Import Libraries

In [ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

import warnings
warnings.simplefilter('ignore')
```

Load Data

In [2]:
```
df=pd.read_excel('superstore_sales.xlsx')
```

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

Out[3]:

	order_id	order_date	ship_date	ship_mode	customer_name	segment	state	coun
0	AG-2011-2040	2011-01-01	2011-01-06	Standard Class	Toby Braunhardt	Consumer	Constantine	Alge
1	IN-2011-47883	2011-01-01	2011-01-08	Standard Class	Joseph Holt	Consumer	New South Wales	Austra
2	HU-2011-1220	2011-01-01	2011-01-05	Second Class	Annie Thurman	Consumer	Budapest	Hung
3	IT-2011-3647632	2011-01-01	2011-01-05	Second Class	Eugene Moren	Home Office	Stockholm	Swec
4	IN-2011-47883	2011-01-01	2011-01-08	Standard Class	Joseph Holt	Consumer	New South Wales	Austra

5 rows × 21 columns

In [4]:
```
df.tail()
```

Out[4]:

	order_id	order_date	ship_date	ship_mode	customer_name	segment	state	
51285	CA-2014-115427	2014-12-31	2015-01-04	Standard Class	Erica Bern	Corporate	California	
51286	MO-2014-2560	2014-12-31	2015-01-05	Standard Class	Liz Preis	Consumer	Souss-Massa-Draâ	I
51287	MX-2014-110527	2014-12-31	2015-01-02	Second Class	Charlotte Melton	Consumer	Managua	Ni
51288	MX-2014-114783	2014-12-31	2015-01-06	Standard Class	Tamara Dahlen	Consumer	Chihuahua	
51289	CA-2014-156720	2014-12-31	2015-01-04	Standard Class	Jill Matthias	Consumer	Colorado	

5 rows × 21 columns

Overview

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 51290 entries, 0 to 51289
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   order_id        51290 non-null  object
 1   order_date      51290 non-null  datetime64[ns]
 2   ship_date       51290 non-null  datetime64[ns]
 3   ship_mode       51290 non-null  object
 4   customer_name   51290 non-null  object
 5   segment         51290 non-null  object
 6   state           51290 non-null  object
 7   country         51290 non-null  object
 8   market          51290 non-null  object
 9   region          51290 non-null  object
 10  product_id      51290 non-null  object
 11  category        51290 non-null  object
 12  sub_category    51290 non-null  object
 13  product_name    51290 non-null  object
 14  sales           51290 non-null  float64
 15  quantity        51290 non-null  int64
 16  discount        51290 non-null  float64
 17  profit          51290 non-null  float64
 18  shipping_cost   51290 non-null  float64
 19  order_priority  51290 non-null  object
 20  year            51290 non-null  int64
dtypes: datetime64[ns](2), float64(4), int64(2), object(13)
memory usage: 8.2+ MB
```

In [6]:
```
df.shape
```

Out[6]:
```
(51290, 21)
```

In [7]:
```
df.size
```

Out[7]:
```
1077090
```

In [8]:
```
df.columns
```

Out[8]:
```
Index(['order_id', 'order_date', 'ship_date', 'ship_mode', 'customer_nam
e',
       'segment', 'state', 'country', 'market', 'region', 'product_id',
       'category', 'sub_category', 'product_name', 'sales', 'quantity',
       'discount', 'profit', 'shipping_cost', 'order_priority', 'year'],
      dtype='object')
```

Data Preprocessing

In [9]:
```
df.isnull().sum()
```

Out[9]:
```
order_id          0
order_date        0
ship_date         0
ship_mode         0
customer_name     0
segment           0
state             0
country           0
market            0
region            0
product_id        0
category          0
sub_category      0
product_name      0
sales             0
quantity          0
discount          0
profit            0
shipping_cost     0
order_priority    0
year              0
dtype: int64
```

In [10]:
```
df.duplicated().sum()
```

Out[10]:
```
0
```

In [11]:
```
# Feature Separation
numerical_cols=df.select_dtypes(include=['float64','int64']).columns
categorical_cols=df.select_dtypes(include=['object']).columns
```

In [12]:
```
numerical_cols
```

Out[12]:
```
Index(['sales', 'quantity', 'discount', 'profit', 'shipping_cost', 'yea
r'], dtype='object')
```

In [13]:
```
categorical_cols
```

Out[13]:
```
Index(['order_id', 'ship_mode', 'customer_name', 'segment', 'state', 'coun
try',
       'market', 'region', 'product_id', 'category', 'sub_category',
       'product_name', 'order_priority'],
      dtype='object')
```

In [14]:
```
df.drop(columns=['customer_name', 'order_id', 'product_id'],inplace=True)
```

In [15]:
```
df['category'].unique()
```

Out[15]:
```
array(['Office Supplies', 'Furniture', 'Technology'], dtype=object)
```

In [16]:
```
df['category'].value_counts()
```

Out[16]:
```
category
Office Supplies    31273
Technology         10141
Furniture           9876
Name: count, dtype: int64
```

In [17]:
```
df['sub_category'].unique()
```

Out[17]:
```
array(['Storage', 'Supplies', 'Paper', 'Furnishings', 'Machines',
       'Appliances', 'Copiers', 'Chairs', 'Tables', 'Bookcases', 'Phones',
       'Accessories', 'Labels', 'Art', 'Envelopes', 'Fasteners',
       'Binders'], dtype=object)
```

In [18]:
```
df['sub_category'].value_counts()
```

Out[18]:
```
sub_category
Binders        6152
Storage        5059
Art            4883
Paper          3538
Chairs         3434
Phones         3357
Furnishings    3170
Accessories    3075
Labels         2606
Envelopes      2435
Supplies       2425
Fasteners      2420
Bookcases      2411
Copiers        2223
Appliances     1755
Machines       1486
Tables          861
Name: count, dtype: int64
```

In [19]:
```
df['segment'].unique()
```

Out[19]:
```
array(['Consumer', 'Home Office', 'Corporate'], dtype=object)
```

In [20]:
```
df['segment'].value_counts()
```

Out[20]:
```
segment
Consumer       26518
Corporate      15429
Home Office     9343
Name: count, dtype: int64
```

In [21]:
```
df['region'].unique()
```

Out[21]:
```
array(['Africa', 'Oceania', 'EMEA', 'North', 'Canada', 'Southeast Asia',
       'Central', 'South', 'Caribbean', 'North Asia', 'East', 'West',
       'Central Asia'], dtype=object)
```

In [22]:
```
df['region'].value_counts()
```

Out[22]:
```
region
Central           11117
South              6645
EMEA               5029
North              4785
Africa             4587
Oceania            3487
West               3203
Southeast Asia     3129
East               2848
North Asia         2338
Central Asia       2048
Caribbean          1690
Canada              384
Name: count, dtype: int64
```

In [23]:
```
df['order_priority'].unique()
```

Out[23]:
```
array(['Medium', 'High', 'Critical', 'Low'], dtype=object)
```

In [24]:
```
df['order_priority'].value_counts()
```

Out[24]:
```
order_priority
Medium      29433
High        15501
Critical     3932
Low          2424
Name: count, dtype: int64
```

In [25]:
```
df['product_name'].unique()
```

Out[25]:
```
array(['Tenex Lockers, Blue', 'Acme Trimmer, High Speed',
       'Tenex Box, Single Width', ...,
       'Panasonic Business\xa0Telephones\xa0KX-T7736',
       'Bush Saratoga Collection 5-Shelf Bookcase, Hanover Cherry, *Specia
l Order',
       'Acco Glide Clips'], dtype=object)
```

In [26]:
```
df['product_name'].value_counts()
```

Out[26]:
```
product_name
Staples
227
Cardinal Index Tab, Clear
92
Eldon File Cart, Single Width
90
Rogers File Cart, Single Width
84
Ibico Index Tab, Clear
83

...
Xerox Blank Computer Paper
1
Panasonic KX MB2061 Multifunction Printer
1
Grip Seal Envelopes
1
Snap-A-Way Black Print Carbonless Speed Message, No Reply Area, Duplicate
1
Acco Glide Clips
1
Name: count, Length: 3788, dtype: int64
```

In [27]:
```
df['ship_mode'].unique()
```

Out[27]:
```
array(['Standard Class', 'Second Class', 'Same Day', 'First Class'],
      dtype=object)
```

In [28]:
```
df['ship_mode'].value_counts()
```

Out[28]:
```
ship_mode
Standard Class    30775
Second Class      10309
First Class        7505
Same Day           2701
Name: count, dtype: int64
```

In [29]:
```
df['state'].unique()
```

Out[29]:
```
array(['Constantine', 'New South Wales', 'Budapest', ..., 'Karaman',
       'Sikasso', 'Atsimo-Andrefana'], dtype=object)
```

In [30]:
```
df['state'].value_counts()
```

Out[30]:
```
state
California          2001
England             1499
New York            1128
Texas                985
Ile-de-France        981
                    ...
Rize                   1
Meta                   1
Ar Raqqah              1
Pernik                 1
Atsimo-Andrefana       1
Name: count, Length: 1094, dtype: int64
```

In [31]:
```
df['country'].unique()
```

Out[31]:
```
array(['Algeria', 'Australia', 'Hungary', 'Sweden', 'Canada',
       'New Zealand', 'Iraq', 'Philippines', 'United Kingdom', 'Malaysia',
       'Guatemala', 'Iran', 'Thailand', 'Tanzania', 'Brazil', 'Mexico',
       'Cuba', 'France', 'United States', 'Japan', 'Sudan', 'Taiwan',
       'Indonesia', 'Vietnam', 'Angola', 'China', 'Mozambique', 'Lebanon',
       'Singapore', 'Netherlands', 'Nigeria', 'Egypt', 'Venezuela',
       'South Africa', 'Spain', 'India', 'Turkey', 'Austria', 'Italy',
       'Germany', 'Nicaragua', 'Dominican Republic', 'El Salvador',
       'Denmark', 'Saudi Arabia', 'Zambia', 'Myanmar (Burma)', 'Russia',
       'Mongolia', 'Belgium', 'Kenya', 'Colombia', 'Estonia',
       'Madagascar', 'Portugal', 'Morocco', 'Sierra Leone', 'Norway',
       'Central African Republic', 'Czech Republic', 'Benin',
       'Bangladesh', 'Panama', 'Chile', 'South Korea', 'Switzerland',
       'Moldova', 'Uganda', 'Zimbabwe', 'Niger', 'Senegal', 'Hong Kong',
       'Democratic Republic of the Congo', 'Poland', 'Ireland',
       'Pakistan', 'Azerbaijan', 'Ukraine', 'Albania', 'Romania',
       'Honduras', 'Israel', 'Cameroon', 'Cambodia', 'Georgia',
       'Argentina', 'Finland', 'Lithuania', 'Peru', 'Somalia', 'Haiti',
       "Cote d'Ivoire", 'Afghanistan', 'Guinea', 'Liberia', 'South Sudan',
       'Turkmenistan', 'Kazakhstan', 'Lesotho', 'Burundi', 'Qatar',
       'Bulgaria', 'Martinique', 'Croatia', 'Ghana', 'Rwanda', 'Ecuador',
       'Paraguay', 'Ethiopia', 'Syria', 'Tajikistan', 'Slovakia',
       'Belarus', 'Papua New Guinea', 'Togo', 'Libya', 'Djibouti',
       'Yemen', 'United Arab Emirates', 'Barbados', 'Uzbekistan',
       'Jamaica', 'Bolivia', 'Uruguay', 'Republic of the Congo',
       'Swaziland', 'Kyrgyzstan', 'Guinea-Bissau',
       'Bosnia and Herzegovina', 'Tunisia', 'Armenia', 'Mali', 'Jordan',
       'Trinidad and Tobago', 'Namibia', 'Gabon', 'Macedonia', 'Nepal',
       'Mauritania', 'Guadeloupe', 'Sri Lanka', 'Chad', 'Eritrea',
       'Bahrain', 'Equatorial Guinea', 'Slovenia', 'Montenegro'],
      dtype=object)
```

In [32]:
```
df['country'].value_counts()
```

Out[32]:
```
country
United States    9994
Australia        2837
France           2827
Mexico           2644
Germany          2065
                 ...
Burundi             2
Chad                2
Eritrea             2
Bahrain             2
South Sudan         2
Name: count, Length: 147, dtype: int64
```

In [33]:
```
df['market'].unique()
```

Out[33]:
```
array(['Africa', 'APAC', 'EMEA', 'EU', 'Canada', 'LATAM', 'US'],
      dtype=object)
```

In [34]:
```
df['market'].value_counts()
```

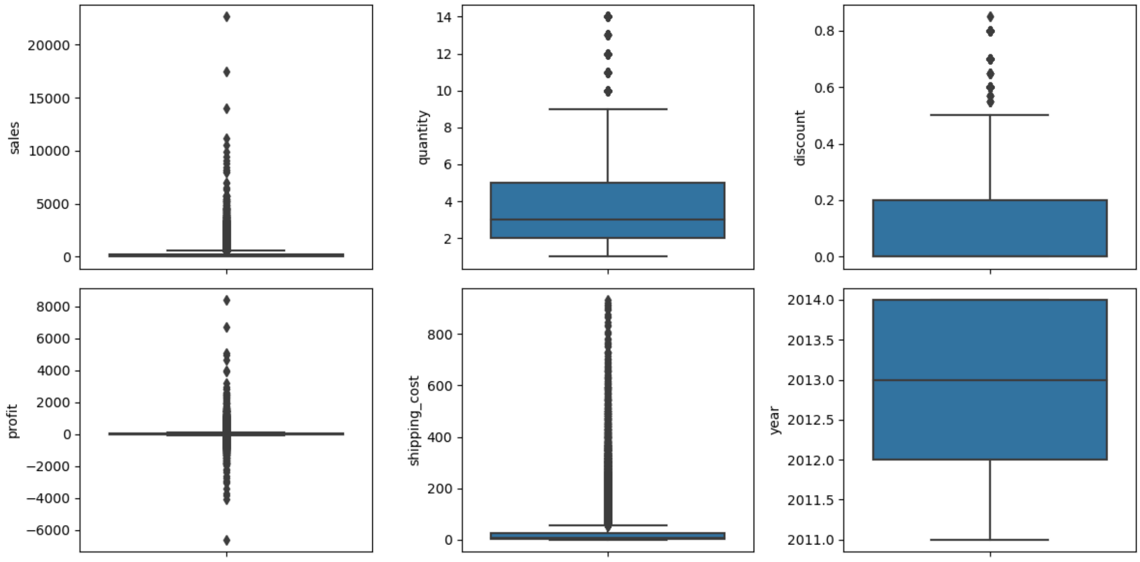
Out[34]:
```
market
APAC      11002
LATAM     10294
EU        10000
US         9994
EMEA       5029
Africa     4587
Canada      384
Name: count, dtype: int64
```

In [35]:
```
df[numerical_cols].describe()
```

Out[35]:

	sales	quantity	discount	profit	shipping_cost	year
count	51290.000000	51290.000000	51290.000000	51290.000000	51290.000000	51290.000000
mean	246.490581	3.476545	0.142908	28.641740	26.375818	2012.777208
std	487.565361	2.278766	0.212280	174.424113	57.296810	1.098931
min	0.444000	1.000000	0.000000	-6599.978000	0.002000	2011.000000
25%	30.758625	2.000000	0.000000	0.000000	2.610000	2012.000000
50%	85.053000	3.000000	0.000000	9.240000	7.790000	2013.000000
75%	251.053200	5.000000	0.200000	36.810000	24.450000	2014.000000
max	22638.480000	14.000000	0.850000	8399.976000	933.570000	2014.000000

In [36]:
```python
# Step 5: Outlier Detection and Treatment
# Boxplot for visual inspection
plt.figure(figsize=(12, 6))
for i, col in enumerate(numerical_cols):
    plt.subplot(2, len(numerical_cols) // 2, i + 1)
    sns.boxplot(data=df, y=col)
plt.tight_layout()
plt.show()
```



In [37]:
```
import numpy as np

def treat_outliers_iqr(df, col):
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    # Option 1: Remove outliers
    df = df[(df[col] >= lower_bound) & (df[col] <= upper_bound)]

    # Option 2: Cap outliers
    df[col] = np.where(df[col] > upper_bound, upper_bound, df[col])
    df[col] = np.where(df[col] < lower_bound, lower_bound, df[col])

    return df

# Apply the function to the columns of interest
for col in ['sales', 'quantity', 'discount', 'profit', 'shipping_cost']:
    df = treat_outliers_iqr(df, col)

# Check the updated DataFrame
print(df.describe())
```

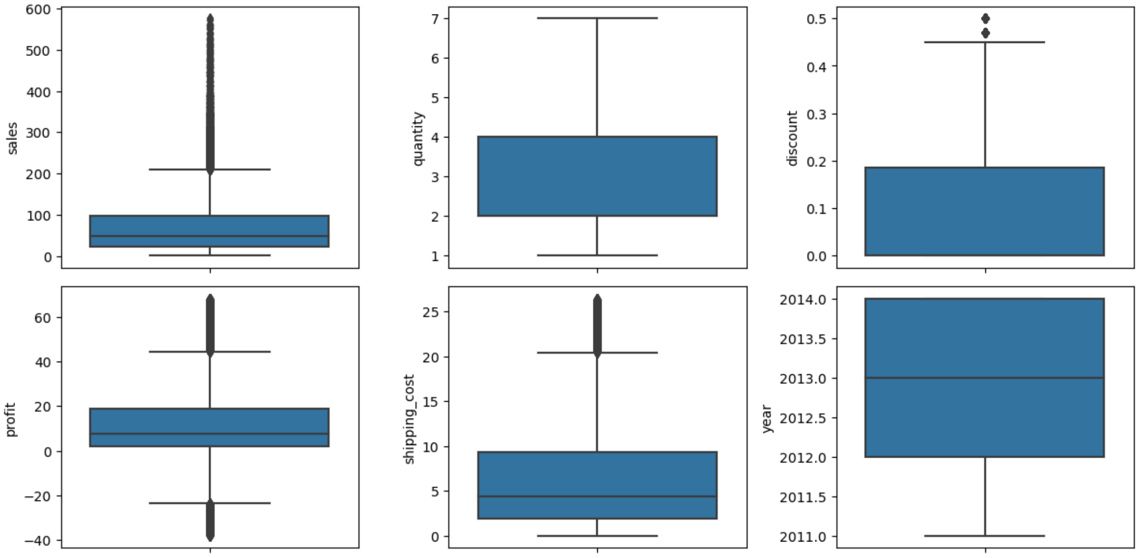
```
                          order_date                      ship_date  \
count                          30879                          30879   
mean   2013-05-11 23:45:35.412416256  2013-05-16 01:08:16.298455296   
min              2011-01-01 00:00:00            2011-01-03 00:00:00   
25%              2012-06-19 00:00:00            2012-06-24 00:00:00   
50%              2013-07-09 00:00:00            2013-07-12 00:00:00   
75%              2014-05-22 00:00:00            2014-05-26 00:00:00   
max              2014-12-31 00:00:00            2015-01-07 00:00:00   
std                              NaN                            NaN   

              sales      quantity      discount        profit  shipping_co
st  \
count  30879.000000  30879.000000  30879.000000  30879.000000   30879.0000
00   
mean      72.592784      2.849704      0.090738     11.282549       6.5242
97   
min        0.990000      1.000000      0.000000    -38.220000       0.0020
00   
25%       23.520000      2.000000      0.000000      1.860000       1.9100
00   
50%       48.660000      2.000000      0.000000      7.540000       4.3830
00   
75%       97.680000      4.000000      0.185000     18.893850       9.3100
00   
max      575.880000      7.000000      0.500000     68.280000      26.4200
00   
std       72.288147      1.600585      0.148741     17.415512       6.0737
31   

               year  
count  30879.000000  
mean    2012.777098  
min     2011.000000  
25%     2012.000000  
50%     2013.000000  
75%     2014.000000  
max     2014.000000  
std        1.098179  
```

In [38]:
```
df[numerical_cols].describe()
```

Out[38]:

	sales	quantity	discount	profit	shipping_cost	year
count	30879.000000	30879.000000	30879.000000	30879.000000	30879.000000	30879.000000
mean	72.592784	2.849704	0.090738	11.282549	6.524297	2012.777098
std	72.288147	1.600585	0.148741	17.415512	6.073731	1.098179
min	0.990000	1.000000	0.000000	-38.220000	0.002000	2011.000000
25%	23.520000	2.000000	0.000000	1.860000	1.910000	2012.000000
50%	48.660000	2.000000	0.000000	7.540000	4.383000	2013.000000
75%	97.680000	4.000000	0.185000	18.893850	9.310000	2014.000000
max	575.880000	7.000000	0.500000	68.280000	26.420000	2014.000000

In [39]:
```
# Step 5: Outlier Detection and Treatment
# Boxplot for visual inspection
plt.figure(figsize=(12, 6))
for i, col in enumerate(numerical_cols):
    plt.subplot(2, len(numerical_cols) // 2, i + 1)
    sns.boxplot(data=df, y=col)
plt.tight_layout()
plt.show()
```



In [40]:
```
df[numerical_cols].skew()
```

Out[40]:
```
sales            2.179652
quantity         0.847992
discount         1.525753
profit           0.667032
shipping_cost    1.301028
year            -0.343176
dtype: float64
```

In [41]:
```
from scipy import stats
df['sales'],a=stats.boxcox(df['sales'])
```

In [45]:
```
df['shipping_cost'],b=stats.boxcox(df['shipping_cost'])
```

In [51]:
```
df['discount'] = df['discount'] + 1  # Adjust as necessary
df['discount'],c = stats.boxcox(df['discount'])
```

In [52]:
```
df[numerical_cols].skew()
```

Out[52]:
```
sales           -0.011857
quantity         0.847992
discount         0.753123
profit           0.667032
shipping_cost   -0.044108
year            -0.343176
dtype: float64
```

Sales Analysis

Calculate total sales and analyze sales by category.

Identify the top products by sales.

In [54]:
```
# Total sales
total_sales = df['sales'].sum()
print(f'Total Sales: {total_sales}')
```

```
Total Sales: 141403.4751941205
```

In [77]:
```
# Set the style for the plots
sns.set(style="whitegrid")

# Plot for Total Sales
plt.figure(figsize=(8, 5))
plt.bar(x=['Total Sales'], height=[total_sales], color='skyblue')
plt.title('Total Sales')
plt.ylabel('Sales Amount')
plt.show()
```

The above plot shows the total sales value, which stands at 141,403.48.

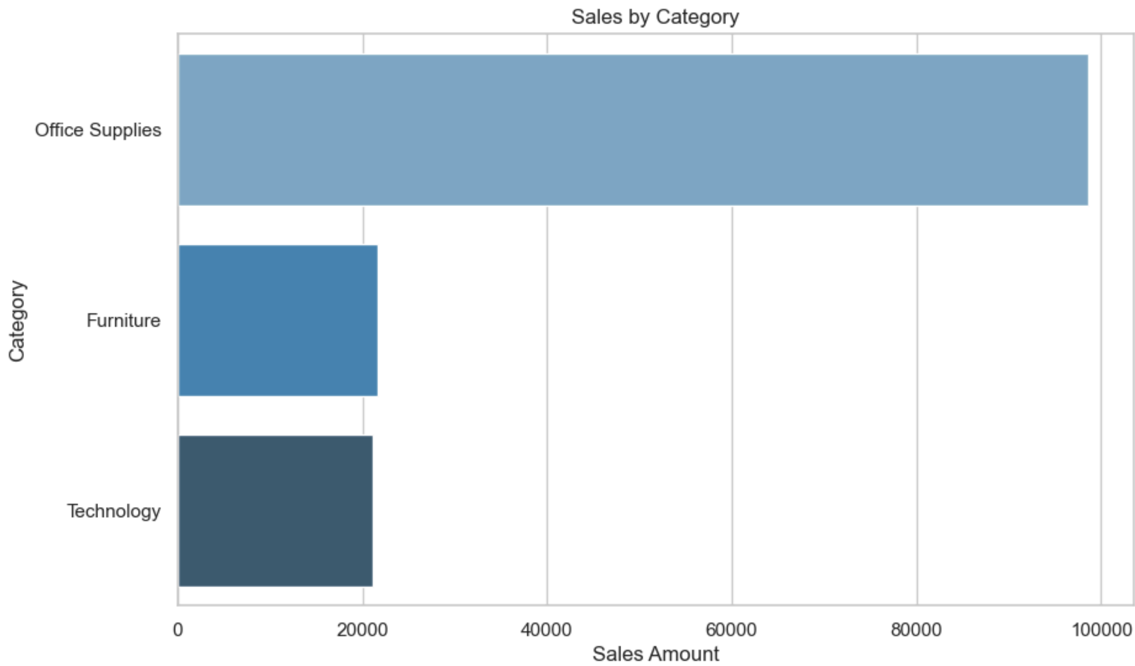
This amount visually represented by the height of the bar chart, highlights the overall sales generated.

The visualization provides a clear indication of the total sales figure, allowing for a quick and effective understanding of sales performance at a glance.

In [55]:
```
# Sales by category
sales_by_category = df.groupby('category')['sales'].sum().sort_values(ascend
print("Sales by Category:")
print(sales_by_category)
```

```
Sales by Category:
category
Office Supplies    98590.216252
Furniture          21693.165816
Technology         21120.093126
Name: sales, dtype: float64
```

In [78]:
```
#  Plot for Sales by Category
plt.figure(figsize=(10, 6))
sns.barplot(data=sales_by_category.reset_index(), x='sales', y='category', 
plt.title('Sales by Category')
plt.xlabel('Sales Amount')
plt.ylabel('Category')
plt.show()
```



The plot illustrates the distribution of total sales across three primary categories: Office Supplies, Furniture, and Technology.

The 'Office Supplies' category leads with the highest sales at 98,590.22, followed by 'Furniture' at 21,693.17, and 'Technology' at 21,120.09.

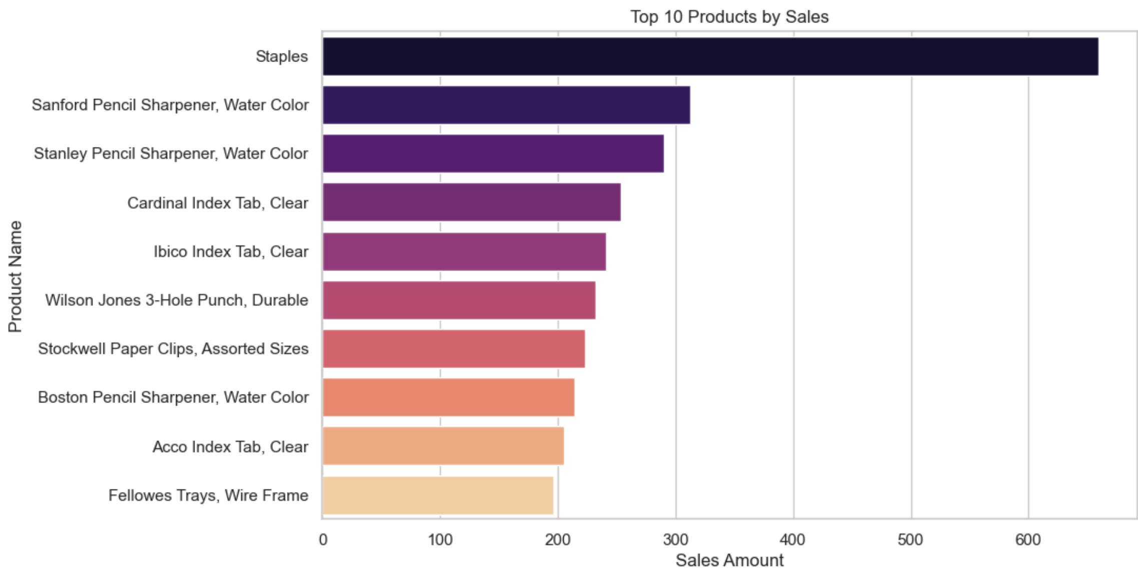
This breakdown helps highlight which category contributes the most to overall sales, with Office Supplies accounting for a significant majority.

The visualization enables easy comparison among categories, providing insights into areas of strong performance and potential growth.

In [56]:
```
# Top 10 products by sales
top_products = df.groupby('product_name', as_index=False)['sales'].sum().sor
print("Top 10 Products by Sales:")
print(top_products)
```

```
Top 10 Products by Sales:
                                  product_name       sales
2807                                   Staples  659.963475
2622  Sanford Pencil Sharpener, Water Color  312.916717
2798  Stanley Pencil Sharpener, Water Color  290.258549
783                Cardinal Index Tab, Clear  253.449649
1676                  Ibico Index Tab, Clear  241.324351
3033     Wilson Jones 3-Hole Punch, Durable  232.486049
2859  Stockwell Paper Clips, Assorted Sizes  223.183842
627    Boston Pencil Sharpener, Water Color  214.344914
79                     Acco Index Tab, Clear  205.496420
1266               Fellowes Trays, Wire Frame  196.702881
```

In [79]:
```
# Plot for Top 10 Products by Sales
plt.figure(figsize=(10, 6))
sns.barplot(data=top_products, x='sales', y='product_name', palette='magma')
plt.title('Top 10 Products by Sales')
plt.xlabel('Sales Amount')
plt.ylabel('Product Name')
plt.show()
```



The plot displays the top 10 products based on sales, led by 'Staples' with a sales total of 659.96.

Other top products include 'Sanford Pencil Sharpener, Water Color' (312.92) and 'Stanley Pencil Sharpener, Water Color' (290.26). Products like 'Cardinal Index Tab, Clear' and 'Ibico Index Tab, Clear' also show strong sales figures, along with various office supplies such as 'Wilson Jones 3-Hole Punch, Durable' and 'Stockwell Paper Clips, Assorted Sizes.'

This ranking highlights the best-performing items in terms of sales, allowing for quick identification of high-demand products.

The visualization serves as an effective tool for understanding which products drive the most revenue.

Customer Segmentation

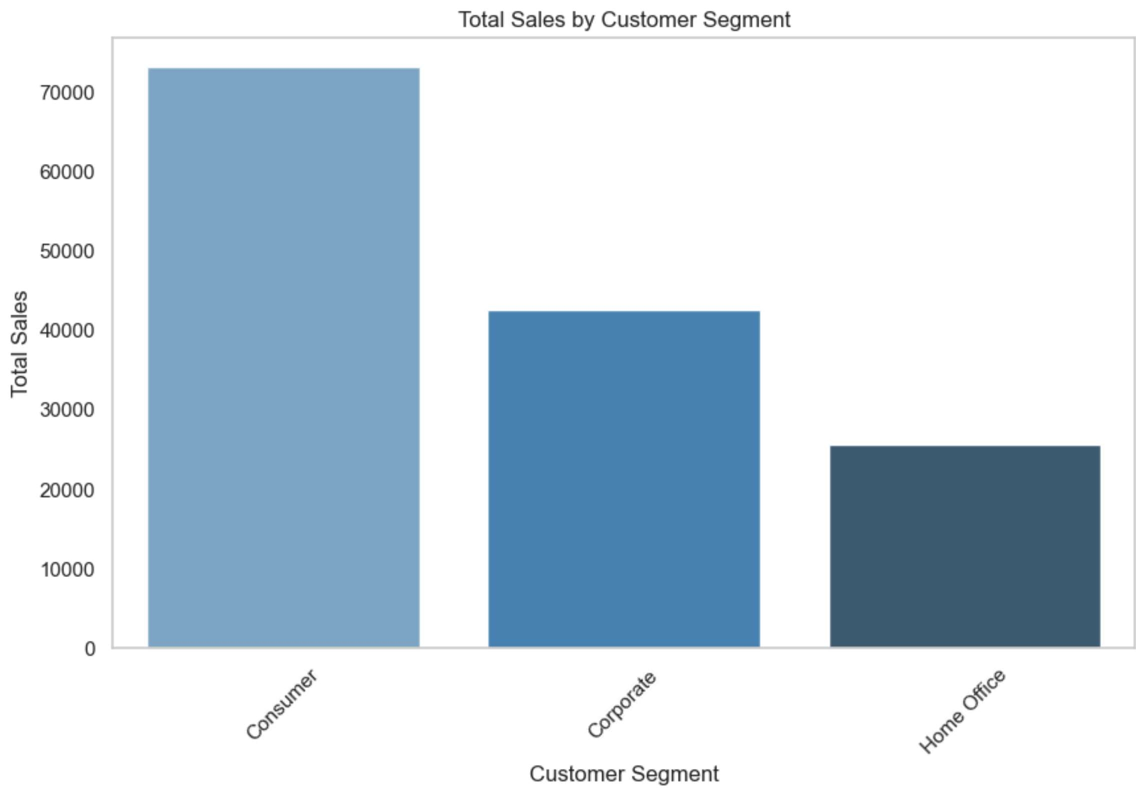
Analyze sales by customer segment.

Plotting total sales by customer segment.

In [60]:
```
# Sales by customer segment
sales_by_segment = df.groupby('segment')['sales'].sum().sort_values(ascendi
print("Sales by Segment:")
print(sales_by_segment)
```

```
Sales by Segment:
       segment         sales
0     Consumer  73150.109897
1    Corporate  42657.869067
2  Home Office  25595.496230
```

In [61]:
```
# Plotting Sales by Customer Segment
plt.figure(figsize=(10, 6))
sns.barplot(data=sales_by_segment, x='segment', y='sales', palette='Blues_d
plt.title('Total Sales by Customer Segment')
plt.xlabel('Customer Segment')
plt.ylabel('Total Sales')
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.show()
```



The plot presents the breakdown of sales across different customer segments.

The 'Consumer' segment leads with the highest sales, amounting to 73,150.11, followed by the 'Corporate' segment with 42,657.87, and finally, the 'Home Office' segment with 25,595.50.

This distribution indicates that the Consumer segment is the largest contributor to total sales, while the Home Office segment generates the lowest.

This visualization enables a clear comparison across segments, helping to identify where the majority of sales revenue originates and highlighting potential areas for targeted sales strategies

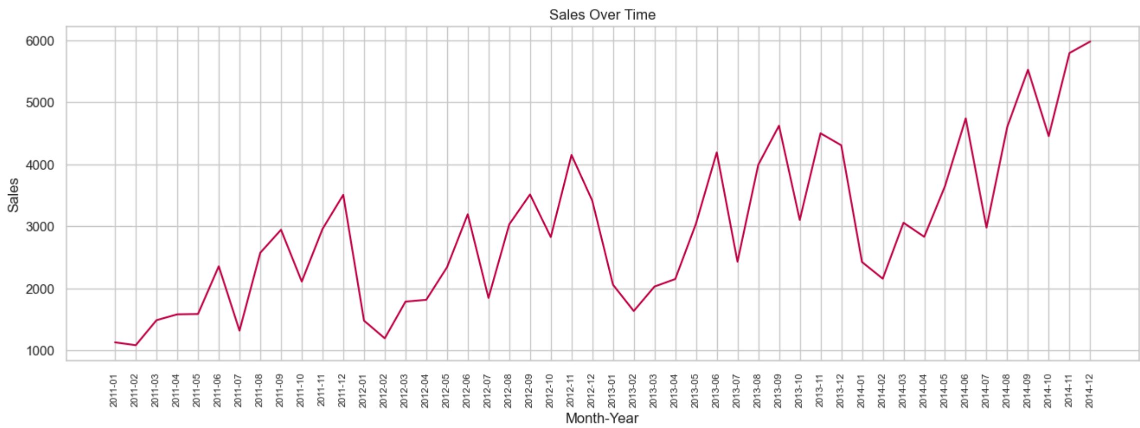
Temporal Analysis

Convert order_date to datetime and analyze sales over time.

In [62]:
```
# Convert order_date to datetime
df['order_date'] = pd.to_datetime(df['order_date'])
```

In [63]:
```
# Group by month-year
df['month_year'] = df['order_date'].dt.to_period('M')
sales_over_time = df.groupby('month_year')['sales'].sum().reset_index()
```

In [64]:
```
# Plotting Sales Over Time
plt.figure(figsize=(16, 5))
plt.plot(sales_over_time['month_year'].astype(str), sales_over_time['sales']
plt.xticks(rotation='vertical', size=8)
plt.title('Sales Over Time')
plt.xlabel('Month-Year')
plt.ylabel('Sales')
plt.show()
```



The line plot illustrates sales trends over time, with the x-axis representing the month and year, and the y-axis showing the corresponding sales figures.

Profit Analysis

Analyze total profit and profit by category.

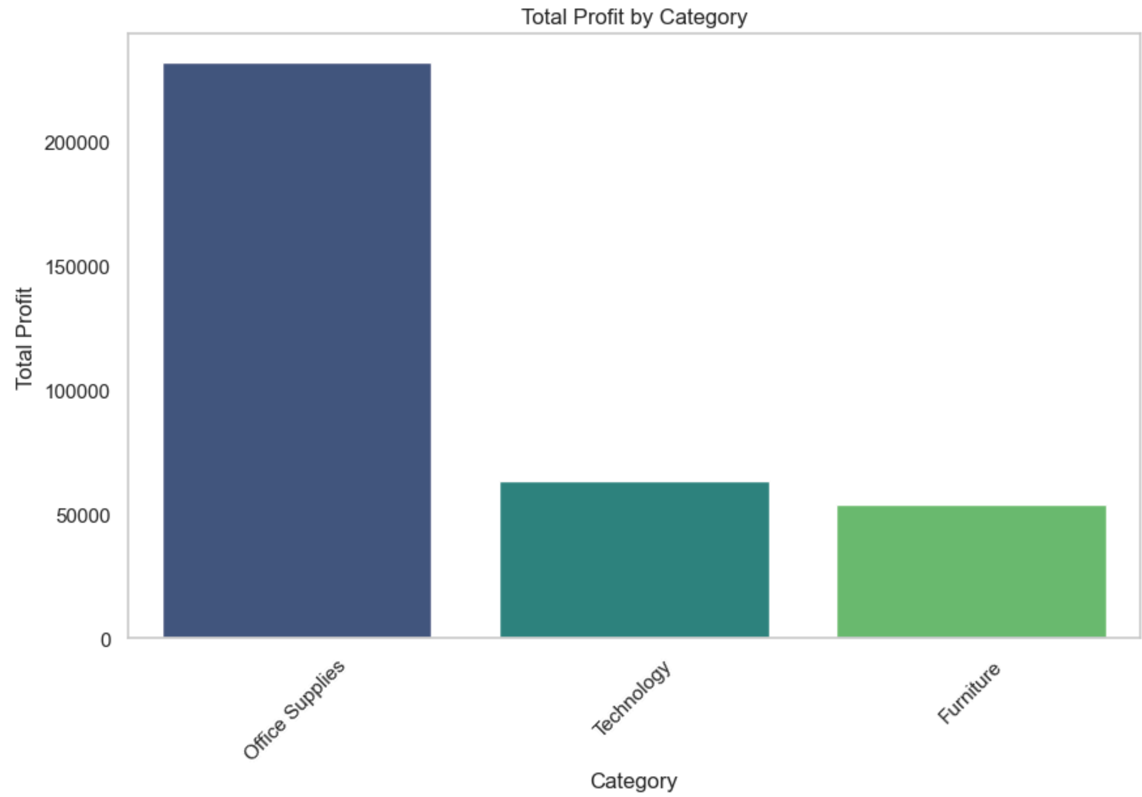
In [65]:
```
# Total profit
total_profit = df['profit'].sum()
print(f'Total Profit: {total_profit}')
```

```
Total Profit: 348393.82548
```

In [66]:
```
# Profit by category
profit_by_category = df.groupby('category')['profit'].sum().sort_values(asce
print("Profit by Category:")
print(profit_by_category)
```

```
Profit by Category:
         category       profit
0  Office Supplies  231353.90710
1       Technology   63116.99958
2        Furniture   53922.91880
```

In [67]:
```
# Plotting Total Profit by Category
plt.figure(figsize=(10, 6))
sns.barplot(data=profit_by_category, x='category', y='profit', palette='vir
plt.title('Total Profit by Category')
plt.xlabel('Category')
plt.ylabel('Total Profit')
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.show()
```



The plot shows the profit distribution across three key categories: Office Supplies, Technology, and Furniture. 'Office Supplies' is the most profitable category, with a total profit of 231,353.91, significantly outpacing the other categories.

'Technology' follows with a profit of 63,117.00, while 'Furniture' contributes 53,922.92 in profit.

This breakdown highlights that Office Supplies not only drive substantial sales but also generate the highest profit, suggesting that it is a core area of profitability.

This visualization effectively illustrates profit margins by category, enabling focused analysis for business strategy

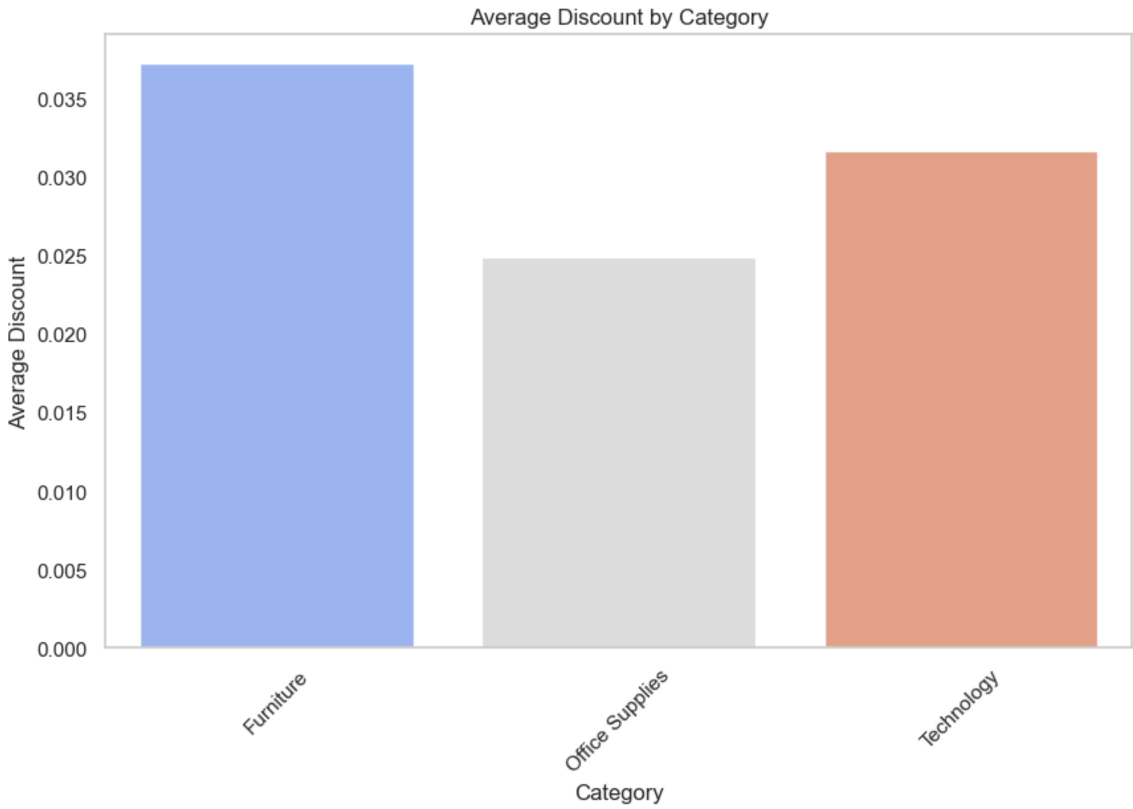
Discount Analysis

Analyze average discount by category.

In [68]:
```
# Average discount by category
avg_discount_by_category = df.groupby('category')['discount'].mean().reset_i
print("Average Discount by Category:")
print(avg_discount_by_category)
```

```
Average Discount by Category:
          category  discount
0        Furniture  0.037187
1  Office Supplies  0.024874
2       Technology  0.031625
```

In [69]:
```
# Plotting Average Discount by Category
plt.figure(figsize=(10, 6))
sns.barplot(data=avg_discount_by_category, x='category', y='discount', palet
plt.title('Average Discount by Category')
plt.xlabel('Category')
plt.ylabel('Average Discount')
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.show()
```



The plot illustrates the average discount applied across three main categories: Furniture, Office Supplies, and Technology.

'Furniture' has the highest average discount at 3.72%, followed by 'Technology' with a 3.16% discount, and 'Office Supplies' with the lowest average discount of 2.49%.

This information provides insight into the discounting strategies for each category, with Furniture receiving the most frequent or largest discounts, which could be a tactic to boost sales in that category.

The visualization aids in understanding pricing strategies and their variation across

Shipping Cost Analysis

Analyze total and category-wise shipping costs.

In [70]:
```
# Total shipping cost
total_shipping_cost = df['shipping_cost'].sum()
print(f'Total Shipping Cost: {total_shipping_cost}')
```

```
Total Shipping Cost: 53685.508961100306
```

In [72]:
```
# Set the style for the plots
sns.set(style="whitegrid")

# 1. Plot for Total Shipping Cost
plt.figure(figsize=(8, 5))
plt.bar(x=['Total Shipping Cost'], height=[total_shipping_cost], color='ligh
plt.title('Total Shipping Cost')
plt.ylabel('Shipping Cost Amount')
plt.show()
```

The plot displays the total shipping cost, amounting to 53,685.51.

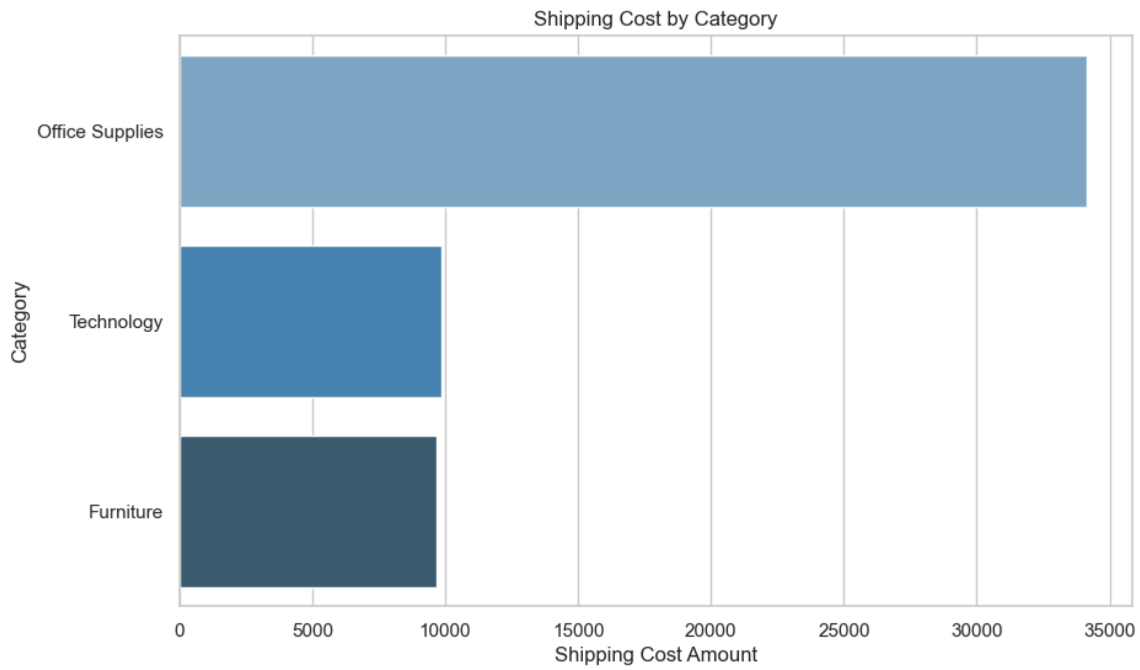
This value represents the cumulative cost associated with shipping across all categories or segments.

The visualization highlights the overall expense dedicated to logistics, helping to contextualize it within the broader cost structure and allowing for an understanding of its impact on total expenses.

In [71]:
```
# Shipping cost by category
shipping_cost_by_category = df.groupby('category')['shipping_cost'].sum().sc
print("Shipping Cost by Category:")
print(shipping_cost_by_category)
```

```
Shipping Cost by Category:
category
Office Supplies    34136.889318
Technology          9868.025991
Furniture           9680.593652
Name: shipping_cost, dtype: float64
```

In [73]:
```
# 2. Plot for Shipping Cost by Category
plt.figure(figsize=(10, 6))
sns.barplot(data=shipping_cost_by_category.reset_index(), x='shipping_cost',
plt.title('Shipping Cost by Category')
plt.xlabel('Shipping Cost Amount')
plt.ylabel('Category')
plt.show()
```



The plot breaks down the total shipping cost by category, showing that 'Office Supplies' incurs the highest shipping cost at 34,136.89, followed by 'Technology' with 9,868.03, and 'Furniture' with 9,680.59.

This distribution indicates that Office Supplies not only dominate in sales and profit but also carry the highest logistics expenses.

The visualization enables a clear comparison of shipping costs across categories, providing insight into how shipping expenses align with each category's demand and volume

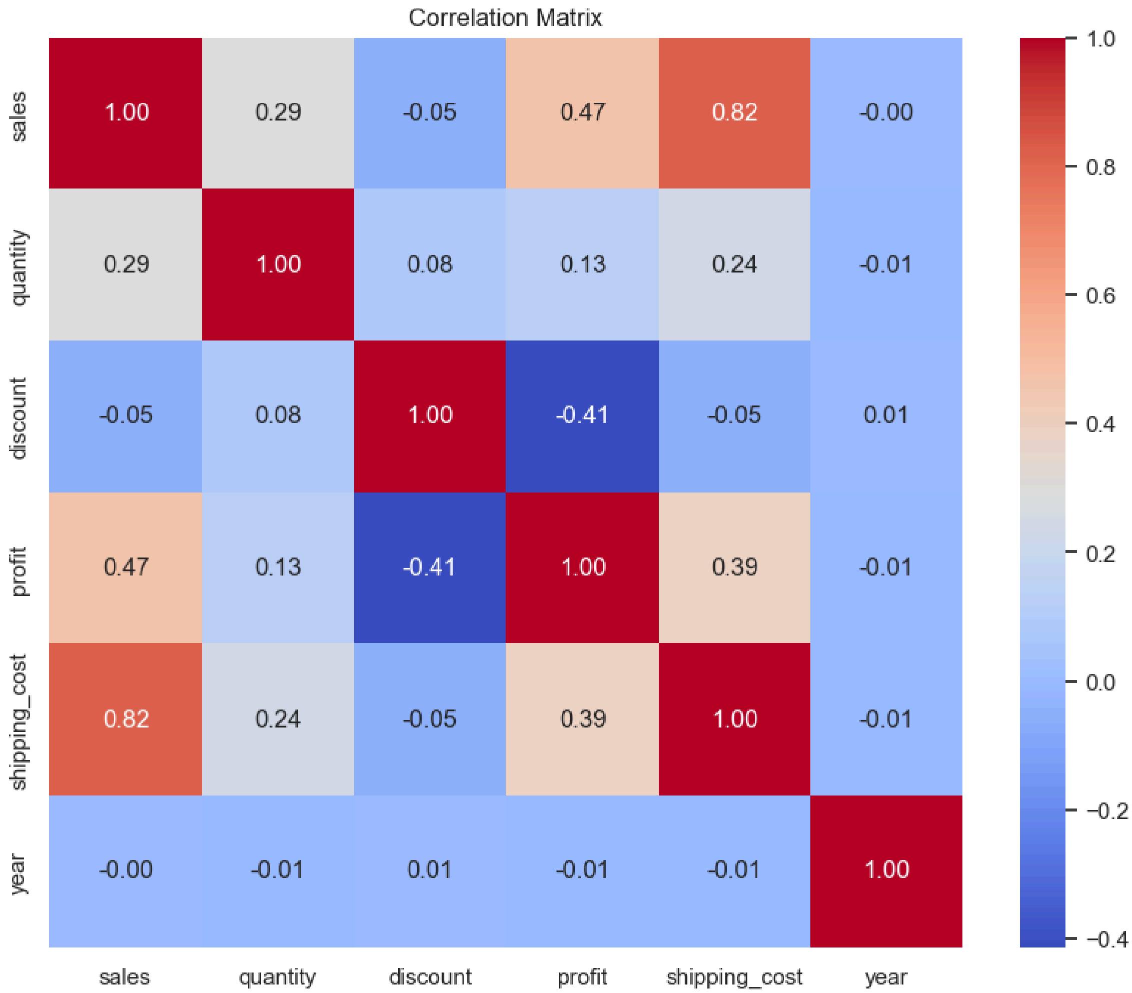
Correlation Analysis

Explore correlations among numeric features.

In [74]:
```
# Select only numeric columns
numeric_df = df.select_dtypes(include=['float64', 'int64'])
```

In [75]:
```
# Compute the correlation matrix
correlation_matrix = numeric_df.corr()
```

In [76]:
```
# Plotting the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix')
plt.show()
```



The heatmap visualizes the correlation matrix, providing insights into the relationships between different variables.

The color gradient highlights positive correlations in shades of red and negative correlations in shades of blue.

The numerical annotations display the correlation coefficients, giving a precise view of how closely the variables are related

IN SUMMARY

The data reveals that 'Office Supplies' is the dominant category in terms of both sales and shipping costs, with a total sales value of 98,590.22 and corresponding shipping costs of 34,136.89.

While 'Furniture' and 'Technology' show lower sales figures, their shipping costs remain relatively close to each other, with Furniture slightly higher.

Profit margins are strongest in the Office Supplies category, indicating that this segment is the most profitable.

The average discount applied is also highest in Furniture, suggesting a strategy to stimulate sales in this category.

Overall, the data suggests that while Office Supplies are leading in sales and profitability, careful attention should be given to shipping costs, especially in high-volume categories like Office Supplies, to optimize cost efficiency.

In [ ]:

```

```