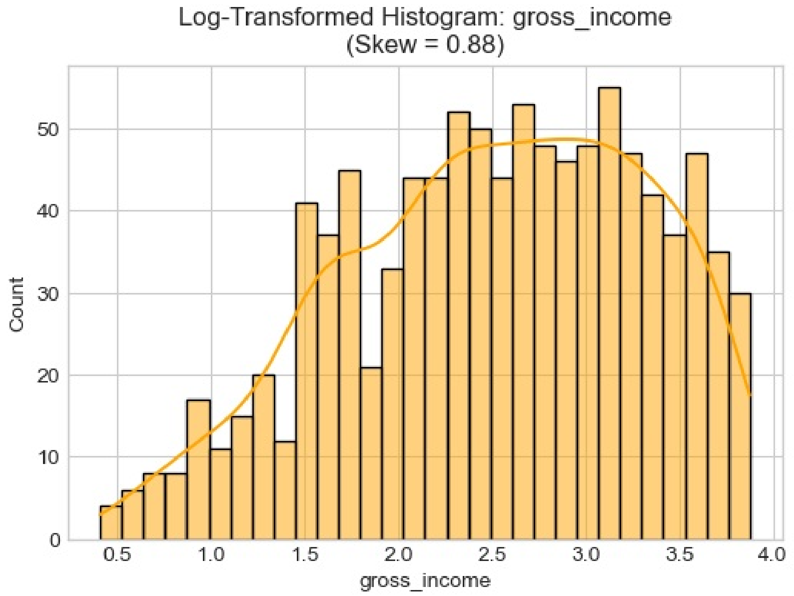


In [21]:
```
# Columns with moderate skewness based on your results
skewed_cols = ['5pct_markup','revenue','cogs','gross_income']

for col in skewed_cols:
    if col in df.columns and (df[col] >= 0).all():   # log works only on positive values
        plt.figure(figsize=(6,4))
        sns.histplot(np.log1p(df[col]), bins=30, kde=True, color="orange")
        plt.title(f'Log-Transformed Histogram: {col}\n(Skew = {df[col].skew():.2f})')
        plt.show()
```

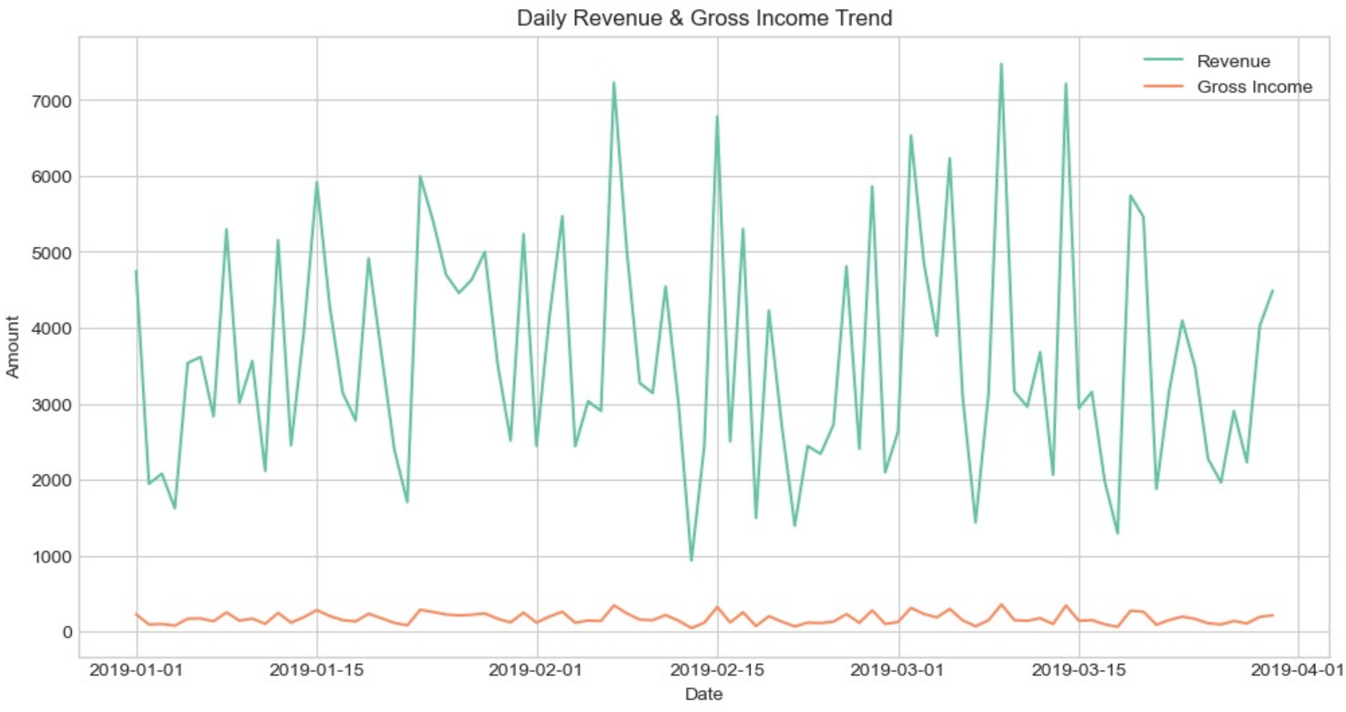

Log-Transformed Histogram: 5pct_markup
(Skew = 0.88)
Count
5pct_markup
0
10
20
30
40
50
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0


Log-Transformed Histogram: revenue
(Skew = 0.88)
Count
revenue
0
10
20
30
40
50
60
3
4
5
6
7

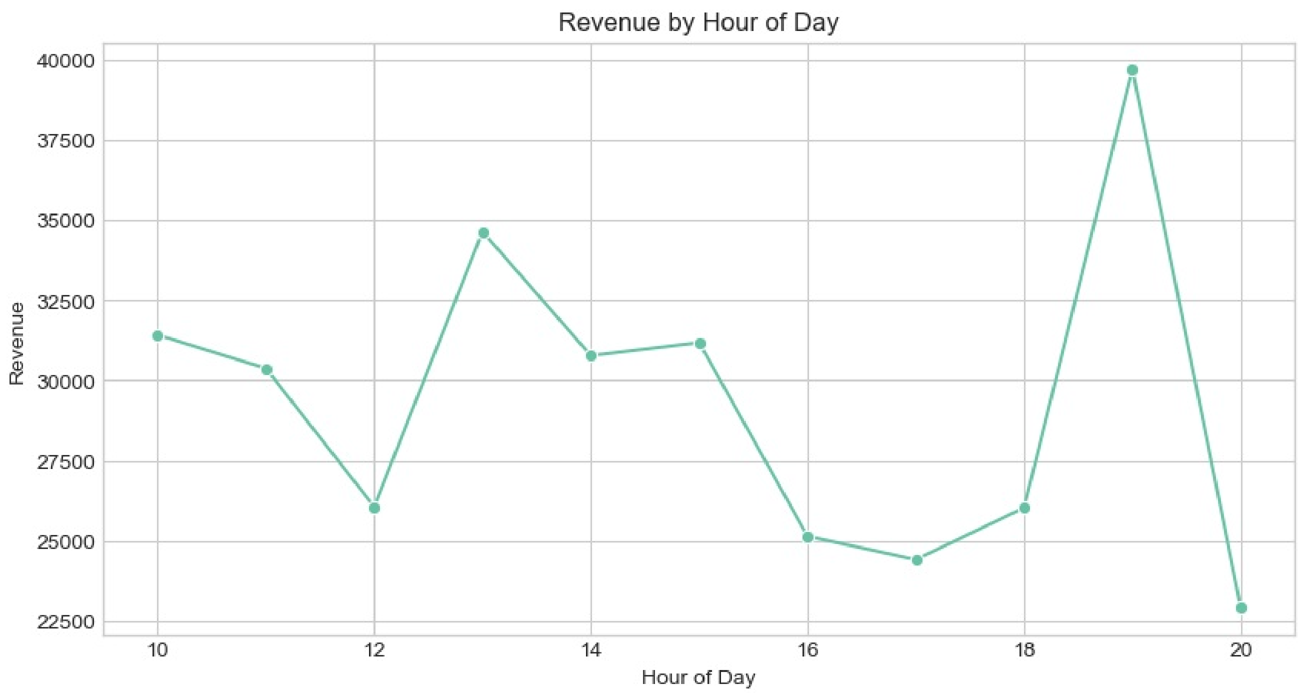

Log-Transformed Histogram: cogs
(Skew = 0.88)
Count
cogs
0
10
20
30
40
50
60
3
4
5
6
7



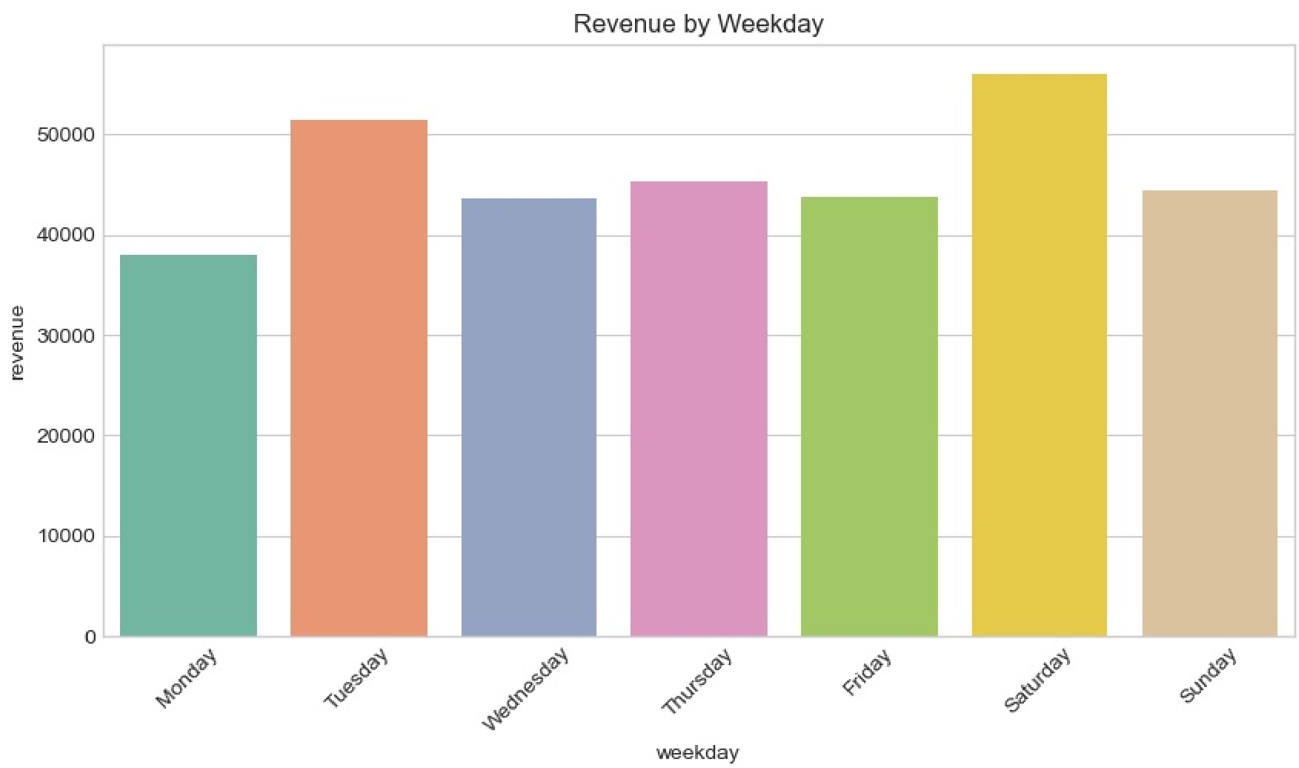
In [22]:
```
# Revenue and gross income trends by date
daily_sales = df.groupby('date_parsed').agg({'revenue':'sum','gross_income':'sum'}).reset_index()

plt.figure(figsize=(12,6))
sns.lineplot(data=daily_sales, x='date_parsed', y='revenue', label='Revenue')
sns.lineplot(data=daily_sales, x='date_parsed', y='gross_income', label='Gross Income')
plt.title("Daily Revenue & Gross Income Trend")
plt.xlabel("Date")
plt.ylabel("Amount")
plt.legend()
plt.show()
```



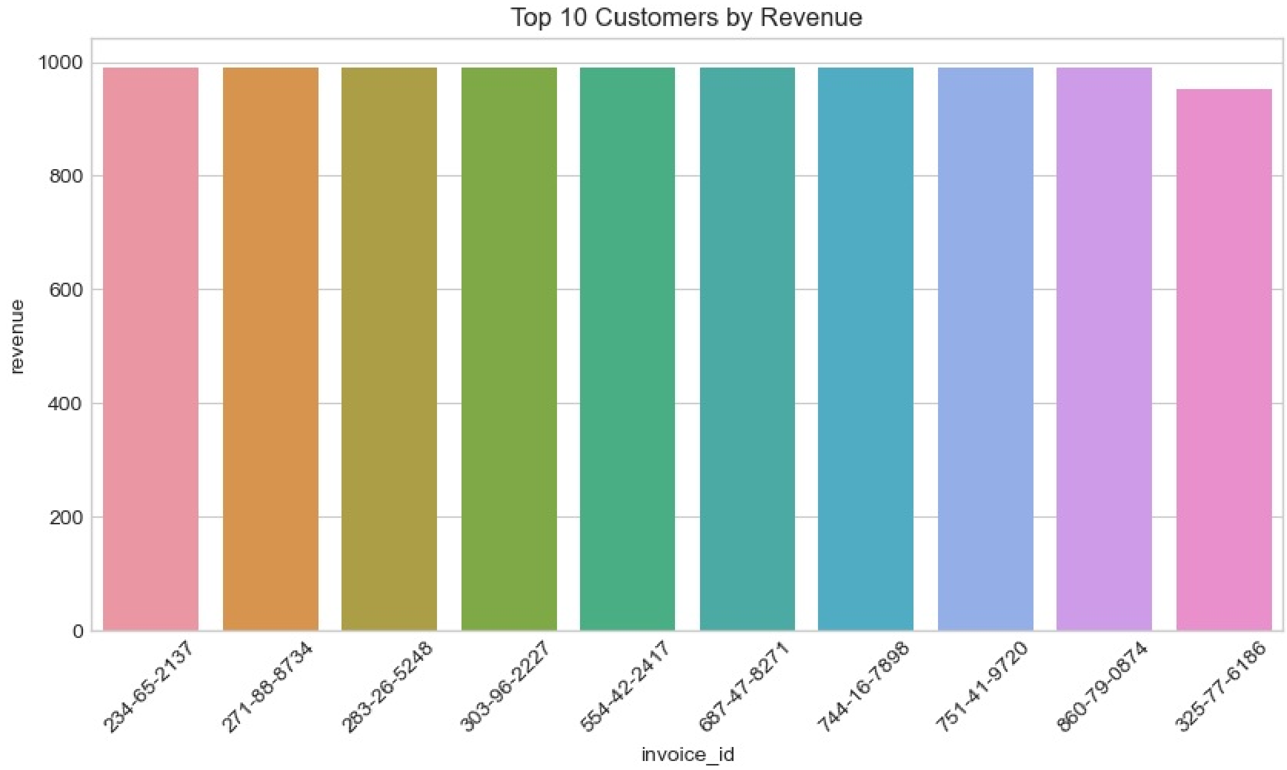
In [23]:
```
# Peak Sales by Hour of Day
plt.figure(figsize=(10,5))
sns.lineplot(data=df.groupby('hour')['revenue'].sum().reset_index(),
             x='hour', y='revenue', marker="o")
plt.title("Revenue by Hour of Day")
plt.xlabel("Hour of Day")
plt.ylabel("Revenue")
plt.show()
```



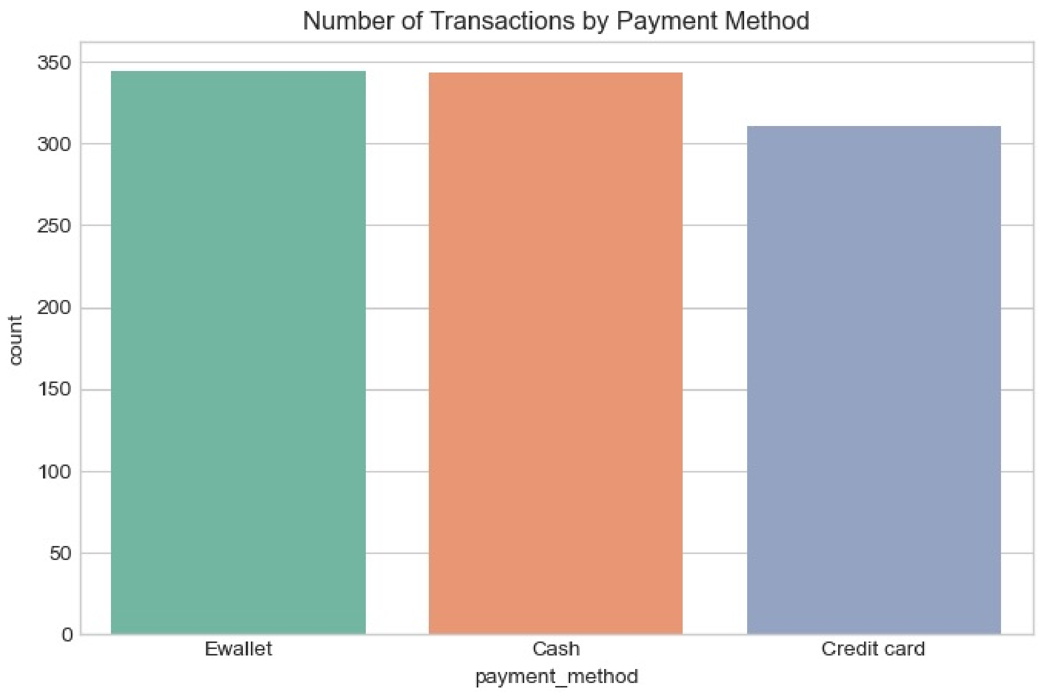
In [25]:
```
# Revenue by Weekday
weekday_order = ['Monday','Tuesday','Wednesday','Thursday','Friday','Saturday','Sunday']
plt.figure(figsize=(10,5))
sns.barplot(data=df, x='weekday', y='revenue',
            estimator=sum, order=weekday_order, ci=None)
plt.title("Revenue by Weekday")
plt.xticks(rotation=45)
plt.show()
```

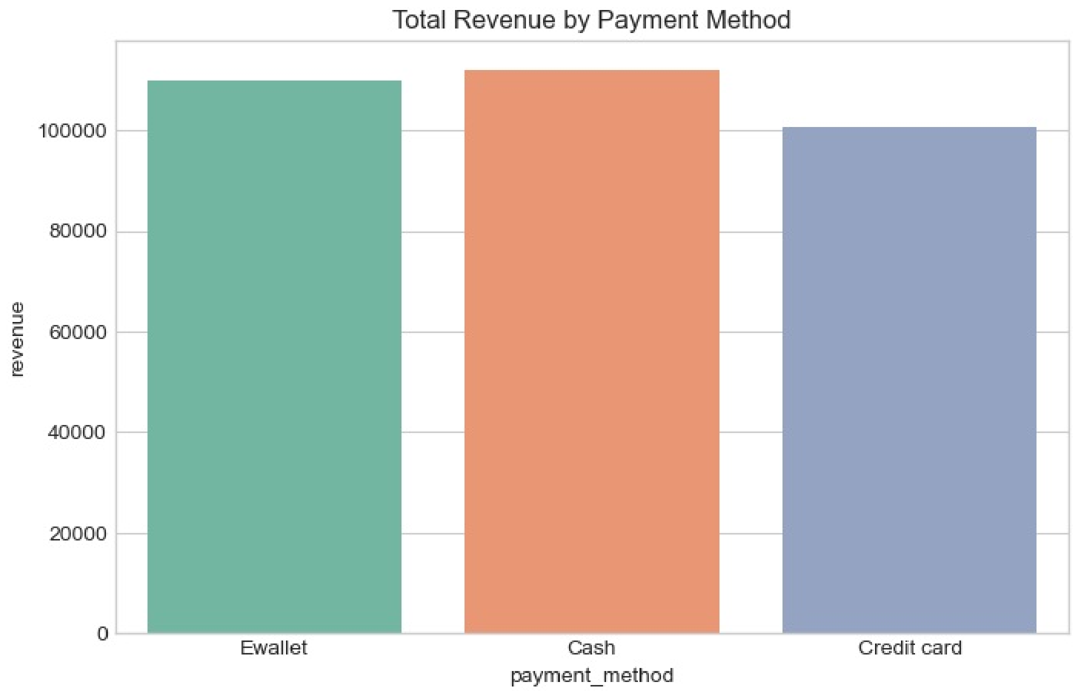


In [26]:
```
# Top 10 Customers by Revenue
top_customers = df.groupby('invoice_id')['revenue'].sum().nlargest(10).reset_index()
plt.figure(figsize=(10,5))
sns.barplot(data=top_customers, x='invoice_id', y='revenue')
plt.title("Top 10 Customers by Revenue")
plt.xticks(rotation=45)
plt.show()
```

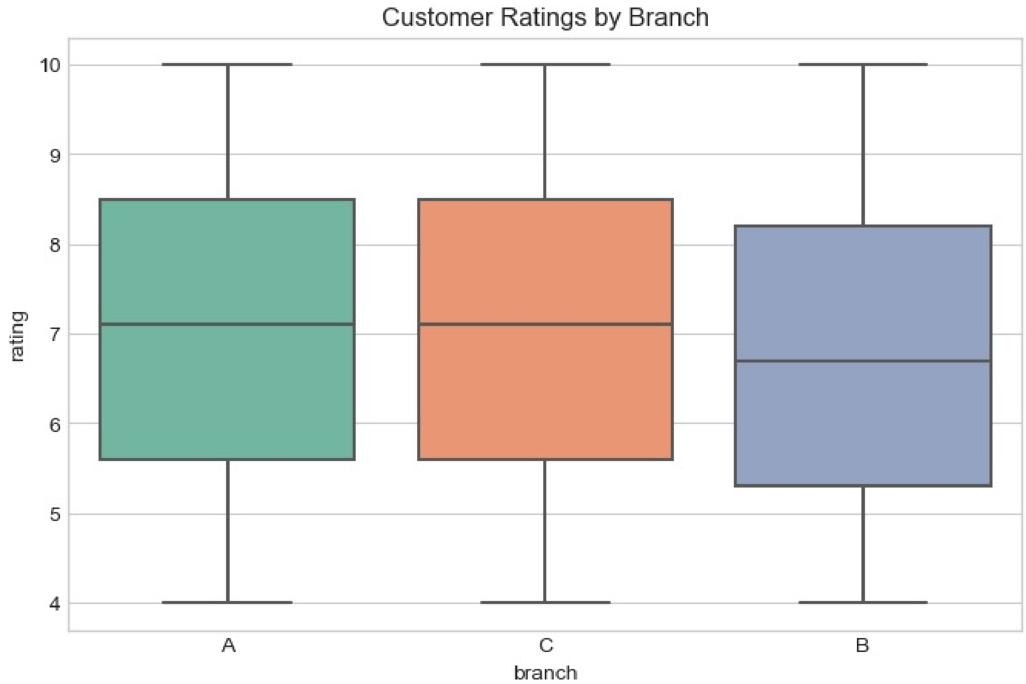


In [27]:
```
# Payment Method Preferences
plt.figure(figsize=(8,5))
sns.countplot(data=df, x='payment_method')
plt.title("Number of Transactions by Payment Method")
plt.show()

plt.figure(figsize=(8,5))
sns.barplot(data=df, x='payment_method', y='revenue', estimator=sum, ci=None)
plt.title("Total Revenue by Payment Method")
plt.show()
```

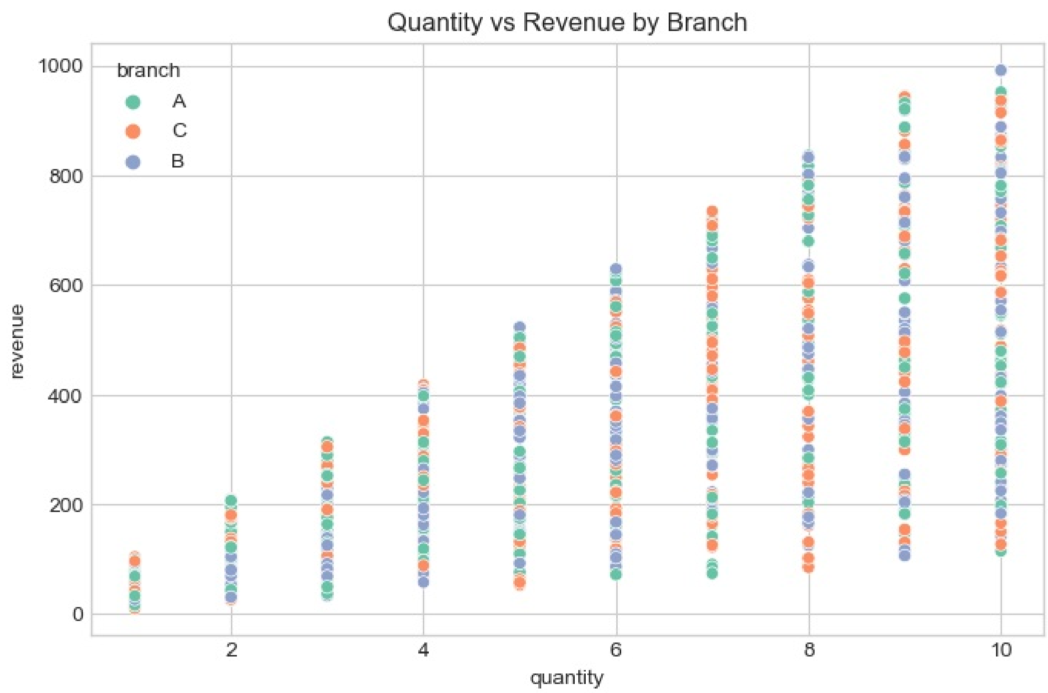




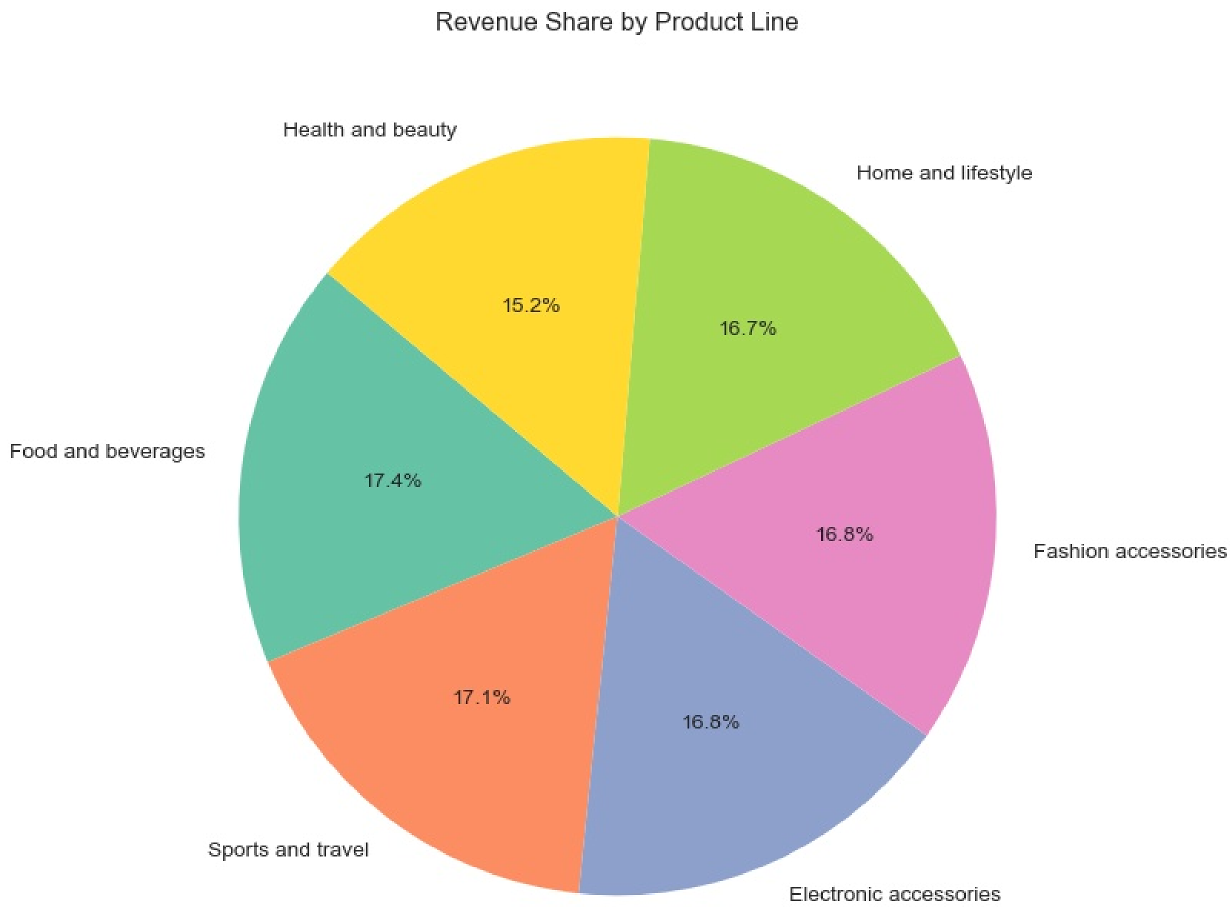
In [28]:
```python
# Customer Rating Distribution by Branch
plt.figure(figsize=(8,5))
sns.boxplot(data=df, x='branch', y='rating')
plt.title("Customer Ratings by Branch")
plt.show()
```



In [33]:
```python
# Quantity vs. Revenue
plt.figure(figsize=(8,5))
sns.scatterplot(data=df, x='quantity', y='revenue', hue='branch')
plt.title("Quantity vs Revenue by Branch")
plt.show()
```



In [34]:
```
# Product Line Revenue Share
product_revenue = df.groupby('product_line')['revenue'].sum().sort_values(ascending=False)
plt.figure(figsize=(8,8))
plt.pie(product_revenue, labels=product_revenue.index, autopct='%1.1f%%', startangle=140)
plt.title("Revenue Share by Product Line")
plt.show()
```



Business Insights from Supermarket Sales EDA

1. Sales Performance Over Time

✅ Revenue and profit fluctuate across days, with visible peaks on some weekdays.

✅ Some branches experience higher weekend sales, suggesting customer shopping patterns.

✅ Seasonal or monthly trends can help with stock planning and promotions.

✅ Action: Allocate staff and stock strategically during peak days and hours.

2. Branch-Level Performance

✅ One branch (e.g., Branch C) generates consistently higher revenue compared to others.

✅ Customer ratings are quite balanced, though some branches show slightly lower satisfaction.

✔ Action:

✅ Learn best practices from high-performing branches.

✅ Investigate lower-rated branches to improve customer experience.

3. Product Line Analysis

✅ Some product categories (e.g., Food & Beverages, Health & Beauty) contribute the largest share of revenue.

✅ Other categories show smaller shares but may have higher margins.

✔ Action:

✅ Focus marketing & promotions on high-revenue product lines.

✅ Explore cross-selling strategies for lower-revenue categories.

4. Customer Type & Demographics

✅ Members (loyalty customers) generally spend more and bring higher revenue compared to normal customers.

✅ Gender distribution is balanced, but in some branches, females contribute slightly more revenue.

✔ Action:

✅ Strengthen loyalty programs to retain members.

✅ Personalize promotions by branch based on customer mix.

5. Time-Based Patterns

✅ Peak shopping hours are during the afternoon and evening (around 1–6 PM).

✅ Morning sales are comparatively lower.

✅ Weekday analysis shows higher revenue on weekends in some branches.

✔ Action:

✅ Schedule more staff during busy hours.

✅ Run weekday promotions to boost slow periods.

6. Payment Methods

✅ Customers mostly prefer E-Wallets and Cash, while credit cards are less used.

✅ Payment method also correlates with total revenue—e.g., E-Wallet users spend slightly more per transaction.

✔ Action:

✅ Expand digital wallet offers/discounts to encourage repeat usage.

✅ Keep multiple payment options to avoid losing sales.

7. Customer Ratings

✅ Ratings are generally between 6–9 (out of 10), suggesting satisfactory service overall.

✅ Some branches receive slightly lower ratings, which could indicate service inconsistencies.

✔ Action:

✅ Maintain quality by training staff and standardizing customer service.

✅ Encourage feedback to improve weaker areas.

8. Outliers & Skewness

✅ A few invoices show very high spending, suggesting VIP or bulk customers.

✅ Revenue and gross income are right-skewed (most transactions are small, a few are very large).

✔ Action:

✅ Identify high-value customers and provide personalized offers/loyalty rewards.

✅ Consider segmenting customers into low, medium, and high spenders.

Final Summary

✅ The supermarket sales dataset reveals that:

✅ Branch C and categories like Food & Beverages are key revenue drivers.

✅ Members and E-Wallet users are more profitable.

✅ Afternoon hours and weekends are peak times.

✅ Service quality is good overall, but can be improved in some branches.

✅ A few VIP customers contribute disproportionately to revenue.

In [ ]:

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