In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import sqlite3
from scipy.stats import ttest_ind
import scipy.stats as stats
warnings.filterwarnings('ignore')
```

Loading the dataset

In [2]:
```python
#creating database connection
conn = sqlite3.connect('inventory.db')

# fetching vendor summary data
df = pd.read_sql_query("select * from vendor_sales_summary", conn)
df.head()
```

Out[2]:

	VendorNumber	VendorName	Brand	Description	PurchasePrice	ActualPrice
0	1128	BROWN-FORMAN CORP	1233	Jack Daniels No 7 Black	26.27	36.99
1	4425	MARTIGNETTI COMPANIES	3405	Tito's Handmade Vodka	23.19	28.99
2	17035	PERNOD RICARD USA	8068	Absolut 80 Proof	18.24	24.99
3	3960	DIAGEO NORTH AMERICA INC	4261	Capt Morgan Spiced Rum	16.17	22.99
4	3960	DIAGEO NORTH AMERICA INC	3545	Ketel One Vodka	21.89	29.99

Explotary Data Analysis

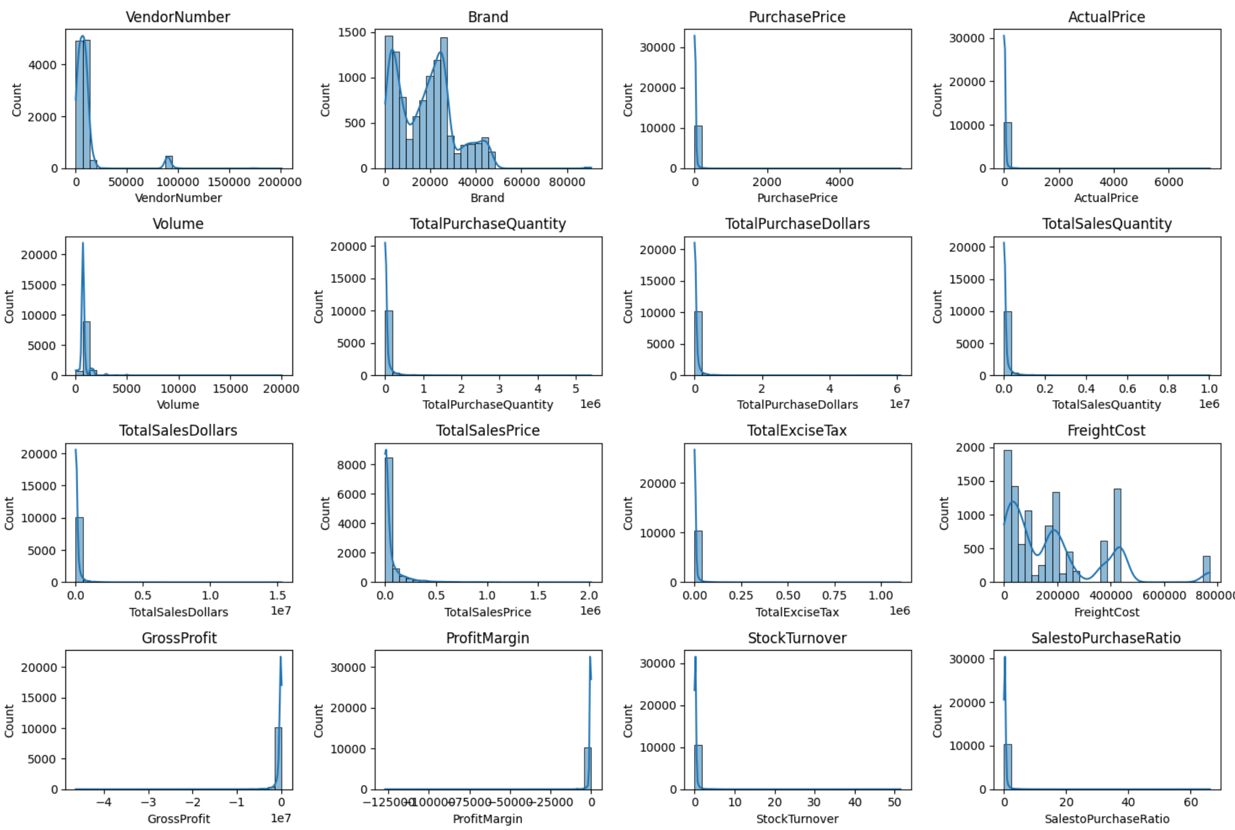
-previously, we examined the various tables in the database to identify key variables, understand their relationships, and determine which ones should be included in the final analysis. -In this phase of EDA, we will analyze the resultant table to gain insights into the distribution of each column. This will help us understand data patterns, identify anomalies, and ensure data quality before proceeding with further anlysis.

In [3]:
```python
df.describe().T
#summary statistics
```

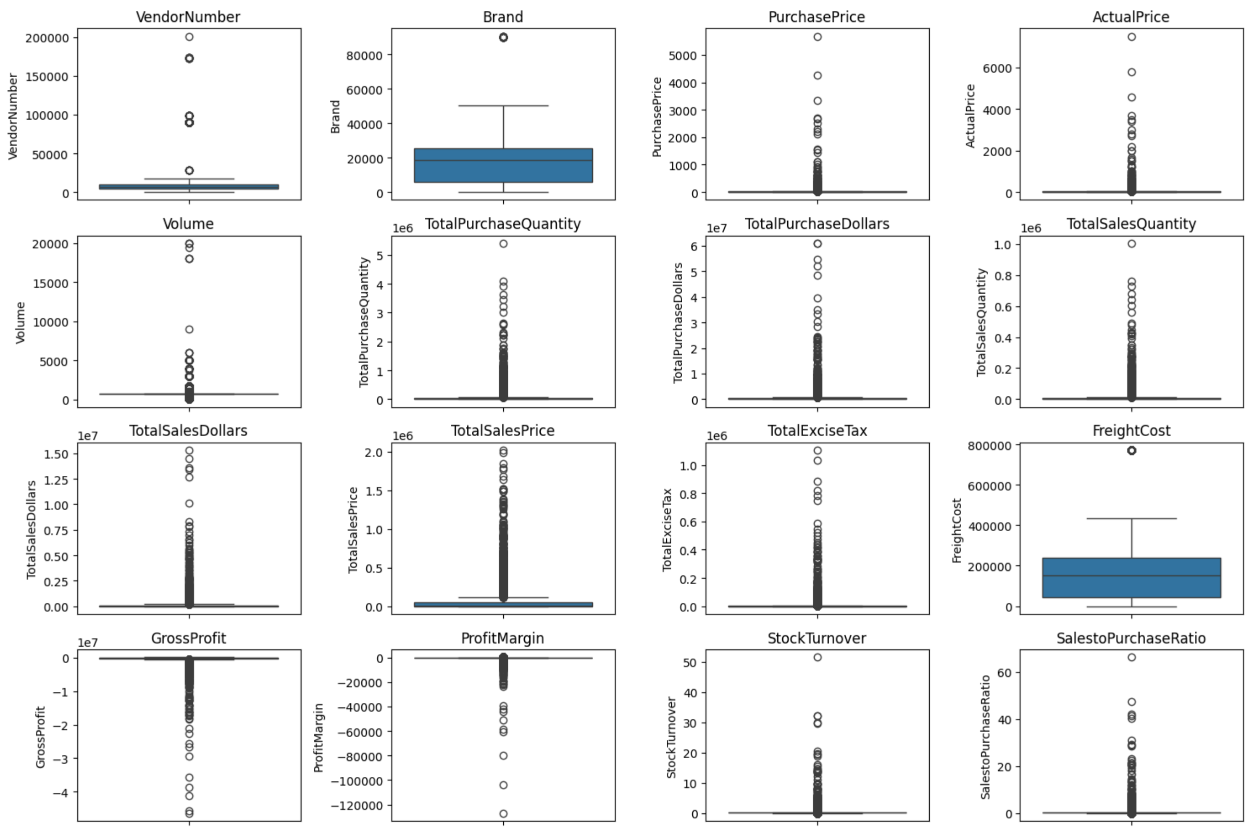
Out[3]:

	count	mean	std	min	
VendorNumber	10692.0	1.065065e+04	1.875352e+04	2.00	3
Brand	10692.0	1.803923e+04	1.266219e+04	58.00	5
PurchasePrice	10692.0	2.438530e+01	1.092694e+02	0.36	
ActualPrice	10692.0	3.564367e+01	1.482460e+02	0.49	
Volume	10692.0	8.473605e+02	6.643092e+02	50.00	
TotalPurchaseQuantity	10692.0	5.025419e+04	1.775214e+05	16.00	
TotalPurchaseDollars	10692.0	4.817071e+05	1.969085e+06	11.36	7
TotalSalesQuantity	10692.0	9.232446e+03	3.285855e+04	0.00	
TotalSalesDollars	10692.0	1.267172e+05	5.029658e+05	0.00	2
TotalSalesPrice	10692.0	5.638135e+04	1.348583e+05	0.00	
TotalExciseTax	10692.0	5.322679e+03	3.292675e+04	0.00	
FreightCost	10692.0	1.843013e+05	1.828154e+05	0.27	42
GrossProfit	10692.0	-3.549899e+05	1.468550e+06	-46407439.05	-244
ProfitMargin	10692.0	-inf	NaN	-inf	-
StockTurnover	10692.0	3.200238e-01	1.128836e+00	0.00	
SalestoPurchaseRatio	10692.0	4.695731e-01	1.586075e+00	0.00	

In [4]:
```python
# distribution plots for numericals columns
numerical_cols = df.select_dtypes(include=np.number).columns

plt.figure(figsize=(15, 10))
for i, col in enumerate(numerical_cols):
    plt.subplot(4, 4, i+1) # adjust grid layout as needed
    sns.histplot(df[col], kde=True, bins=30)
    plt.title(col)
plt.tight_layout()
plt.show()
```



In [5]:
```python
#outliers detection with boxplots
plt.figure(figsize=(15, 10))
for i, col in enumerate(numerical_cols):
    plt.subplot(4,4, i+1)
    sns.boxplot(y=df[col])
    plt.title(col)
plt.tight_layout()
plt.show()
```



summary Statistics insights:

Negative & Zero values:

- Gross profit: minimum value is -52,002.78, indicating losses. some products or transactions may be selling at a loss due to high costs or selling at discounts lower than the purchase price.
- Profit margin: has a minimum of -infinity, which suggests cases where revenue is zero or even lower than costs.
- Total sales quantity & sales dollars: minimum calues are 0, meaning some products were purchased but never sold. these could be slow-moving or obsolete stock.

Outliers indicated by high standard deviations:

- Purchases & actual prices: the max values(5,681.81, 7,499.99) are siginificantly higher than the mean (24.39& 35.64) indicating potential premium products.
- freight cost: huge variation, from (0.09 to 257,032.07), suggests

logistics inefficiencies or bulk shipments.

- stock turnover: ranges from 0 to 274.5, implying some products sell extremely fast while others remain in stock indefinitely. value more than 1 indicates that sold quantity for that product is higher than purchased quantity due to either sales are being fulfilled from older stock.

In [6]:
```
# let's filter the data by removing inconsistencies
df =pd.read_sql_query(""" select * from vendor_sales_summary
                        where GrossProfit >0
                        and ProfitMargin > 0
                        and TotalSalesQuantity > 0""", conn)
```

In [7]:
```
df
```

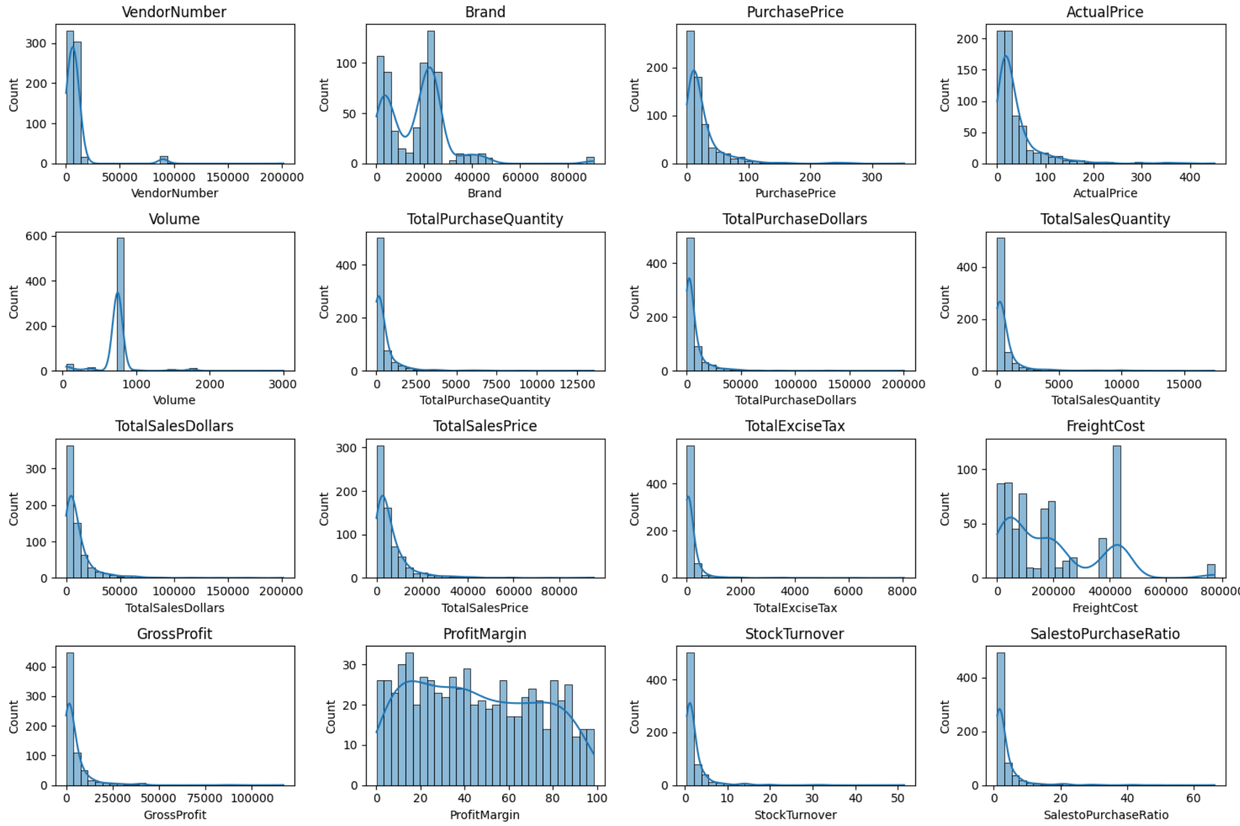
Out[7]:

	VendorNumber	VendorName	Brand	Description	PurchasePrice	Actual
0	480	BACARDI USA INC	4881	Bacardi Twin Pack 2/ 750mls	14.81	
1	2555	DISARONNO INTERNATIONAL LLC	1212	DiSaronna Amaretto Sour VAP	14.38	
2	10754	PERFECTA WINES	10264	Fort Ross Pnt Nr Sonoma Cst	19.60	
3	653	STATE WINE & SPIRITS	23256	Robert Hall Cab Svgn	9.39	
4	1128	BROWN-FORMAN CORP	1722	Jack Daniels Sinatra Century	351.55	4
...	...	...	...	...	...	
664	3960	DIAGEO NORTH AMERICA INC	2626	Crown Royal Apple	1.42	
665	9815	WINE GROUP INC	8527	Concannon Glen Ellen Wh Zin	1.32	
666	8004	SAZERAC CO INC	5683	Dr McGillicuddy's Apple Pie	0.39	
667	3960	DIAGEO NORTH AMERICA INC	6127	The Club Strawbry Margarita	1.47	
668	7245	PROXIMO SPIRITS INC.	3065	Three Olives Grape Vodka	0.71	

669 rows × 18 columns

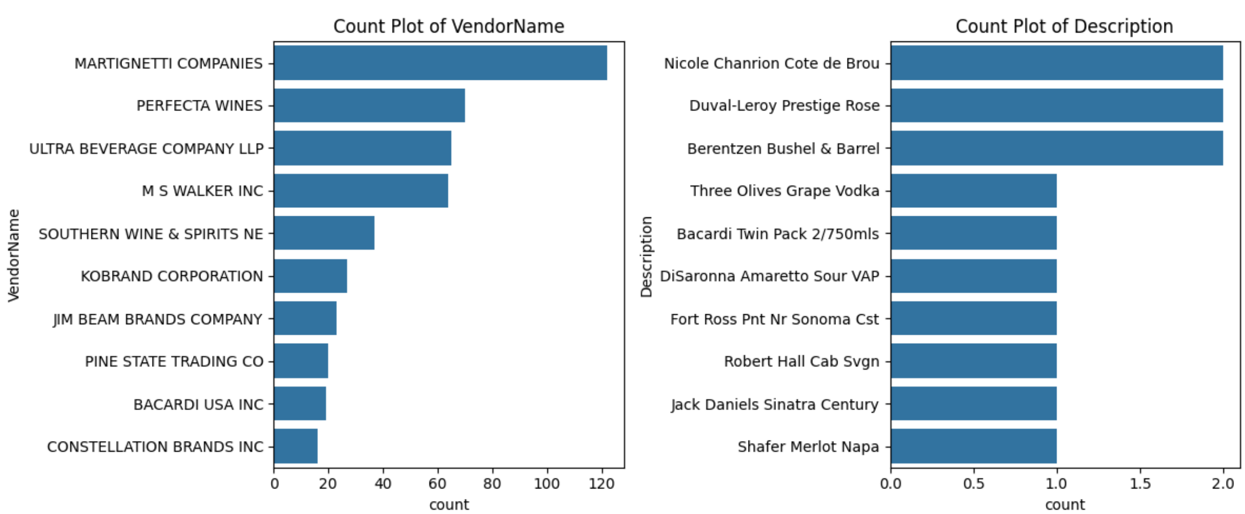
In [8]:

```
# distribution plots for numericals columns
numerical_cols = df.select_dtypes(include=np.number).columns

plt.figure(figsize=(15, 10))
for i, col in enumerate (numerical_cols):
    plt.subplot(4, 4, i+1) # adjust grid layout as needed
    sns.histplot(df[col], kde=True, bins=30)
    plt.title(col)
plt.tight_layout()
plt.show()
```



In [9]:

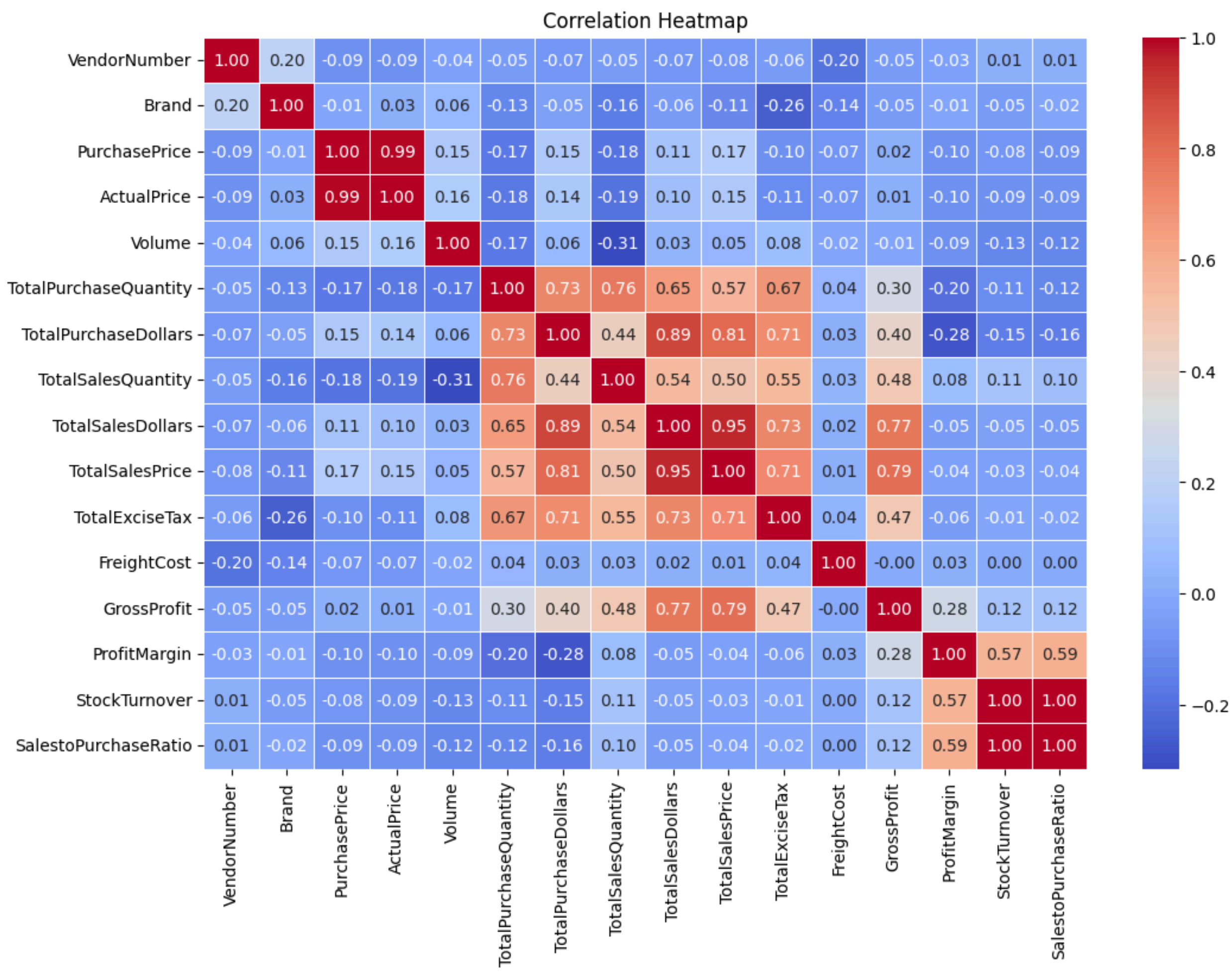
```python
# count plots for categorical columns
categorical_cols = ["VendorName", "Description"]

plt.figure(figsize=(12, 5))
for i, col in enumerate(categorical_cols):
    plt.subplot(1, 2, i+1)
    sns.countplot(y=df[col], order=df[col].value_counts().index[:10]) # top 10
    plt.title(f"Count Plot of {col}")
plt.tight_layout()
plt.show()
```



In [10]:

```python
# correlation heatmap
```

```
plt.figure(figsize=(12, 8))
correlation_matrix = df[numerical_cols].corr()
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap="coolwarm", linewi
plt.title("Correlation Heatmap")
plt.show()
```



Correaltions Insights

- PurchasePrice has weak correaltions with totalsalesdollars (-0.012) and grossprofit (-0.016) , suggesting that price variations do not significantly impact sales revenue or profit.
- strong correlation between profit margin & total sales quantity (0.999) , confirming efficient inventory turnover.
- negative correlation between profit margin & total sales price (-0.179) suggests that a as sales price increases, margins decrease, possibly due to competitive pricing pressures.
- stock turnover has weak negative correlations with both grossprofit (-0.038) and profitmargin (-0.055) indicating that faster turnover does not necessarily result in higher profitability.

Data Analysis

- Identify brands that needs promotional or pricing adjustments which exhibit lower sales performance but higher profit margins.

In [13]:
```
brand_performance = df.groupby('Description').agg({
    'TotalSalesDollars':'sum',
    'ProfitMargin': 'mean'}).reset_index()
```

In [14]:
```
low_sales_threshold = brand_performance['TotalSalesDollars'].quantile(0.15)
high_margin_threshold = brand_performance['ProfitMargin'].quantile(0.85)
```

In [15]:
```
low_sales_threshold
```

Out[15]:
```
np.float64(1667.25)
```

In [16]:
```
high_margin_threshold
```

Out[16]:
```
np.float64(80.53179377674624)
```

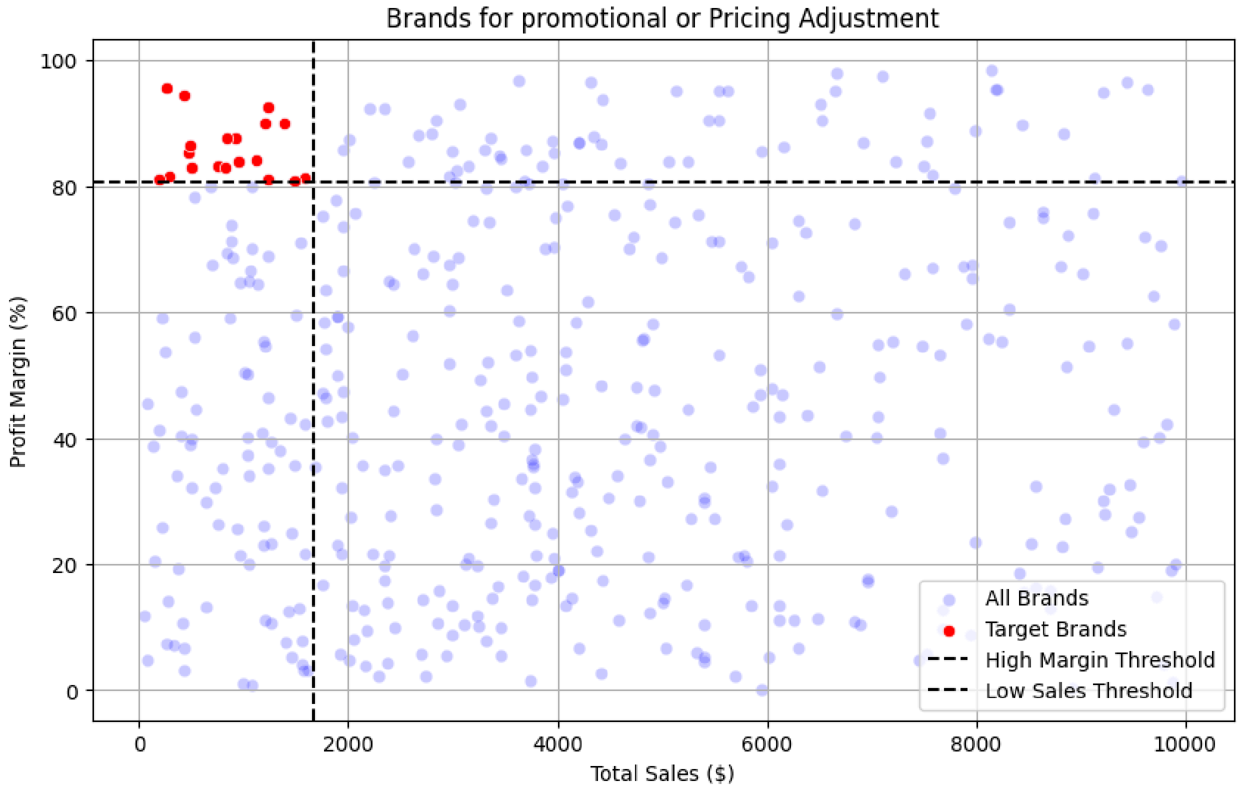
In [17]:
```
# filter brands with low sales but high profit margins
target_brands = brand_performance[
    (brand_performance['TotalSalesDollars'] <= low_sales_threshold) &
    (brand_performance['ProfitMargin'] >= high_margin_threshold)
    ]
print("Brands with low sales but high profit margins: ")
display(target_brands.sort_values('TotalSalesDollars'))
```

```
Brands with low sales but high profit margins:
```

	Description	TotalSalesDollars	ProfitMargin
267	Dr McGillicuddy's Apple Pie	196.98	80.992994
608	Three Olives Grape Vodka	255.42	95.552423
33	Aresti Pnt Nr Curico Vly	284.43	81.549063
600	The Club Strawbry Margarita	429.84	94.528197
481	Piehole Apple Pie	469.26	85.270426
515	Riunite Sweet White	485.19	86.479523
531	Sauza Sparkling Margarita	503.28	82.896201
251	DeKuyper Mixed Berry Medley	758.31	83.204758
642	Vigne A Porrona Rosso	818.37	83.068783
415	Mad Dogs & Englishmen Jumil	839.40	87.553014
0	12 Days of Pearls Gift Set	929.07	87.617725
437	Mojoshot Blue Lagoon RTD	950.40	84.023569
571	St Germain Liqueur	1124.25	84.202802
50	Bacardi Oakheart Spiced Trav	1198.80	90.043377
48	Bacardi Limon Traveler	1228.77	81.015162
570	St Elder Elderflower Liqueur	1232.55	92.626668
215	Chi Chi's Chocolate Malt RTD	1384.74	89.924462
159	Ch La Fleur Patris-Querre 09	1481.43	80.775332
21	Altadonna Vermentino	1591.23	81.297487

In [18]:
```
brand_performance = brand_performance[brand_performance['TotalSalesDollars']<1
```

In [19]:
```
plt.figure(figsize=(10,6))
sns.scatterplot(data=brand_performance, x='TotalSalesDollars', y='ProfitMargin
sns.scatterplot(data=target_brands, x='TotalSalesDollars', y='ProfitMargin', c

plt.axhline(high_margin_threshold, linestyle='--', color='black', label="High 
plt.axvline(low_sales_threshold, linestyle='--', color='black', label="Low Sal

plt.xlabel("Total Sales ($)")
plt.ylabel("Profit Margin (%)")
plt.title("Brands for promotional or Pricing Adjustment")
plt.legend()
plt.grid(True)
plt.show()
```



Which vendors and brands demonstrate the highest sales performance

In [20]:
```
def format_dollars(value):
    if value>=1_000_000:
        return f"{value / 1_000_000:.2f}M"
    elif value>=1_000:
        return f"{value / 1_000: .2f}K"
    else:
        return str(value)
```

In [53]:
```
# top vendors & brands by sales performance
top_vendors = df.groupby("VendorName")["TotalSalesDollars"].sum().nlargest(10)
top_brands = df.groupby("Description")["TotalSalesDollars"].sum().nlargest(10)
top_vendors
```

Out[53]:
```
VendorName
MARTIGNETTI COMPANIES          1476319.59
ULTRA BEVERAGE COMPANY LLP      966800.94
M S WALKER INC                  677901.96
BACARDI USA INC                 547922.16
PERFECTA WINES                  537688.74
SOUTHERN WINE & SPIRITS NE      423435.87
BROWN-FORMAN CORP               365208.69
STATE WINE & SPIRITS            217284.45
DISARONNO INTERNATIONAL LLC     185169.15
PERNOD RICARD USA               173913.69
Name: TotalSalesDollars, dtype: float64
```

In [46]:
```
top_brands
```

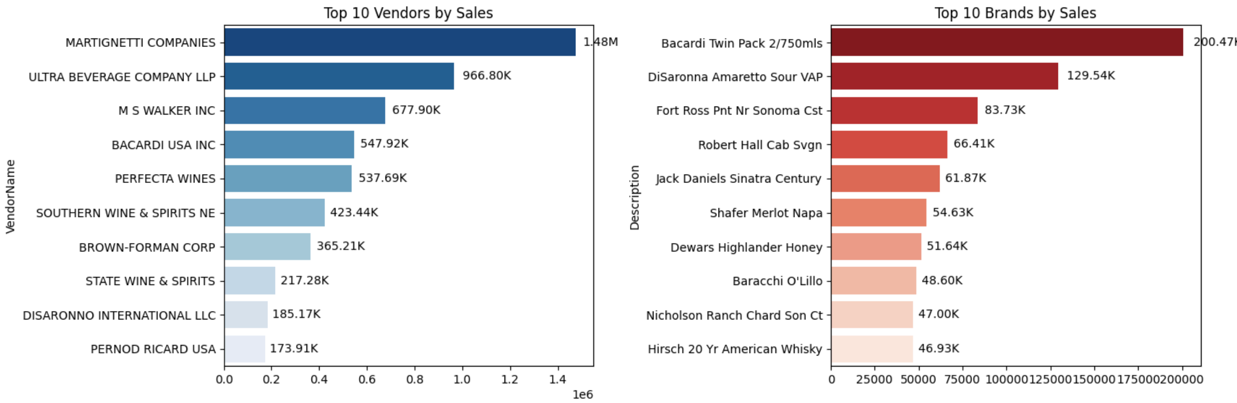
Out[46]:
```
Description
Bacardi Twin Pack 2/750mls      200468.16
DiSaronna Amaretto Sour VAP     129535.04
Fort Ross Pnt Nr Sonoma Cst      83731.20
Robert Hall Cab Svgn             66406.08
Jack Daniels Sinatra Century     61872.80
Shafer Merlot Napa               54628.80
Dewars Highlander Honey          51636.48
Baracchi O'Lillo                 48600.00
Nicholson Ranch Chard Son Ct     46996.32
Hirsch 20 Yr American Whisky     46931.52
Name: TotalPurchaseDollars, dtype: float64
```

In [47]:
```
top_brands.apply(lambda x: format_dollars(x))
```

Out[47]:
```
Description
Bacardi Twin Pack 2/750mls       200.47K
DiSaronna Amaretto Sour VAP      129.54K
Fort Ross Pnt Nr Sonoma Cst       83.73K
Robert Hall Cab Svgn              66.41K
Jack Daniels Sinatra Century      61.87K
Shafer Merlot Napa                54.63K
Dewars Highlander Honey           51.64K
Baracchi O'Lillo                  48.60K
Nicholson Ranch Chard Son Ct      47.00K
Hirsch 20 Yr American Whisky      46.93K
Name: TotalPurchaseDollars, dtype: object
```

In [48]:
```
plt.figure(figsize=(15, 5))

# 🔹 Plot for top vendors (Barplot)
plt.subplot(1, 2, 1)
ax1 = sns.barplot(y=top_vendors.index.astype(str), x=top_vendors.values, palet
plt.title("Top 10 Vendors by Sales")

# Add value labels
for bar in ax1.patches:
    ax1.text(
        bar.get_width() + (bar.get_width() * 0.02),
        bar.get_y() + bar.get_height() / 2,
        format_dollars(bar.get_width()),
        ha='left', va='center', fontsize=10, color='black')

# 🔹 Plot for top brands (Barplot)
plt.subplot(1, 2, 2)
ax2 = sns.barplot(y=top_brands.index.astype(str), x=top_brands.values, palette
plt.title("Top 10 Brands by Sales")

# Add value labels
for bar in ax2.patches:
    ax2.text(
        bar.get_width() + (bar.get_width() * 0.02),
```

```
        bar.get_y() + bar.get_height() / 2,
        format_dollars(bar.get_width()),
        ha='left', va='center', fontsize=10, color='black')

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



Which vendors contrubute the most to total purchases dollars

In [150…

```
df.groupby('VendorName').agg({
    'TotalSalesDollars':'sum',
    'GrossProfit':'sum',
    'TotalPurchaseDollars':'sum',
}).reset_index()
```

Out[150…

	VendorName	TotalSalesDollars	GrossProfit	TotalPurchaseDollars
0	ALISA CARR BEVERAGES	126806.04	31234.20	95571.84
1	ATLANTIC IMPORTING COMPANY	11366.31	1109.03	10257.28
2	BACARDI USA INC	547922.16	207461.36	340460.80
3	BANFI PRODUCTS CORP	14442.36	5243.48	9198.88
4	BROWN-FORMAN CORP	365208.69	191207.89	174000.80
...	...	...	...	...
57	VINILANDIA USA	78212.13	47681.41	30530.72
58	VRANKEN AMERICA	8378.19	5495.15	2883.04
59	WESTERN SPIRITS BEVERAGE CO	4977.51	1930.47	3047.04
60	WILLIAM GRANT & SONS INC	53669.58	15360.14	38309.44
61	WINE GROUP INC	14204.67	7878.59	6326.08

62 rows × 4 columns

In [151…

```
vendor_performance = df.groupby('VendorName').agg({
    'TotalPurchaseDollars':'sum',
    'GrossProfit':'sum',
    'TotalSalesDollars': 'sum'
}).reset_index()
vendor_performance.shape
```

Out[151… (62, 4)

In [154…

```
print(vendor_performance.columns)
```

```
Index(['VendorName', 'TotalPurchaseDollars', 'GrossProfit',
       'TotalSalesDollars', 'Purchase_Contribution%'],
      dtype='object')
```

In [153…

```
vendor_performance['Purchase_Contribution%'] = vendor_performance['TotalPurcha
```

In [155…

```
round(vendor_performance.sort_values('Purchase_Contribution%', ascending=False
```

Out[155…

	VendorName	TotalPurchaseDollars	GrossProfit	TotalSalesDollars	Purchase
29	MARTIGNETTI COMPANIES	881010.40	595309.19	1476319.59	
55	ULTRA BEVERAGE COMPANY LLP	571004.80	395796.14	966800.94	
2	BACARDI USA INC	340460.80	207461.36	547922.16	
36	PERFECTA WINES	310116.32	227572.42	537688.74	
27	M S WALKER INC	308977.92	368924.04	677901.96	
...	...	...	...	...	
13	DUGGANS DISTILLED PRODUCTS	556.32	85.29	641.61	
34	OLE SMOKY DISTILLERY LLC	402.88	28.85	431.73	
17	FLAVOR ESSENCE INC	272.00	4151.23	4423.23	
9	Circa Wines	257.60	581.80	839.40	
45	SAZERAC NORTH AMERICA INC.	139.52	1245.22	1384.74	

62 rows × 5 columns

In [156…

```
# display top 10 vendors
top_vendors = vendor_performance.head(10)
top_vendors ['TotalSalesDollars'] = top_vendors['TotalSalesDollars'].apply(for
top_vendors ['TotalPurchaseDollars'] = top_vendors['TotalPurchaseDollars'].app
top_vendors ['GrossProfit'] = top_vendors['GrossProfit'].apply(format_dollars)
top_vendors
```

Out[156…

	VendorName	TotalPurchaseDollars	GrossProfit	TotalSalesDollars	Purchase
0	ALISA CARR BEVERAGES	95.57K	31.23K	126.81K	
1	ATLANTIC IMPORTING COMPANY	10.26K	1.11K	11.37K	
2	BACARDI USA INC	340.46K	207.46K	547.92K	
3	BANFI PRODUCTS CORP	9.20K	5.24K	14.44K	
4	BROWN-FORMAN CORP	174.00K	191.21K	365.21K	
5	CAMPARI AMERICA	40.62K	13.05K	53.68K	
6	CASTLE BRANDS CORP.	13.38K	7.01K	20.39K	
7	CONSTELLATION BRANDS INC	99.65K	55.92K	155.57K	
8	CRUSH WINES	10.99K	6.88K	17.87K	
9	Circa Wines	257.6	581.8	839.4	

In [157…

```
top_vendors['Purchase_Contribution%'].sum()
```

Out[157…

```
np.float64(17.966480848825473)
```

In [160…

```
print(top_vendors.columns)
```

```
Index(['VendorName', 'TotalPurchaseDollars', 'GrossProfit',
       'TotalSalesDollars', 'Purchase_Contribution%',
       'Cumulative_Contribution%'],
      dtype='object')
```

In [159…

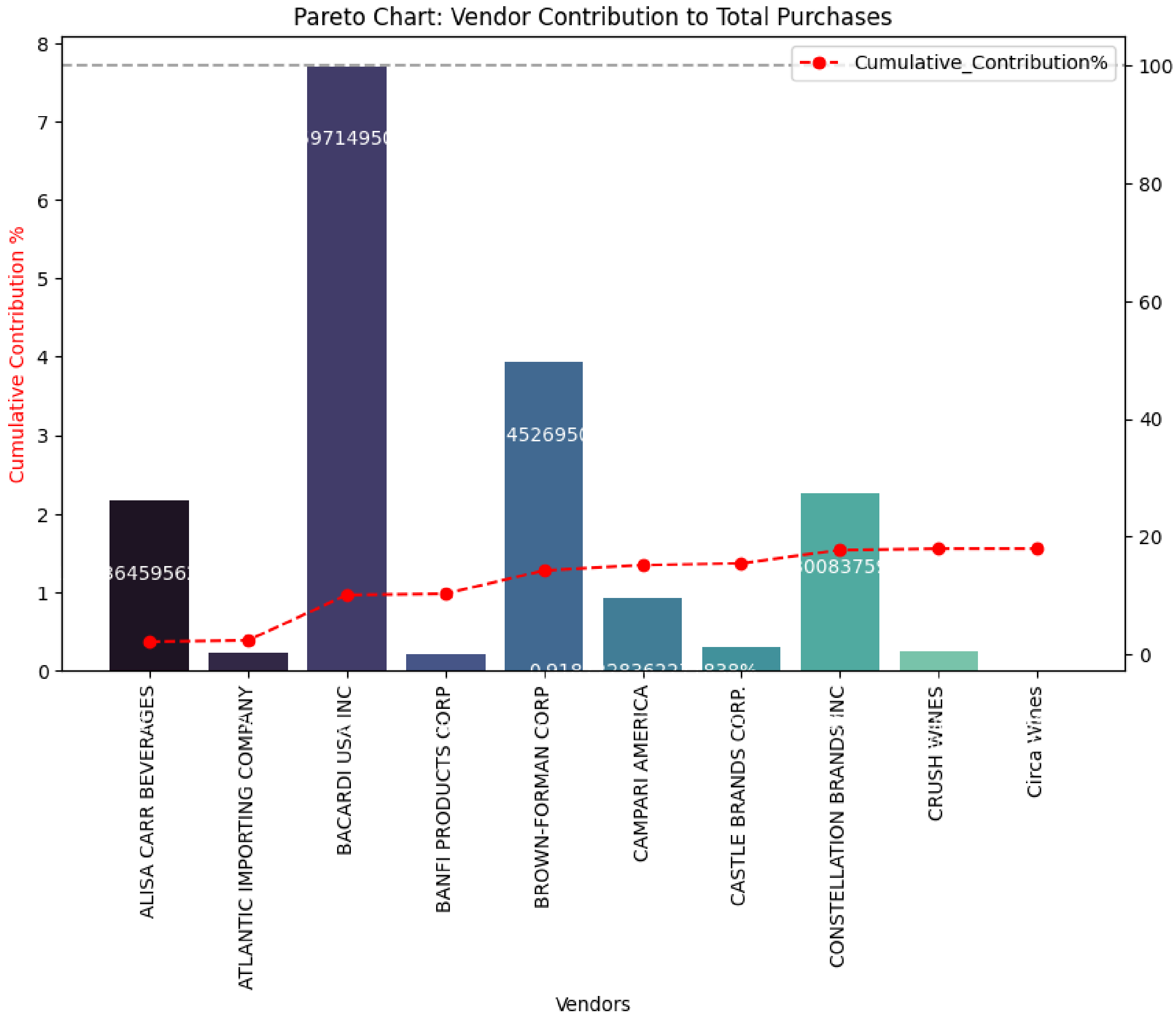
```
top_vendors['Cumulative_Contribution%'] = top_vendors['Purchase_Contribution%'
top_vendors
```

Out[159…

	VendorName	TotalPurchaseDollars	GrossProfit	TotalSalesDollars	Purchase
0	ALISA CARR BEVERAGES	95.57K	31.23K	126.81K	
1	ATLANTIC IMPORTING COMPANY	10.26K	1.11K	11.37K	
2	BACARDI USA INC	340.46K	207.46K	547.92K	
3	BANFI PRODUCTS CORP	9.20K	5.24K	14.44K	
4	BROWN-FORMAN CORP	174.00K	191.21K	365.21K	
5	CAMPARI AMERICA	40.62K	13.05K	53.68K	
6	CASTLE BRANDS CORP.	13.38K	7.01K	20.39K	
7	CONSTELLATION BRANDS INC	99.65K	55.92K	155.57K	
8	CRUSH WINES	10.99K	6.88K	17.87K	
9	Circa Wines	257.6	581.8	839.4	

In [161…

```
top_vendors['Cumulative_Contribution%'] = top_vendors['Purchase_Contribution%'

fig, ax1 = plt.subplots(figsize=(10, 6))

# Bar plot for purchase contrubution%
sns.barplot(x=top_vendors['VendorName'], y=top_vendors['Purchase_Contribution%

for i, value in enumerate(top_vendors['Purchase_Contribution%']):
    ax1.text(i, value-1, str(value)+'%', ha='center', fontsize=10, color='whit

#line plot for cumulative contribution%
ax2 = ax1.twinx()
ax2.plot(top_vendors['VendorName'], top_vendors['Cumulative_Contribution%'], c

ax1.set_xticklabels(top_vendors['VendorName'], rotation=90)
ax1.set_ylabel('Purchase Contribution %', color='blue')
ax1.set_ylabel('Cumulative Contribution %', color='red')
ax1.set_xlabel('Vendors')
ax1.set_title('Pareto Chart: Vendor Contribution to Total Purchases')

ax2.axhline(y=100, color='gray', linestyle='dashed', alpha=0.7)
ax2.legend(loc='upper right')

plt.show()
```



How much to total procurement is dependent on the top vendors?

In [162…

```
print(f"Total Purchase Contribution of top 10 vendors is {round(top_vendors['P
```

```
Total Purchase Contribution of top 10 vendors is 17.97 %
```

In [163…

```
print(type(top_vendors))
```

```
<class 'pandas.core.frame.DataFrame'>
```

In [164…

```
print(top_vendors.columns)
```

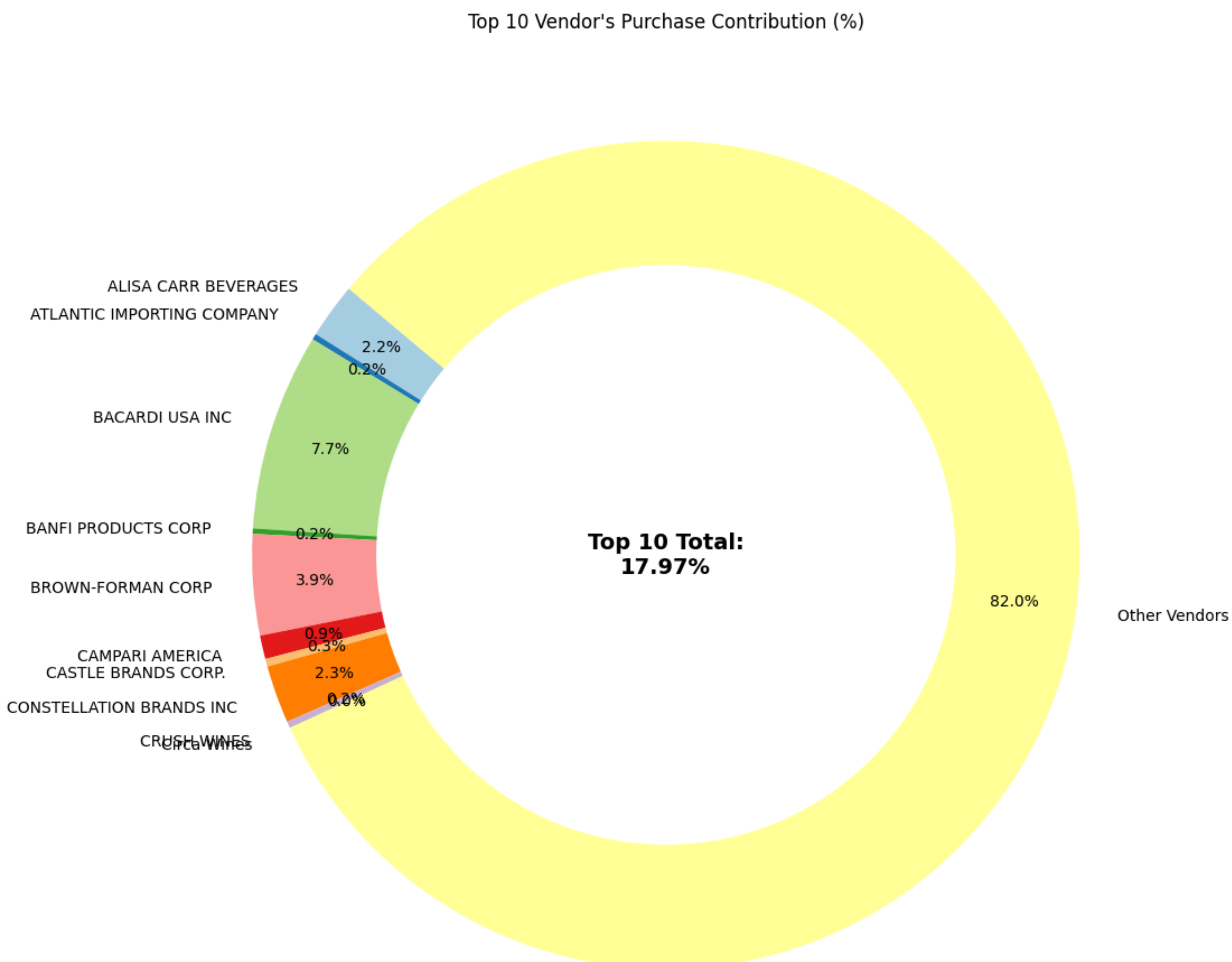
```
Index(['VendorName', 'TotalPurchaseDollars', 'GrossProfit',
       'TotalSalesDollars', 'Purchase_Contribution%',
       'Cumulative_Contribution%'],
      dtype='object')
```

In [177…

```
import matplotlib.pyplot as plt
```

```
# Yahan pehle check karo actual columns
print(top_vendors.columns)

# Correct column name use karo (agar naam 'PurchaseContribution%' hai to neech
vendors = list(top_vendors['VendorName'].values)
purchase_contributions = list(top_vendors['Purchase_Contribution%'].values)  #

# Contribution calculate
total_contribution = sum(purchase_contributions)
remaining_contribution = 100 - total_contribution

# Append "Other Vendors" category
vendors.append("Other Vendors")
purchase_contributions.append(remaining_contribution)

# Donut Chart
fig, ax = plt.subplots(figsize=(12, 12))
wedges, texts, autotexts = ax.pie(
    purchase_contributions,
    labels=vendors,
    autopct='%1.1f%%',
    startangle=140,
    pctdistance=0.85,
    colors=plt.cm.Paired.colors
)

# Draw a white circle in the center to create a "donut" effect.
centre_circle = plt.Circle((0, 0), 0.7, fc='white')
fig.gca().add_artist(centre_circle)

# Add Total Contribution annotation in the centre
plt.text(
    0, 0,
    f"Top 10 Total:\n{total_contribution:.2f}%",
    fontsize=14,
    fontweight='bold',
    ha='center',
    va='center'
)

plt.title("Top 10 Vendor's Purchase Contribution (%)")
plt.show()
```

```
Index(['VendorName', 'TotalPurchaseDollars', 'GrossProfit',
       'TotalSalesDollars', 'Purchase_Contribution%',
       'Cumulative_Contribution%'],
      dtype='object')
```



Does purchasing in bulk reduce the unit price, and what is the optimal purchase volume for cost savings?

In [112…

```
df['UnitPurchasePrice'] = df['TotalPurchaseDollars'] / df['TotalPurchaseQuanti
```

In [114…

```
df["OrderSize"] = pd.qcut(df["TotalPurchaseQuantity"], q =3, labels=["Small",
```

In [117…

```
df[['OrderSize','TotalPurchaseQuantity']]
```

Out[117…

	OrderSize	TotalPurchaseQuantity
0	Large	13536
1	Large	9008
2	Large	4272
3	Large	7072
4	Medium	176
...	...	...
664	Small	32
665	Small	32
666	Medium	96
667	Small	16
668	Small	16

669 rows × 2 columns

In [118…

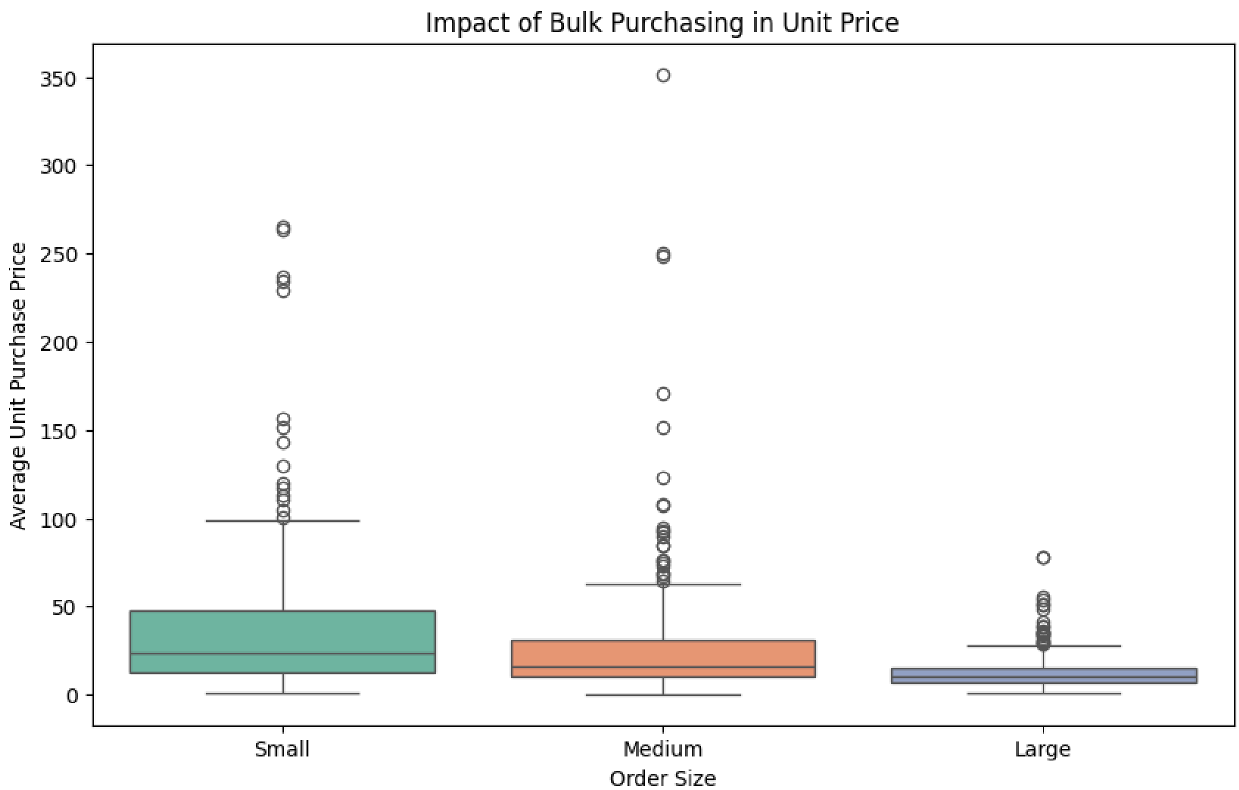
```
df.groupby('OrderSize')[['UnitPurchasePrice']].mean()
```

Out[118…

	UnitPurchasePrice
OrderSize	
Small	37.902423
Medium	28.452227
Large	13.319189

In [119…

```
plt.figure(figsize=(10, 6))
sns.boxplot(data=df, x="OrderSize", y="UnitPurchasePrice", palette="Set2")
plt.title("Impact of Bulk Purchasing in Unit Price")
plt.xlabel("Order Size")
plt.ylabel("Average Unit Purchase Price")
plt.show()
```



- Vendors buying in bulk (large ordersize) get the lowest unit price($10.78per unit), meaning higher if they can manage inventory efficiently.
- The price difference between small and large orders is substantial (~72% reduction in unit cost)
- This suggests that bulk pricing startegies successfully encourage vendors to purchase in large volumes, leading to higher overall sales despite lower per-unit revenue.

Which vendors have low inventory turnover , indicating excess stock and slow-moving producgs?

In [123…

```
df[df['StockTurnover']<1].groupby('VendorName')[['StockTurnover']].mean().sort
```

Out[123…

VendorName	StockTurnover
WINE GROUP INC	0.468750
PROXIMO SPIRITS INC.	0.679861
THE PIERPONT GROUP LLC	0.721154
BROWN-FORMAN CORP	0.735109
KLIN SPIRITS LLC	0.735577
BACARDI USA INC	0.739187
R.P.IMPORTS INC	0.743750
ATLANTIC IMPORTING COMPANY	0.743952
FORTUNE WINE BROKERS LLC	0.750000
BANFI PRODUCTS CORP	0.750000

In [124…

```
df["UnsoldInventoryValue"] = (df["TotalPurchaseQuantity"] - df["TotalSalesQuar
print('Total Unsold Captical:', format_dollars(df["UnsoldInventoryValue"].sum(
```

```
Total Unsold Captical: -936540.19
```

In [126…

```
# Aggregate capital locked per vendor
inventory_value_per_vendor = df.groupby("VendorName")["UnsoldInventoryValue"].

#Sort vendors with the highest locked capital
inventory_value_per_vendor = inventory_value_per_vendor.sort_values(by="Unsolc
inventory_value_per_vendor['UnsoldInventoryValue'] = inventory_value_per_vendc
inventory_value_per_vendor.head(10)
```

Out[126…

	VendorName	UnsoldInventoryValue
0	ALISA CARR BEVERAGES	11.77K
12	DISARONNO INTERNATIONAL LLC	6.28K
52	THE PIERPONT GROUP LLC	5.84K
33	NICHE W & S	3.72K
32	MOET HENNESSY USA INC	3.59K
41	R.P.IMPORTS INC	3.20K
1	ATLANTIC IMPORTING COMPANY	2.63K
11	DIAGEO NORTH AMERICA INC	2.24K
43	Russian Standard Vodka	1.30K
39	POVERTY LANE ORCHARDS	952.24

In [ ]:

```

```

In [127…

```
top_threshold = df["TotalSalesDollars"].quantile(0.75)
low_threshold = df["TotalSalesDollars"].quantile(0.25)
```

In [130…

```
top_vendors = df[df["TotalSalesDollars"] >=top_threshold] ["ProfitMargin"].drc
low_vendors = df[df["TotalSalesDollars"] <= low_threshold]["ProfitMargin"].drc
```

In [131…

```
top_vendors
```

Out[131…

```
0       0.641123
1      24.171209
2      25.188353
3      13.962626
4       4.515162
         ...
401    88.495058
485    95.645673
513    93.972120
597    97.515874
600    97.617315
Name: ProfitMargin, Length: 168, dtype: float64
```

In [133…

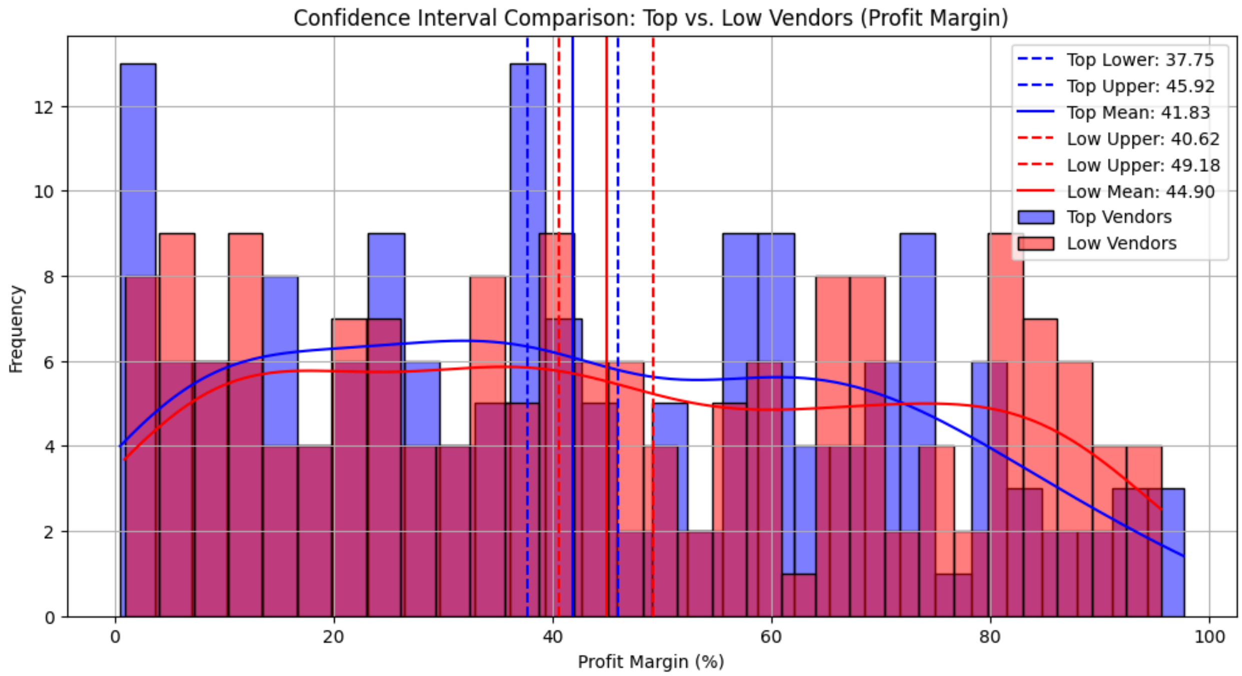
```
def confidence_interval(data, confidence=0.95):
    mean_val = np.mean(data)
    std_err = np.std(data, ddof=1) / np.sqrt(len(data)) # standard error
    t_critical = stats.t.ppf((1+ confidence) / 2, df=len(data)-1)
    margin_of_error = t_critical * std_err
    return mean_val, mean_val-margin_of_error, mean_val + margin_of_error
```

In [137…

```
top_mean, top_lower, top_upper = confidence_interval(top_vendors)
low_mean, low_lower, low_upper = confidence_interval(low_vendors)

print(f"Top Vendors 95% CI: ({top_lower:.2f}, {top_upper:.2f}), Mean: {top_mea
print(f"Low Vendors 95% CI: ({low_lower:.2f}, {low_upper:.2f}), Mean: {low_mea

plt.figure(figsize=(12, 6))

# Top Vendors Plot
sns.histplot(top_vendors, kde=True, color="blue", bins=30, alpha=0.5, label="T
plt.axvline(top_lower, color="blue", linestyle="--", label=f"Top Lower: {top_l
plt.axvline(top_upper, color="blue", linestyle="--", label=f"Top Upper: {top_u
plt.axvline(top_mean, color="blue", linestyle="-", label=f"Top Mean: {top_mear

# Low Vendors Plot
sns.histplot(low_vendors, kde=True, color="red", bins=30, alpha=0.5, label="Lc
plt.axvline(low_lower, color="red", linestyle="--", label=f"Low Upper: {low_lc
plt.axvline(low_upper, color="red", linestyle="--", label=f"Low Upper: {low_up
plt.axvline(low_mean, color="red", linestyle="-", label=f"Low Mean: {low_mean:

#Finalize Plot
plt.title("Confidence Interval Comparison: Top vs. Low Vendors (Profit Margin)
```

```
plt.xlabel("Profit Margin (%)")
plt.ylabel("Frequency")
plt.legend()
plt.grid(True)
plt.show()
```

```
Top Vendors 95% CI: (37.75, 45.92), Mean: 41.83
Low Vendors 95% CI: (40.62, 49.18), Mean: 44.90
```



In [ ]:

In [ ]:

In [145…

```
top_threshold = df["TotalSalesDollars"].quantile(0.75)
low_threshold = df["TotalSalesDollars"].quantile(0.25)

top_vendors = df[df["TotalSalesDollars"] >= top_threshold]["ProfitMargin"].drc
low_vendors = df[df["TotalSalesDollars"] <= low_threshold]["ProfitMargin"].drc

# Perform two-sample t-test
t_stat, p_value = ttest_ind(top_vendors, low_vendors, equal_var=False)

# Print Results
print(f"T-Statistics: {t_stat:.4f}, P-Value, {p_value:.4f}")
if p_value < 0.05:
    print("Reject H0 : There is a significant difference in profit margins bet
else:
    print("Fall to Reject H0: No significant difference in profit margins.")
```

```
T-Statistics: -1.0218, P-Value, 0.3076
Fall to Reject H0: No significant difference in profit margins.
```