Car Sales EDA

01- Importing libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
```

02- Load dataset

In [2]:
```
car = pd.read_excel("Car Dashboard Source (2).xlsx", sheet_name="Orders")
car.head()
```

Out[2]:

	Row ID	Order ID	Order Date	Ship Date	Delivery-TAT	Ship Mode	Customer ID	Customer Name	Segment	Country/Region	...	State/Province	Postal Code
0	1	US-2019-103800	2019-01-03	2019-01-07	4	Standard Class	DP-13000	Darren Powers	Replacement	United States	...	Texas	77095
1	2	US-2019-112326	2019-01-04	2019-01-08	4	Standard Class	PO-19195	Phillina Ober	Other	United States	...	Illinois	60540
2	3	US-2019-112326	2019-01-04	2019-01-08	4	Standard Class	PO-19195	Phillina Ober	Other	United States	...	Illinois	60540
3	4	US-2019-112326	2019-01-04	2019-01-08	4	Standard Class	PO-19195	Phillina Ober	Other	United States	...	Illinois	60540
4	5	US-2019-141817	2019-01-05	2019-01-12	7	Standard Class	MB-18085	Mick Brown	Replacement	United States	...	Pennsylvania	19143

5 rows × 21 columns

03- EDA Steps

In [3]:
```
car.shape
```

Out[3]:
```
(10194, 21)
```

In [4]:
```
car.dtypes
```

Out[4]:
```
Row ID                       int64
Order ID                    object
Order Date          datetime64[ns]
Ship Date           datetime64[ns]
Delivery-TAT                 int64
Ship Mode                   object
Customer ID                 object
Customer Name               object
Segment                     object
Country/Region              object
City                        object
State/Province              object
Postal Code                 object
Region                      object
Product ID                  object
Category                    object
Sub-Category                object
Sales                      float64
Quantity                     int64
Discount                   float64
Profit                     float64
dtype: object
```

In [5]:
```
car.describe().T
```

Out[5]:

	count	mean	min	25%	50%	75%	max	std
Row ID	10194.0	5097.5	1.0	2549.25	5097.5	7645.75	10194.0	2942.898656
Order Date	10194	2021-04-29 11:48:25.002942976	2019-01-03 00:00:00	2020-05-14 00:00:00	2021-06-25 00:00:00	2022-05-14 00:00:00	2022-12-30 00:00:00	NaN
Ship Date	10194	2021-05-03 10:52:45.626839296	2019-01-07 00:00:00	2020-05-19 00:00:00	2021-06-28 00:00:00	2022-05-18 00:00:00	2023-01-05 00:00:00	NaN
Delivery-TAT	10194.0	3.96135	0.0	3.0	4.0	5.0	11.0	1.742829
Sales	10194.0	228.225854	0.444	17.22	53.91	209.5	22638.48	619.906839
Quantity	10194.0	3.791838	1.0	2.0	3.0	5.0	14.0	2.228317
Discount	10194.0	0.155385	0.0	0.0	0.2	0.2	0.8	0.206249
Profit	10194.0	28.673417	-6599.978	1.7608	8.69	29.297925	8399.976	232.465115

In [6]:

```
car.isnull().sum()
```

Out[6]:

```
Row ID            0
Order ID          0
Order Date        0
Ship Date         0
Delivery-TAT      0
Ship Mode         0
Customer ID       0
Customer Name     0
Segment           0
Country/Region    0
City              0
State/Province    0
Postal Code       0
Region            0
Product ID        0
Category          0
Sub-Category      0
Sales             0
Quantity          0
Discount          0
Profit            0
dtype: int64
```

In [7]:

```
car.nunique()
```

Out[7]:

```
Row ID            10194
Order ID           5111
Order Date         1242
Ship Date          1338
Delivery-TAT          9
Ship Mode             4
Customer ID         804
Customer Name       800
Segment               3
Country/Region        2
City                542
State/Province       59
Postal Code         654
Region                4
Product ID         1862
Category              4
Sub-Category         17
Sales              5837
Quantity             14
Discount             12
Profit             7362
dtype: int64
```

In [8]:

```
car.columns
```

Out[8]:

```
Index(['Row ID', 'Order ID', 'Order Date', 'Ship Date', 'Delivery-TAT',
       'Ship Mode', 'Customer ID', 'Customer Name', 'Segment',
       'Country/Region', 'City', 'State/Province', 'Postal Code', 'Region',
       'Product ID', 'Category', 'Sub-Category', 'Sales', 'Quantity',
       'Discount', 'Profit'],
      dtype='object')
```

04- Data Visualization

Shipping Mode vs Delivery TAT

This barplot shows us average TAT for different shipping modes.

In [9]:
```
plt.figure(figsize=(8, 5))
sns.barplot(x="Ship Mode", y="Delivery-TAT", data=car, errorbar=None)
plt.gca().bar_label(plt.gca().containers[0], fmt='%.1f')  # Data labels
plt.title("Ship Mode vs Delivery TAT")
plt.tight_layout()
plt.show()
```

Sales by Segment and Country

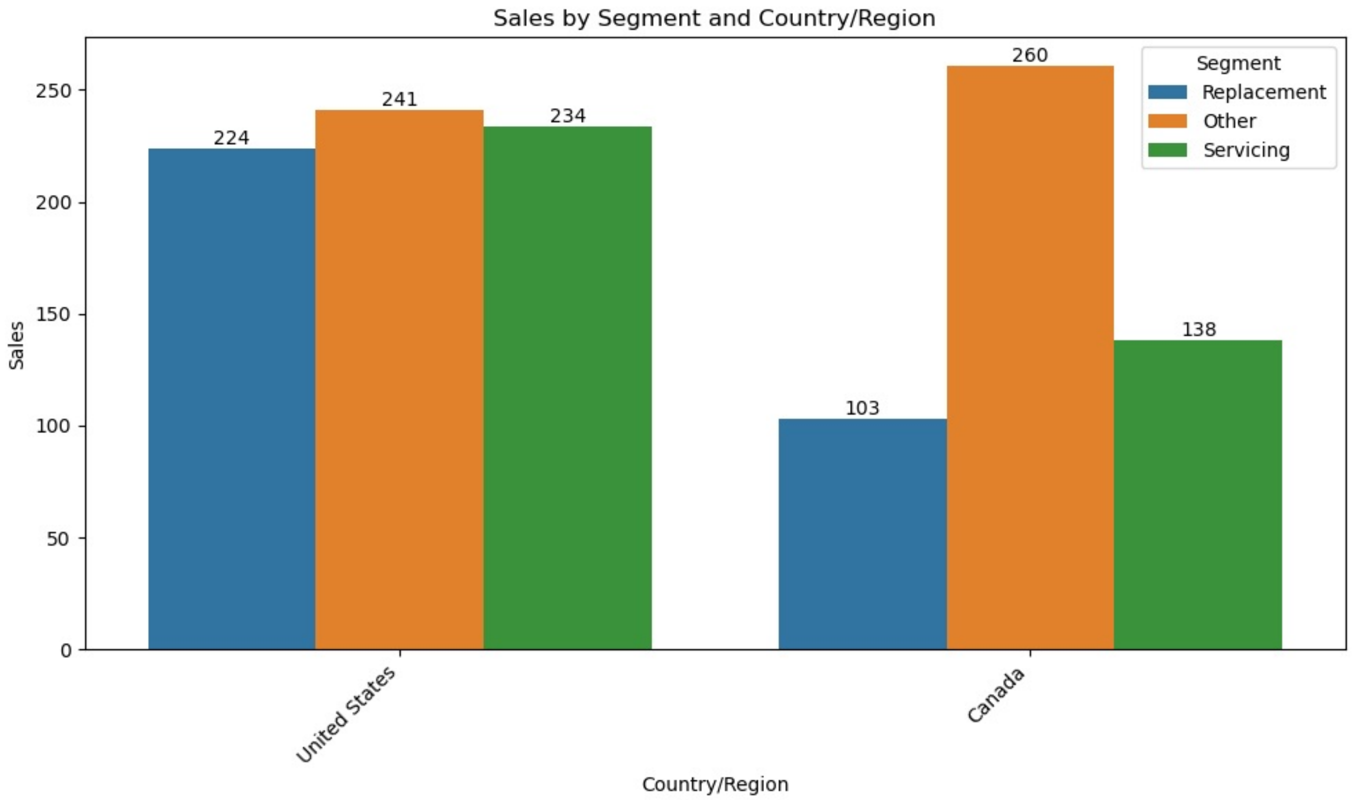
This barplot explains us the number of sales per Country with bifurcation of each Segment.

In [10]:
```
import matplotlib.pyplot as plt
fig, ax = plt.subplots(figsize=(10, 6))
sns.barplot(x='Country/Region', y='Sales', data=car, hue='Segment', ci=None, ax=ax)
for container in ax.containers:
    ax.bar_label(container, fmt='%.0f', label_type='edge')
plt.title('Sales by Segment and Country/Region')
plt.xlabel('Country/Region')
plt.ylabel('Sales')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```

```
C:\Users\Yawar Ali\AppData\Local\Temp\ipykernel_9040\2710382807.py:3: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(x='Country/Region', y='Sales', data=car, hue='Segment', ci=None, ax=ax)
```



Sales Trend Analysis

This detailed analysis shows us the sales over daily, monthly and quarterly period of time.

In [11]:
```
import pandas as pd
import plotly.graph_objects as go
from plotly.subplots import make_subplots

# Load and prep data
car['Order Date'] = pd.to_datetime(car['Order Date'])
car['Sales'] = pd.to_numeric(car['Sales'])

# Aggregations
daily_sales = car.groupby('Order Date')['Sales'].sum().reset_index().sort_values('Order Date')
daily_sales['MA_7'] = daily_sales['Sales'].rolling(7).mean()  # Add moving average

monthly_sales = car.set_index('Order Date').resample('M')['Sales'].sum().reset_index()
quarterly_sales = car.set_index('Order Date').resample('Q')['Sales'].sum().reset_index()

# Create figure
fig = make_subplots(
    rows=3, cols=1,
    subplot_titles=('Daily Sales with 7-Day MA', 'Monthly Sales', 'Quarterly Sales'),
    vertical_spacing=0.1,
    shared_xaxes=False
)
```

```python
# Add traces
fig.add_trace(
    go.Scatter(x=daily_sales['Order Date'], y=daily_sales['Sales'],
               name='Daily Sales', line=dict(color='blue', width=1)),
    row=1, col=1
)
fig.add_trace(
    go.Scatter(x=daily_sales['Order Date'], y=daily_sales['MA_7'],
               name='7-Day MA', line=dict(color='red', width=2)),
    row=1, col=1
)

fig.add_trace(
    go.Bar(x=monthly_sales['Order Date'], y=monthly_sales['Sales'],
           name='Monthly', marker_color='#1f77b4'),  # Seaborn default blue
    row=2, col=1
)

fig.add_trace(
    go.Bar(x=quarterly_sales['Order Date'], y=quarterly_sales['Sales'],
           name='Quarterly', marker_color='#2ca02c'),  # Seaborn default green
    row=3, col=1
)

# Update layout
fig.update_layout(
    height=900,
    title="<b>Sales Trend Analysis</b><br><sup>Daily, Monthly & Quarterly Patterns</sup>",
    hovermode="x unified",
    template="plotly_white"
)

# Axis formatting
for i, unit in enumerate(['Day', 'Month', 'Quarter'], 1):
    fig.update_xaxes(title_text=f"Time ({unit})", row=i, col=1,
                     tickformat='%b %Y' if i>1 else None)
    fig.update_yaxes(title_text="Sales ($)", row=i, col=1)

fig.show()
```

```
C:\Users\Yawar Ali\AppData\Local\Temp\ipykernel_9040\470193796.py:13: FutureWarning: 'M' is deprecated and will
be removed in a future version, please use 'ME' instead.
  monthly_sales = car.set_index('Order Date').resample('M')['Sales'].sum().reset_index()
C:\Users\Yawar Ali\AppData\Local\Temp\ipykernel_9040\470193796.py:14: FutureWarning: 'Q' is deprecated and will
be removed in a future version, please use 'QE' instead.
  quarterly_sales = car.set_index('Order Date').resample('Q')['Sales'].sum().reset_index()
```

Sales Statistics

This detailed summary helps us to understand different parameters and trends for sales made.

In [12]:

```python
import pandas as pd

# Prepare data
car['Order Date'] = pd.to_datetime(car['Order Date'])
car['Sales'] = pd.to_numeric(car['Sales'])
daily_sales = car.groupby('Order Date')['Sales'].sum().reset_index()
monthly_sales = car.set_index('Order Date').resample('M')['Sales'].sum().reset_index()

# Calculate statistics
stats = {
    'Total Sales': f"${car['Sales'].sum():,.2f}",
    'Average Daily Sales': f"${daily_sales['Sales'].mean():,.2f}",
    'Median Daily Sales': f"${daily_sales['Sales'].median():,.2f}",
    'Daily Sales Std Dev': f"${daily_sales['Sales'].std():,.2f}",
    'Coefficient of Variation': f"{(daily_sales['Sales'].std()/daily_sales['Sales'].mean())*100:.1f}%",
    'Min Daily Sales': f"${daily_sales['Sales'].min():,.2f}",
    'Max Daily Sales': f"${daily_sales['Sales'].max():,.2f}",
    'Sales Range': f"${daily_sales['Sales'].max()-daily_sales['Sales'].min():,.2f}",
    'Number of Trading Days': f"{len(daily_sales):,} days",
    'Date Range': f"{daily_sales['Order Date'].min().strftime('%Y-%m-%d')} to {daily_sales['Order Date'].max().s
    'Average Monthly Sales': f"${monthly_sales['Sales'].mean():,.2f}",
    'Monthly Sales Std Dev': f"${monthly_sales['Sales'].std():,.2f}",
    'Monthly Coefficient of Variation': f"{(monthly_sales['Sales'].std()/monthly_sales['Sales'].mean())*100:.1f
    'Best Month': f"{monthly_sales.loc[monthly_sales['Sales'].idxmax(), 'Order Date'].strftime('%b %Y')} (${mon
    'Worst Month': f"{monthly_sales.loc[monthly_sales['Sales'].idxmin(), 'Order Date'].strftime('%b %Y')} (${mo
}

# Convert to DataFrame
pd.DataFrame(list(stats.items()), columns=['Metric', 'Value'])
```

```
C:\Users\Yawar Ali\AppData\Local\Temp\ipykernel_9040\3339078402.py:7: FutureWarning:

'M' is deprecated and will be removed in a future version, please use 'ME' instead.
```

Out[12]:

	Metric	Value
0	Total Sales	$2,326,534.35
1	Average Daily Sales	$1,873.22
2	Median Daily Sales	$1,066.20
3	Daily Sales Std Dev	$2,330.28
4	Coefficient of Variation	124.4%
5	Min Daily Sales	$2.02
6	Max Daily Sales	$28,106.72
7	Sales Range	$28,104.69
8	Number of Trading Days	1,242 days
9	Date Range	2019-01-03 to 2022-12-30
10	Average Monthly Sales	$48,469.47
11	Monthly Sales Std Dev	$25,415.68
12	Monthly Coefficient of Variation	52.4%
13	Best Month	Nov 2022 ($118,454.51)
14	Worst Month	Feb 2019 ($4,519.89)

Product Category Performance Analysis

This detailed analysis shows the different trends for sub-category of products against sales.

In [13]:

```
import pandas as pd
import plotly.graph_objects as go
from plotly.subplots import make_subplots

# Data Preparation
car['Order Date'] = pd.to_datetime(car['Order Date'])
car['Sales'] = pd.to_numeric(car['Sales'])

# Time-based aggregations
monthly_sales = car.set_index('Order Date').groupby([pd.Grouper(freq='M'), 'Category'])['Sales'].sum().reset_in
quarterly_sales = car.set_index('Order Date').groupby([pd.Grouper(freq='Q'), 'Category'])['Sales'].sum().reset_

# Category statistics
cat_stats = car.groupby('Category')['Sales'].agg(['sum', 'mean', 'std', 'count'])
cat_stats['CV%'] = (cat_stats['std'] / cat_stats['mean'] * 100).round(1)

# Visualization Setup
fig = make_subplots(
    rows=3, cols=2,
    specs=[[{"type": "scatter"}, {"type": "box"}],
           [{"type": "scatter"}, {"type": "bar"}],
           [{"colspan": 2}, None]],
    subplot_titles=(
        'Monthly Sales Trend', 'Sales Distribution by Category',
        'Quarterly Sales Pattern', 'Sales Volatility (CV%)',
        'Category Market Share Over Time'
    )
)

# Color scheme
colors = px.colors.qualitative.Set3

# Plot 1: Monthly Trend (Stacked Area)
for i, (cat, data) in enumerate(monthly_sales.groupby('Category')):
    fig.add_trace(
        go.Scatter(
            x=data['Order Date'], y=data['Sales'],
            name=cat, stackgroup='one',
            line=dict(color=colors[i]),
            hovertemplate="%{x|%b %Y}: %{y:$,.0f}<extra>%{fullData.name}</extra>"
        ), row=1, col=1)

# Plot 2: Sales Distribution (Boxplot)
for i, (cat, data) in enumerate(car.groupby('Category')):
    fig.add_trace(
        go.Box(
```

```
            y=data['Sales'], name=cat,
            marker_color=colors[i],
            boxmean=True,
            hovertemplate="%{y:$,.0f}<extra>%{fullData.name}</extra>"
        ), row=1, col=2)

# Plot 3: Quarterly Trends
for i, (cat, data) in enumerate(quarterly_sales.groupby('Category')):
    fig.add_trace(
        go.Scatter(
            x=data['Order Date'], y=data['Sales'],
            mode='lines+markers',
            line=dict(color=colors[i]),
            showlegend=False,
            hovertemplate="Q%{x|%q %Y}: %{y:$,.0f}<extra>%{fullData.name}</extra>"
        ), row=2, col=1)

# Plot 4: Volatility (CV%)
fig.add_trace(
    go.Bar(
        x=cat_stats.index, y=cat_stats['CV%'],
        marker_color=colors[:len(cat_stats)],
        text=cat_stats['CV%'],
        texttemplate='%{text:.1f}%',
        textposition='outside',
        hovertemplate="%{x}: %{y:.1f}%<extra></extra>"
    ), row=2, col=2)

# Plot 5: Market Share
monthly_total = monthly_sales.groupby('Order Date')['Sales'].sum()
for i, (cat, data) in enumerate(monthly_sales.groupby('Category')):
    share = (data.set_index('Order Date')['Sales'] / monthly_total * 100).reset_index()
    fig.add_trace(
        go.Scatter(
            x=share['Order Date'], y=share['Sales'],
            line=dict(color=colors[i]),
            showlegend=False,
            hovertemplate="%{x|%b %Y}: %{y:.1f}%<extra>%{fullData.name}</extra>"
        ), row=3, col=1)

# Layout Configuration
fig.update_layout(
    height=1000,
    title="Product Category Performance Analysis",
    hovermode="x unified",
    template="plotly_white",
    margin=dict(t=100))

# Axis Labels
fig.update_xaxes(title_text="Date", row=1, col=1)
fig.update_xaxes(title_text="Category", row=1, col=2)
fig.update_xaxes(title_text="Date", row=2, col=1)
fig.update_xaxes(title_text="Category", row=2, col=2)
fig.update_xaxes(title_text="Date", row=3, col=1)

fig.update_yaxes(title_text="Sales ($)", row=1, col=1)
fig.update_yaxes(title_text="Sales ($)", row=1, col=2)
fig.update_yaxes(title_text="Sales ($)", row=2, col=1)
fig.update_yaxes(title_text="CV (%)", row=2, col=2)
fig.update_yaxes(title_text="Market Share (%)", row=3, col=1)

fig.show()
```

```
C:\Users\Yawar Ali\AppData\Local\Temp\ipykernel_9040\3505472780.py:10: FutureWarning:

'M' is deprecated and will be removed in a future version, please use 'ME' instead.

C:\Users\Yawar Ali\AppData\Local\Temp\ipykernel_9040\3505472780.py:11: FutureWarning:

'Q' is deprecated and will be removed in a future version, please use 'QE' instead.
```

Product Category Statistics

This summary helps us to understand the trends for each product sub-category in detail.

In [14]:
```
import pandas as pd
car['Order Date'] = pd.to_datetime(car['Order Date'])
car['Sales'] = pd.to_numeric(car['Sales'])

# Category Analysis
def format_currency(x):
```

```
    return f"${x:,.2f}"

category_stats = (
    car.groupby('Category')['Sales']
    .agg(Total_Sales='sum',
         Avg_Order_Value='mean',
         Std_Dev='std',
         Order_Count='count',
         Min_Sale='min',
         Max_Sale='max')
    .assign(
        Market_Share=lambda x: (x['Total_Sales']/x['Total_Sales'].sum()*100).round(1),
        CV_Order=lambda x: (x['Std_Dev']/x['Avg_Order_Value']*100).round(1),
        Sales_Range=lambda x: x['Max_Sale'] - x['Min_Sale']
    )
)

# Monthly Volatility Analysis
monthly_stats = (
    car.assign(Year_Month=car['Order Date'].dt.to_period('M'))
    .groupby(['Year_Month', 'Category'])['Sales']
    .sum()
    .groupby('Category')
    .agg(Monthly_Avg='mean',
         Monthly_Std='std')
    .assign(Monthly_CV=lambda x: (x['Monthly_Std']/x['Monthly_Avg']*100).round(1))
    .reset_index()
)

# Merge and Format Results
final_output = (
    category_stats.reset_index()
    .merge(monthly_stats, on='Category')
    .assign(
        **{f'{col}_Formatted': lambda x: x[col].apply(format_currency)
        for col in ['Total_Sales', 'Avg_Order_Value', 'Std_Dev',
                    'Min_Sale', 'Max_Sale', 'Sales_Range',
                    'Monthly_Avg', 'Monthly_Std']
    })
)

# Create Summary Table
summary_table = final_output[[
    'Category', 'Total_Sales_Formatted', 'Market_Share',
    'Avg_Order_Value_Formatted', 'Order_Count',
    'CV_Order', 'Monthly_CV'
]].rename(columns={
    'Total_Sales_Formatted': 'Total Sales',
    'Market_Share': 'Market Share (%)',
    'Avg_Order_Value_Formatted': 'Avg Order Value',
    'CV_Order': 'Order Volatility (CV%)',
    'Monthly_CV': 'Monthly Volatility (CV%)'
})

summary_table
```

Out[14]:

	Category	Total Sales	Market Share (%)	Avg Order Value	Order_Count	Order Volatility (CV%)	Monthly Volatility (CV%)
0	Direct Sale	$9,834.20	30.0	$9,834.20	2007	146.6	66.2
1	Other	$19,937.06	7.6	$19,937.06	959	197.8	123.3
2	Pre Book	$11,094.53	33.3	$11,094.53	1707	250.5	67.3
3	Third Party	$9,437.92	29.0	$9,437.92	5521	326.2	65.7

Sales & Profit Relationship Analysis

This analysis depicts the different relations for sales and profit with profit-margin distribution.

In [15]:

```
import pandas as pd
import numpy as np
import plotly.graph_objects as go
from plotly.subplots import make_subplots

# Data Preparation
car['Order Date'] = pd.to_datetime(car['Order Date'])
car['Sales'] = pd.to_numeric(car['Sales'])
car['Profit'] = pd.to_numeric(car['Profit'])
car['Profit_Margin_%'] = (car['Profit'] / car['Sales'] * 100).round(2)

# Create aggregations
daily = car.groupby('Order Date').agg({'Sales':'sum', 'Profit':'sum'}).reset_index()
```

```python
monthly = car.set_index('Order Date').resample('M').agg({'Sales':'sum', 'Profit':'sum'}).reset_index()
monthly['Profit_Margin_%'] = (monthly['Profit'] / monthly['Sales'] * 100).round(2)
categories = car.groupby('Category').agg({'Sales':'sum', 'Profit':'sum'}).reset_index()

# Visualization Setup
fig = make_subplots(
    rows=3, cols=2,
    subplot_titles=(
        'Order-Level Profitability', 'Profit Margin Distribution',
        'Daily Performance', 'Monthly Performance',
        'Category Comparison', 'Margin Trend'
    ),
    specs=[[{}, {}], [{}, {}], [{}, {}]],
    vertical_spacing=0.1,
    horizontal_spacing=0.1
)

# Color scheme
colors = px.colors.qualitative.Set3

# 1. Order-Level Scatter with Trendline
fig.add_trace(
    go.Scatter(
        x=car['Sales'], y=car['Profit'],
        mode='markers', name='Orders',
        marker=dict(size=3, opacity=0.6, color='blue'),
        hovertemplate='Sales: $%{x:,.2f}<br>Profit: $%{y:,.2f}<extra></extra>',
    ), row=1, col=1)

# Add trendline
trend = np.poly1d(np.polyfit(car['Sales'], car['Profit'], 1))
fig.add_trace(
    go.Scatter(
        x=car['Sales'], y=trend(car['Sales']),
        mode='lines', name='Trend',
        line=dict(color='red', width=2),
    ), row=1, col=1)

# 2. Profit Margin Distribution
for i, cat in enumerate(car['Category'].unique()):
    fig.add_trace(
        go.Box(
            y=car[car['Category']==cat]['Profit_Margin_%'],
            name=cat, marker_color=colors[i],
            showlegend=False
        ), row=1, col=2)

# 3. Daily Performance
fig.add_trace(
    go.Scatter(
        x=daily['Sales'], y=daily['Profit'],
        mode='markers', name='Daily',
        marker=dict(size=5, color='green'),
        hovertemplate='$%{x:,.2f} Sales<br>$%{y:,.2f} Profit<extra></extra>',
    ), row=2, col=1)

# 4. Monthly Performance
fig.add_trace(
    go.Scatter(
        x=monthly['Sales'], y=monthly['Profit'],
        mode='markers', name='Monthly',
        marker=dict(size=8, color='orange'),
        text=monthly['Order Date'].dt.strftime('%b %Y'),
        hovertemplate='%{text}<br>$%{x:,.2f} Sales<br>$%{y:,.2f} Profit<extra></extra>',
    ), row=2, col=2)

# 5. Category Comparison
fig.add_trace(
    go.Scatter(
        x=categories['Sales'], y=categories['Profit'],
        mode='markers+text', name='Categories',
        marker=dict(size=15, color=colors),
        text=categories['Category'], textposition='top center',
        hovertemplate='%{text}<br>$%{x:,.2f} Sales<br>$%{y:,.2f} Profit<extra></extra>',
    ), row=3, col=1)

# 6. Margin Trend
fig.add_trace(
    go.Scatter(
        x=monthly['Order Date'], y=monthly['Profit_Margin_%'],
        mode='lines+markers', name='Margin',
        line=dict(color='purple', width=2),
        hovertemplate='%{x|%b %Y}<br>%{y:.1f}% Margin<extra></extra>',
```

```
    ), row=3, col=2)

# Corrected Axis Labels
fig.update_xaxes(title_text="Sales ($)", row=1, col=1)
fig.update_yaxes(title_text="Profit ($)", row=1, col=1)
fig.update_xaxes(title_text="Category", row=1, col=2)
fig.update_yaxes(title_text="Margin (%)", row=1, col=2)
fig.update_xaxes(title_text="Daily Sales ($)", row=2, col=1)
fig.update_yaxes(title_text="Daily Profit ($)", row=2, col=1)
fig.update_xaxes(title_text="Monthly Sales ($)", row=2, col=2)
fig.update_yaxes(title_text="Monthly Profit ($)", row=2, col=2)
fig.update_xaxes(title_text="Category Sales ($)", row=3, col=1)
fig.update_yaxes(title_text="Category Profit ($)", row=3, col=1)
fig.update_xaxes(title_text="Month", row=3, col=2)
fig.update_yaxes(title_text="Margin (%)", row=3, col=2)

# Final Layout
fig.update_layout(
    height=1000,
    title='Sales & Profit Relationship Analysis',
    hovermode='closest',
    template='plotly_white',
    showlegend=False
)

fig.update_xaxes(tickangle=45, row=3, col=2)
fig.show()
```

```
C:\Users\Yawar Ali\AppData\Local\Temp\ipykernel_9040\7368247.py:14: FutureWarning:

'M' is deprecated and will be removed in a future version, please use 'ME' instead.
```

Delivery Impact Analysis

This detailed summary helps us to understand the shipping delays impact sales/profit.

In [16]:

```
import pandas as pd

# Data Preparation
date_cols = ['Order Date', 'Ship Date']
num_cols = ['Sales', 'Profit', 'Delivery-TAT']
car[date_cols] = car[date_cols].apply(pd.to_datetime)
car[num_cols] = car[num_cols].apply(pd.to_numeric)

# Calculations
car['Delivery_Days'] = (car['Ship Date'] - car['Order Date']).dt.days
car['Profit_Margin_%'] = (car['Profit']/car['Sales']*100).round(2)
car['Delivery_Category'] = pd.cut(car['Delivery_Days'],
                                bins=[0, 3, 7, 14, float('inf')],
                                labels=['Fast (0-3)', 'Standard (4-7)', 'Slow (8-14)', 'Very Slow (15+)'])

# Delivery Analysis
delivery_stats = car['Delivery_Days'].agg(['mean', 'median', 'std', 'min', 'max']).round(1)
correlations = car[['Sales', 'Profit', 'Profit_Margin_%']].corrwith(car['Delivery_Days']).round(3)

# Grouped Analysis
delivery_impact = car.groupby('Delivery_Category').agg(
    Order_Count=('Sales', 'count'),
    Avg_Sales=('Sales', 'mean'),
    Total_Sales=('Sales', 'sum'),
    Avg_Profit=('Profit', 'mean'),
    Avg_Margin=('Profit_Margin_%', 'mean'),
    Avg_Delivery=('Delivery_Days', 'mean')
).round(2)

ship_mode_analysis = car.groupby('Ship Mode').agg(
    Avg_Delivery=('Delivery_Days', 'mean'),
    Std_Delivery=('Delivery_Days', 'std'),
    Avg_Sales=('Sales', 'mean'),
    Avg_Profit=('Profit', 'mean'),
    Avg_Margin=('Profit_Margin_%', 'mean')
).round(2)

# Summary Metrics
fast_orders = (car['Delivery_Category'] == 'Fast (0-3)').mean() * 100
slow_orders = (car['Delivery_Days'] > 7).mean() * 100
margin_diff = delivery_impact['Avg_Margin'].max() - delivery_impact['Avg_Margin'].min()

summary_data = {
    'Metric': [
        'Average Delivery Time', 'Median Delivery Time', 'Delivery Time Std Dev',
```

```
        'Fastest Delivery', 'Slowest Delivery', 'Sales-Delivery Correlation',
        'Profit-Delivery Correlation', 'Margin-Delivery Correlation',
        'Best Delivery Category', 'Worst Delivery Category',
        'Fast Delivery Orders (%)', 'Slow Delivery Orders (%)',
        'Margin Impact of Delays', 'Most Reliable Ship Mode', 'Fastest Ship Mode'
    ],
    'Value': [
        f"{delivery_stats['mean']} days", f"{delivery_stats['median']} days",
        f"{delivery_stats['std']} days", f"{delivery_stats['min']} days",
        f"{delivery_stats['max']} days", f"{correlations['Sales']}",
        f"{correlations['Profit']}", f"{correlations['Profit_Margin_%']}",
        f"{delivery_impact['Avg_Margin'].idxmax()} ({delivery_impact['Avg_Margin'].max():.1f}%)",
        f"{delivery_impact['Avg_Margin'].idxmin()} ({delivery_impact['Avg_Margin'].min():.1f}%)",
        f"{fast_orders:.1f}%", f"{slow_orders:.1f}%",
        f"{margin_diff:.1f}% difference",
        f"{ship_mode_analysis['Std_Delivery'].idxmin()} ({ship_mode_analysis['Std_Delivery'].min():.1f} std)",
        f"{ship_mode_analysis['Avg_Delivery'].idxmin()} ({ship_mode_analysis['Avg_Delivery'].min():.1f} days)"
    ]
}

pd.DataFrame(summary_data)
```

```
C:\Users\Yawar Ali\AppData\Local\Temp\ipykernel_9040\3347805202.py:21: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future version of pandas. Pass obse
rved=False to retain current behavior or observed=True to adopt the future default and silence this warning.
```

Out[16]:

	Metric	Value
0	Average Delivery Time	4.0 days
1	Median Delivery Time	4.0 days
2	Delivery Time Std Dev	1.7 days
3	Fastest Delivery	0.0 days
4	Slowest Delivery	11.0 days
5	Sales-Delivery Correlation	-0.007
6	Profit-Delivery Correlation	-0.004
7	Margin-Delivery Correlation	-0.01
8	Best Delivery Category	Slow (8-14) (35.7%)
9	Worst Delivery Category	Standard (4-7) (11.4%)
10	Fast Delivery Orders (%)	27.0%
11	Slow Delivery Orders (%)	0.0%
12	Margin Impact of Delays	24.3% difference
13	Most Reliable Ship Mode	Same Day (0.2 std)
14	Fastest Ship Mode	Same Day (0.0 days)

Customer Segmentation & Behavior

• RFM Analysis (Recency, Frequency, Monetary):

- Recency: When was the last purchase of each customer?
  This summary shows us the indepth analysis for each customer.

In [17]:

```
import pandas as pd

# Data Preparation
car['Order Date'] = pd.to_datetime(car['Order Date'])
car['Sales'] = pd.to_numeric(car['Sales'])

# Customer Last Purchase Analysis
customer_last_purchase = car.groupby('Customer ID').agg(
    Last_Purchase_Date=('Order Date', 'max'),
    Customer_Name=('Customer Name', 'first'),
    Total_Sales=('Sales', 'sum'),
    Order_Count=('Sales', 'count'),
    Segment=('Segment', 'first'),
    Region=('Region', 'first')
).reset_index()

# Calculate days since last purchase
latest_date = car['Order Date'].max()
customer_last_purchase['Days_Since_Last_Purchase'] = (latest_date - customer_last_purchase['Last_Purchase_Date'
```

```
# Categorize recency
def categorize_recency(days):
    if days <= 30: return 'Recent (0-30 days)'
    elif days <= 90: return 'Moderate (31-90 days)'
    elif days <= 180: return 'At Risk (91-180 days)'
    elif days <= 365: return 'Dormant (181-365 days)'
    else: return 'Lost (365+ days)'

customer_last_purchase['Recency_Category'] = customer_last_purchase['Days_Since_Last_Purchase'].apply(categorize

# Keep only requested columns
final_output = customer_last_purchase[[
    'Customer ID', 'Last_Purchase_Date', 'Customer_Name',
    'Total_Sales', 'Order_Count', 'Segment', 'Region'
]].rename(columns={'Customer_ID': 'Customer ID'})

final_output
```

Out[17]:

	Customer ID	Last_Purchase_Date	Customer_Name	Total_Sales	Order_Count	Segment	Region
0	AA-10315	2022-06-29	Alex Avila	5563.560	11	Replacement	West
1	AA-10375	2022-12-11	Allen Armold	1056.390	15	Replacement	West
2	AA-10480	2022-04-15	Andrew Allen	1790.512	12	Replacement	East
3	AA-10645	2022-11-05	Anna Andreadi	5086.935	18	Replacement	East
4	AB-10015	2021-11-10	Aaron Bergman	886.156	6	Replacement	Central
...	...	...	...	...	...	...	...
799	XP-21865	2022-11-17	Xylona Preis	2503.156	34	Replacement	Central
800	YC-21895	2022-12-26	Yoseph Carroll	5454.350	8	Servicing	East
801	YS-21880	2022-12-21	Yana Sorensen	6720.444	12	Servicing	East
802	ZC-21910	2022-11-06	Zuschuss Carroll	8025.707	31	Replacement	West
803	ZD-21925	2022-06-11	Zuschuss Donatelli	1493.944	9	Replacement	West

804 rows × 7 columns

- Frequency: How often do customers buy?
  This detailed summary helps us to understand the customer's behaviour as how often they order.

In [18]:

```
import pandas as pd

# Data Preparation
car['Order Date'] = pd.to_datetime(car['Order Date'])
car['Sales'] = pd.to_numeric(car['Sales'])

# Customer Frequency Analysis
customer_freq = car.groupby('Customer ID').agg(
    Order_Count=('Order Date', 'count'),
    First_Purchase=('Order Date', 'min'),
    Last_Purchase=('Order Date', 'max'),
    Customer_Name=('Customer Name', 'first'),
    Total_Sales=('Sales', 'sum'),
    Avg_Order_Value=('Sales', 'mean'),
    Segment=('Segment', 'first'),
    Region=('Region', 'first')
).reset_index()

# Calculate metrics
customer_freq['Lifespan_Days'] = (customer_freq['Last_Purchase'] - customer_freq['First_Purchase']).dt.days.fil
customer_freq['Purchase_Freq_Per_Year'] = np.where(
    customer_freq['Lifespan_Days'] > 0,
    (customer_freq['Order_Count'] - 1) / (customer_freq['Lifespan_Days'] / 365.25),
    0
)
customer_freq['Days_Between_Orders'] = np.where(
    customer_freq['Order_Count'] > 1,
    customer_freq['Lifespan_Days'] / (customer_freq['Order_Count'] - 1),
    np.nan
)

# Frequency Categories
def freq_category(orders):
    if orders == 1: return 'One-time'
    elif orders <= 3: return 'Occasional'
    elif orders <= 7: return 'Regular'
    elif orders <= 15: return 'Frequent'
    else: return 'Very Frequent'
```

```python
customer_freq['Frequency_Category'] = customer_freq['Order_Count'].apply(freq_category)

# Summary Stats
total_customers = len(customer_freq)
one_time_pct = (customer_freq['Order_Count'] == 1).mean() * 100
repeat_pct = (customer_freq['Order_Count'] > 1).mean() * 100
high_freq_pct = (customer_freq['Order_Count'] >= 8).mean() * 100

stats = {
    'Metric': [
        'Total Customers', 'Avg Orders', 'Median Orders', 'Max Orders',
        'Avg Days Between Orders', 'Median Days Between',
        'Avg Purchase Freq (per year)', 'One-time Customers (%)',
        'Repeat Customers (%)', 'High-Freq Customers (%)',
        'Avg Customer Lifespan (days)', 'Median Lifespan (days)'
    ],
    'Value': [
        f"{total_customers:,}",
        f"{customer_freq['Order_Count'].mean():.1f}",
        f"{customer_freq['Order_Count'].median()}",
        f"{customer_freq['Order_Count'].max()}",
        f"{customer_freq['Days_Between_Orders'].mean():.0f}",
        f"{customer_freq['Days_Between_Orders'].median():.0f}",
        f"{customer_freq['Purchase_Freq_Per_Year'].mean():.1f}",
        f"{one_time_pct:.1f}%",
        f"{repeat_pct:.1f}%",
        f"{high_freq_pct:.1f}%",
        f"{customer_freq['Lifespan_Days'].mean():.0f}",
        f"{customer_freq['Lifespan_Days'].median():.0f}"
    ]
}

pd.DataFrame(stats)
```

Out[18]:

	Metric	Value
0	Total Customers	804
1	Avg Orders	12.7
2	Median Orders	12.0
3	Max Orders	41
4	Avg Days Between Orders	114
5	Median Days Between	93
6	Avg Purchase Freq (per year)	5.7
7	One-time Customers (%)	0.6%
8	Repeat Customers (%)	99.4%
9	High-Freq Customers (%)	77.7%
10	Avg Customer Lifespan (days)	999
11	Median Lifespan (days)	1096

- Monetary: How much do they spend? This helps us to understand customer segmentation.

In [19]:

```python
import pandas as pd

# Data Preparation
car[['Sales', 'Profit']] = car[['Sales', 'Profit']].apply(pd.to_numeric)
car['Order Date'] = pd.to_datetime(car['Order Date'])

# Customer Spending Analysis
customer_spending = car.groupby(['Customer ID', 'Customer Name']).agg(
    Total_Sales=('Sales', 'sum'),
    Order_Count=('Sales', 'count'),
    Avg_Order_Value=('Sales', 'mean'),
    Total_Profit=('Profit', 'sum'),
    Avg_Profit=('Profit', 'mean'),
    First_Purchase=('Order Date', 'min'),
    Last_Purchase=('Order Date', 'max'),
    Segment=('Segment', 'first'),
    Region=('Region', 'first')
).round(2).reset_index()

# Spending Categories
def categorize_spending(x):
    if x >= 10000: return 'VIP ($10,000+)'
```

```
    elif x >= 5000: return 'High Value ($5,000-$9,999)'
    elif x >= 2000: return 'Medium Value ($2,000-$4,999)'
    elif x >= 1000: return 'Regular ($1,000-$1,999)'
    elif x >= 500: return 'Low Value ($500-$999)'
    else: return 'Minimal (<$500)'

customer_spending['Spending_Category'] = customer_spending['Total_Sales'].apply(categorize_spending)
customer_summary = customer_spending.sort_values('Total_Sales', ascending=False)

# Spending Summary
spending_summary = customer_summary.groupby('Spending_Category').agg(
    Customer_Count=('Customer ID', 'count'),
    Total_Sales_Sum=('Total_Sales', 'sum'),
    Avg_Sales_Per_Customer=('Total_Sales', 'mean'),
    Min_Sales=('Total_Sales', 'min'),
    Max_Sales=('Total_Sales', 'max'),
    Avg_Orders=('Order_Count', 'mean'),
    Avg_Order_Value=('Avg_Order_Value', 'mean')
).round(2)

total_customers = len(customer_summary)
total_sales = customer_summary['Total_Sales'].sum()
spending_summary = spending_summary.assign(
    Customer_Pct=(spending_summary['Customer_Count']/total_customers*100).round(1),
    Sales_Pct=(spending_summary['Total_Sales_Sum']/total_sales*100).round(1)
)

# Output Results
print("CUSTOMER SPENDING ANALYSIS SUMMARY".center(50, '='))
print(f"\nTotal Customers: {total_customers:,}")
print(f"Total Sales: ${total_sales:,.2f}")
print(f"Average Sales per Customer: ${customer_summary['Total_Sales'].mean():,.2f}")
print(f"Median Sales per Customer: ${customer_summary['Total_Sales'].median():,.2f}")

print("\nSPENDING CATEGORY BREAKDOWN:".center(40, '='))
for category in spending_summary.index:
    stats = spending_summary.loc[category]
    print(f"\n{category}:")
    print(f"  Customers: {stats['Customer_Count']:,} ({stats['Customer_Pct']}%)")
    print(f"  Total Sales: ${stats['Total_Sales_Sum']:,.2f} ({stats['Sales_Pct']}%)")
    print(f"  Avg per Customer: ${stats['Avg_Sales_Per_Customer']:,.2f}")
    print(f"  Sales Range: ${stats['Min_Sales']:,.2f}-${stats['Max_Sales']:,.2f}")
    print(f"  Avg Orders: {stats['Avg_Orders']:.1f}")
    print(f"  Avg Order Value: ${stats['Avg_Order_Value']:,.2f}")

# Top 20 Customers
top_20 = customer_summary.head(20).assign(
    Total_Sales_Fmt=lambda x: x['Total_Sales'].apply('${:,.2f}'.format),
    Avg_Order_Value_Fmt=lambda x: x['Avg_Order_Value'].apply('${:,.2f}'.format)
)[['Customer Name', 'Total_Sales_Fmt', 'Order_Count', 'Avg_Order_Value_Fmt', 'Segment', 'Region', 'Spending_Cat

print("\nTOP 20 HIGHEST SPENDING CUSTOMERS:".center(50, '='))
print(top_20.to_string(index=False))

# Return summary
spending_summary.reset_index()
```

========CUSTOMER SPENDING ANALYSIS SUMMARY========

Total Customers: 804
Total Sales: $2,326,534.41
Average Sales per Customer: $2,893.70
Median Sales per Customer: $2,243.39
=====
SPENDING CATEGORY BREAKDOWN:======

High Value ($5,000-$9,999):
  Customers: 98.0 (12.2%)
  Total Sales: $657,884.30 (28.3%)
  Avg per Customer: $6,713.11
  Sales Range: $5,016.49-$9,799.92
  Avg Orders: 18.9
  Avg Order Value: $416.17

Low Value ($500-$999):
  Customers: 97.0 (12.1%)
  Total Sales: $75,535.83 (3.2%)
  Avg per Customer: $778.72
  Sales Range: $515.20-$993.90
  Avg Orders: 8.2
  Avg Order Value: $116.34

Medium Value ($2,000-$4,999):
  Customers: 326.0 (40.5%)
  Total Sales: $1,034,767.23 (44.5%)
  Avg per Customer: $3,174.13
  Sales Range: $2,005.60-$4,985.68
  Avg Orders: 14.7
  Avg Order Value: $243.16

Minimal (<$500):
  Customers: 81.0 (10.1%)
  Total Sales: $19,782.74 (0.9%)
  Avg per Customer: $244.23
  Sales Range: $4.83-$497.01
  Avg Orders: 5.0
  Avg Order Value: $53.71

Regular ($1,000-$1,999):
  Customers: 181.0 (22.5%)
  Total Sales: $263,193.18 (11.3%)
  Avg per Customer: $1,454.11
  Sales Range: $1,006.36-$1,990.31
  Avg Orders: 10.6
  Avg Order Value: $159.76

VIP ($10,000+):
  Customers: 21.0 (2.6%)
  Total Sales: $275,371.13 (11.8%)
  Avg per Customer: $13,112.91
  Sales Range: $10,310.88-$25,043.05
  Avg Orders: 19.9
  Avg Order Value: $784.84
=======
TOP 20 HIGHEST SPENDING CUSTOMERS:========

Customer Name	Total_Sales_Fmt	Order_Count	Avg_Order_Value_Fmt	Segment	Region	Spending_Category
Sean Miller	$25,043.05	15	$1,669.54	Other	South	VIP ($10,000+)
Tamara Chand	$19,052.22	12	$1,587.68	Servicing	Central	VIP ($10,000+)
Raymond Buch	$15,117.34	18	$839.85	Replacement	East	VIP ($10,000+)
Tom Ashbrook	$14,595.62	10	$1,459.56	Other	Central	VIP ($10,000+)
Adrian Barton	$14,473.57	20	$723.68	Replacement	Central	VIP ($10,000+)
Ken Lonsdale	$14,175.23	29	$488.80	Replacement	West	VIP ($10,000+)
Sanjit Chand	$14,142.33	22	$642.83	Replacement	West	VIP ($10,000+)
Hunter Lopez	$12,873.30	11	$1,170.30	Replacement	South	VIP ($10,000+)
Sanjit Engle	$12,209.44	19	$642.60	Replacement	West	VIP ($10,000+)
Christopher Conant	$12,129.07	11	$1,102.64	Replacement	East	VIP ($10,000+)
Todd Sumrall	$11,891.75	15	$792.78	Servicing	West	VIP ($10,000+)
Greg Tran	$11,820.12	29	$407.59	Replacement	East	VIP ($10,000+)
Becky Martin	$11,789.63	16	$736.85	Replacement	Central	VIP ($10,000+)
Seth Vernon	$11,470.95	32	$358.47	Replacement	East	VIP ($10,000+)
Caroline Jumper	$11,164.97	20	$558.25	Replacement	East	VIP ($10,000+)
Clay Ludtke	$10,880.55	28	$388.59	Replacement	South	VIP ($10,000+)
Maria Etezadi	$10,663.73	22	$484.71	Other	South	VIP ($10,000+)
Karen Ferguson	$10,604.27	18	$589.13	Other	West	VIP ($10,000+)
Bill Shonely	$10,501.65	9	$1,166.85	Servicing	West	VIP ($10,000+)
Joe Elijah	$10,461.46	30	$348.72	Replacement	Central	VIP ($10,000+)

Out[19]:

	Spending_Category	Customer_Count	Total_Sales_Sum	Avg_Sales_Per_Customer	Min_Sales	Max_Sales	Avg_Orders	Avg_Ord
0	High Value (5, 000 – 9,999)	98	657884.30	6713.11	5016.49	9799.92	18.93	
1	Low Value (500 – 999)	97	75535.83	778.72	515.20	993.90	8.23	
2	Medium Value (2, 000 – 4,999)	326	1034767.23	3174.13	2005.60	4985.68	14.74	
3	Minimal (<$500)	81	19782.74	244.23	4.83	497.01	4.95	
4	Regular (1, 000 – 1,999)	181	263193.18	1454.11	1006.36	1990.31	10.59	
5	VIP ($10,000+)	21	275371.13	13112.91	10310.88	25043.05	19.90	

Top 5 Customers Analysis

This barplot shows us the top 5 customers resulting in most sales.

In [20]:

```
import pandas as pd
import plotly.graph_objects as go

# Data Preparation
car['Order Date'] = pd.to_datetime(car['Order Date'])
car['Sales'] = pd.to_numeric(car['Sales'])
car['Profit'] = pd.to_numeric(car['Profit'])

# Customer Analysis
customer_analysis = car.groupby(['Customer ID', 'Customer Name']).agg(
    Total_Sales=('Sales', 'sum'),
    Order_Count=('Sales', 'count'),
    Avg_Order_Value=('Sales', 'mean'),
    Total_Profit=('Profit', 'sum'),
    Avg_Profit=('Profit', 'mean'),
    First_Purchase=('Order Date', 'min'),
    Last_Purchase=('Order Date', 'max'),
    Segment=('Segment', 'first'),
    Region=('Region', 'first')
).round(2).reset_index()

# Additional Metrics
customer_analysis['Lifespan_Days'] = (customer_analysis['Last_Purchase'] - customer_analysis['First_Purchase'])
customer_analysis['Profit_Margin_%'] = (customer_analysis['Total_Profit'] / customer_analysis['Total_Sales'] * 

# Top 5 Customers
top_5 = customer_analysis.sort_values('Total_Sales', ascending=False).head(5)

# Print Summary
print("TOP 5 HIGHEST-VALUE CUSTOMERS".center(50, '='))
for _, row in top_5.iterrows():
    print(f"\n{row['Customer Name']}")
    print(f"  Total Sales: ${row['Total_Sales']:,.2f}")
    print(f"  Profit: ${row['Total_Profit']:,.2f} ({row['Profit_Margin_%']}%)")
    print(f"  Orders: {row['Order_Count']} (Avg ${row['Avg_Order_Value']:,.2f})")
    print(f"  {row['Segment']} | {row['Region']}")
    print(f"  Customer Since: {row['First_Purchase'].strftime('%Y-%m-%d')}")

# Visualization
fig = go.Figure(go.Bar(
    x=top_5['Customer Name'],
    y=top_5['Total_Sales'],
    text=[f"${x:,.0f}" for x in top_5['Total_Sales']],
    marker_color=px.colors.qualitative.Plotly[:5],
    hovertemplate="<b>%{x}</b><br>Sales: $%{y:,.2f}<extra></extra>"
))

fig.update_layout(
    title='Top 5 Customers by Total Sales',
    xaxis_title='Customer',
    yaxis_title='Total Sales ($)',
    yaxis_tickformat='$,.0f',
    xaxis_tickangle=45,
    plot_bgcolor='white',
    height=500
)

fig.show()
```

```
==========TOP 5 HIGHEST-VALUE CUSTOMERS===========

Sean Miller
  Total Sales: $25,043.05
  Profit: $-1,980.74 (-7.9%)
  Orders: 15 (Avg $1,669.54)
  Other | South
  Customer Since: 2019-03-18

Tamara Chand
  Total Sales: $19,052.22
  Profit: $8,981.32 (47.1%)
  Orders: 12 (Avg $1,587.68)
  Servicing | Central
  Customer Since: 2019-11-07

Raymond Buch
  Total Sales: $15,117.34
  Profit: $6,976.10 (46.1%)
  Orders: 18 (Avg $839.85)
  Replacement | East
  Customer Since: 2021-04-01

Tom Ashbrook
  Total Sales: $14,595.62
  Profit: $4,703.79 (32.2%)
  Orders: 10 (Avg $1,459.56)
  Other | Central
  Customer Since: 2019-09-12

Adrian Barton
  Total Sales: $14,473.57
  Profit: $5,444.81 (37.6%)
  Orders: 20 (Avg $723.68)
  Replacement | Central
  Customer Since: 2019-12-20
```

Top 5 Products Analysis

This barplot shows the top 5 products category contributing to total sales.

In [21]:

```
import pandas as pd
import plotly.graph_objects as go

# Data Preparation
car['Sales'] = pd.to_numeric(car['Sales'])
car['Profit'] = pd.to_numeric(car['Profit'])
car['Quantity'] = pd.to_numeric(car['Quantity'])

# Sub-Category Analysis
subcat_analysis = car.groupby(['Sub-Category', 'Category']).agg(
    Total_Sales=('Sales', 'sum'),
    Order_Count=('Sales', 'count'),
    Avg_Order_Value=('Sales', 'mean'),
    Total_Profit=('Profit', 'sum'),
    Avg_Profit=('Profit', 'mean'),
    Total_Quantity=('Quantity', 'sum')
).round(2).reset_index()

# Additional Metrics
subcat_analysis['Profit_Margin_%'] = (subcat_analysis['Total_Profit'] / subcat_analysis['Total_Sales'] * 100).r
subcat_analysis['Market_Share_%'] = (subcat_analysis['Total_Sales'] / subcat_analysis['Total_Sales'].sum() * 10

# Top 5 Sub-Categories
top_5 = subcat_analysis.sort_values('Total_Sales', ascending=False).head(5)

# Print Summary
print("TOP 5 HIGHEST-VALUE SUB-CATEGORIES".center(55, '='))
for _, row in top_5.iterrows():
    print(f"\n{row['Sub-Category']} ({row['Category']})")
    print(f"  Sales: ${row['Total_Sales']:,.2f} ({row['Market_Share_%']}% share)")
    print(f"  Profit: ${row['Total_Profit']:,.2f} ({row['Profit_Margin_%']}% margin)")
    print(f"  Orders: {row['Order_Count']:,} (Avg ${row['Avg_Order_Value']:,.2f})")
    print(f"  Quantity: {row['Total_Quantity']:,} units")

# Visualization
fig = go.Figure(go.Bar(
    x=top_5['Sub-Category'],
    y=top_5['Total_Sales'],
    text=[f"${x:,.0f}" for x in top_5['Total_Sales']],
    marker_color=px.colors.qualitative.Plotly[:5],
    hovertemplate="<b>%{x}</b><br>Sales: $%{y:,.2f}<extra></extra>"
```

```
))

fig.update_layout(
    title='Top 5 Sub-Categories by Sales',
    xaxis_title='Sub-Category',
    yaxis_title='Total Sales ($)',
    yaxis_tickformat='$,.0f',
    xaxis_tickangle=45,
    plot_bgcolor='white',
    height=500
)

fig.show()
```

```
===========TOP 5 HIGHEST-VALUE SUB-CATEGORIES==========

Chairs (Direct Sale)
  Sales: $308,111.14 (13.2% share)
  Profit: $25,449.75 (8.3% margin)
  Orders: 569 (Avg $541.50)
  Quantity: 2,196 units

Phones (Pre Book)
  Sales: $301,919.91 (13.0% share)
  Profit: $41,487.24 (13.7% margin)
  Orders: 827 (Avg $365.08)
  Quantity: 3,080 units

Storage (Third Party)
  Sales: $204,614.42 (8.8% share)
  Profit: $19,234.62 (9.4% margin)
  Orders: 770 (Avg $265.73)
  Quantity: 2,869 units

Tables (Direct Sale)
  Sales: $197,744.71 (8.5% share)
  Profit: $-16,710.41 (-8.5% margin)
  Orders: 302 (Avg $654.78)
  Quantity: 1,188 units

Binders (Third Party)
  Sales: $193,852.69 (8.3% share)
  Profit: $28,101.32 (14.5% margin)
  Orders: 1,393 (Avg $139.16)
  Quantity: 5,467 units
```

Region Wise Performance Analysis

This detailed analysis helps us to understand different sales parameters based on different regions.

In [22]:

```
import pandas as pd
import plotly.graph_objects as go
from plotly.subplots import make_subplots

# Data Preparation
car['Sales'] = pd.to_numeric(car['Sales'])
car['Profit'] = pd.to_numeric(car['Profit'])
car['Discount'] = pd.to_numeric(car['Discount'])
car['Profit_Margin_%'] = (car['Profit'] / car['Sales'] * 100).round(2)

# Regional Analysis
regional_stats = car.groupby('Region').agg(
    Order_Count=('Sales', 'count'),
    Total_Sales=('Sales', 'sum'),
    Avg_Sales=('Sales', 'mean'),
    Median_Sales=('Sales', 'median'),
    Total_Profit=('Profit', 'sum'),
    Avg_Profit=('Profit', 'mean'),
    Avg_Margin=('Profit_Margin_%', 'mean'),
    Avg_Discount=('Discount', 'mean')
).round(2)

# Print Summary
print("REGIONAL PERFORMANCE SUMMARY".center(50, '='))
for region, stats in regional_stats.iterrows():
    print(f"\n{region} Region:")
    print(f"  Orders: {stats['Order_Count']:,}")
    print(f"  Sales: ${stats['Total_Sales']:,.2f} (Avg ${stats['Avg_Sales']:,.2f})")
    print(f"  Profit: ${stats['Total_Profit']:,.2f} ({stats['Avg_Margin']:.1f}% margin)")
    print(f"  Avg Discount: {stats['Avg_Discount']:.1%}")

# Visualization
fig = make_subplots(
```

```
    rows=2, cols=2,
    subplot_titles=(
        'Sales Distribution', 'Profit Distribution',
        'Discount Distribution', 'Margin Distribution'
    ),
    vertical_spacing=0.15
)

# Create plots
metrics = ['Sales', 'Profit', 'Discount', 'Profit_Margin_%']
titles = ['Sales ($)', 'Profit ($)', 'Discount Rate', 'Margin (%)']
colors = px.colors.qualitative.Plotly

for i, metric in enumerate(metrics):
    row = (i // 2) + 1
    col = (i % 2) + 1

    for j, region in enumerate(car['Region'].unique()):
        fig.add_trace(
            go.Violin(
                y=car[car['Region'] == region][metric],
                name=region,
                box_visible=True,
                fillcolor=colors[j],
                opacity=0.6,
                showlegend=(i == 0)
            ),
            row=row, col=col
        )
    fig.update_yaxes(title_text=titles[i], row=row, col=col)

# Final Layout
fig.update_layout(
    height=800,
    title='Regional Performance Distributions',
    plot_bgcolor='white',
    margin=dict(t=100)
)

fig.show()
```

```
===========REGIONAL PERFORMANCE SUMMARY===========

Central Region:
  Orders: 2,335.0
  Sales: $503,170.67 (Avg $215.49)
  Profit: $39,865.31 (-10.5% margin)
  Avg Discount: 24.0%

East Region:
  Orders: 2,986.0
  Sales: $691,828.17 (Avg $231.69)
  Profit: $94,883.26 (17.1% margin)
  Avg Discount: 14.0%

South Region:
  Orders: 1,620.0
  Sales: $391,721.90 (Avg $241.80)
  Profit: $46,749.43 (16.4% margin)
  Avg Discount: 15.0%

West Region:
  Orders: 3,253.0
  Sales: $739,813.61 (Avg $227.43)
  Profit: $110,798.82 (22.0% margin)
  Avg Discount: 11.0%
```

Discount Strategy Analysis

This detailed analysis shows us the discount impact over sales and profit.

In [23]:
```
import pandas as pd
import plotly.graph_objects as go
from plotly.subplots import make_subplots

# Data Preparation
car['Sales'] = pd.to_numeric(car['Sales'])
car['Profit'] = pd.to_numeric(car['Profit'])
car['Discount'] = pd.to_numeric(car['Discount'])
car['Profit_Margin_%'] = (car['Profit'] / car['Sales'] * 100).round(2)

# Discount Analysis
car['Discount_Range'] = pd.cut(car['Discount'],
```

```python
                             bins=[0, 0.05, 0.10, 0.15, 0.20, 0.25, 0.30, 0.35, 0.40, 1.0],
                             labels=['0-5%', '5-10%', '10-15%', '15-20%', '20-25%', '25-30%', '30-35%', '35-40%

discount_analysis = car.groupby('Discount_Range').agg(
    Order_Count=('Sales', 'count'),
    Total_Sales=('Sales', 'sum'),
    Avg_Sales=('Sales', 'mean'),
    Total_Profit=('Profit', 'sum'),
    Avg_Profit=('Profit', 'mean'),
    Avg_Margin=('Profit_Margin_%', 'mean'),
    Avg_Discount=('Discount', 'mean')
).round(2).reset_index()

discount_analysis['Profit_Per_Order'] = (discount_analysis['Total_Profit'] / discount_analysis['Order_Count']).

# Detailed Analysis
car['Discount_Rounded'] = (car['Discount'] * 100).round(0) / 100
detailed_analysis = car.groupby('Discount_Rounded').agg(
    Order_Count=('Sales', 'count'),
    Total_Sales=('Sales', 'sum'),
    Total_Profit=('Profit', 'sum'),
    Avg_Margin=('Profit_Margin_%', 'mean')
).round(2).reset_index()

significant_discounts = detailed_analysis[detailed_analysis['Order_Count'] >= 50]

# Visualization
fig = make_subplots(
    rows=2, cols=2,
    subplot_titles=(
        'Profit Margin by Discount Range',
        'Total Profit by Discount Range',
        'Profit per Order by Discount Range',
        'Detailed Margin Analysis'
    ),
    specs=[[{}, {}], [{}, {}]]
)

# Add main charts
metrics = ['Avg_Margin', 'Total_Profit', 'Profit_Per_Order']
titles = ['Margin (%)', 'Total Profit ($)', 'Profit per Order ($)']
colors = ['#636EFA', '#00CC96', '#AB63FA']

for i, metric in enumerate(metrics):
    fig.add_trace(
        go.Bar(
            x=discount_analysis['Discount_Range'],
            y=discount_analysis[metric],
            name=titles[i],
            marker_color=colors[i],
            text=[f"{x:,.0f}{'%' if i==0 else '$'}" for x in discount_analysis[metric]],
            textposition='auto'
        ),
        row=(i//2)+1, col=(i%2)+1
    )

# Add detailed scatter plot
fig.add_trace(
    go.Scatter(
        x=significant_discounts['Discount_Rounded']*100,
        y=significant_discounts['Avg_Margin'],
        mode='markers+lines',
        name='Margin by Discount %',
        marker=dict(size=8, color='#EF553B'),
        line=dict(color='#EF553B', width=2)
    ),
    row=2, col=2
)

# Update layout
fig.update_layout(
    height=800,
    title='Discount Strategy Analysis',
    showlegend=False,
    template='plotly_white',
    margin=dict(t=100)
)

# Update axes
fig.update_xaxes(title_text="Discount Range", row=1, col=1)
fig.update_xaxes(title_text="Discount Range", row=1, col=2)
fig.update_xaxes(title_text="Discount Range", row=2, col=1)
fig.update_xaxes(title_text="Discount (%)", row=2, col=2)
```

```
fig.update_yaxes(title_text="Margin (%)", row=1, col=1)
fig.update_yaxes(title_text="Total Profit ($)", row=1, col=2)
fig.update_yaxes(title_text="Profit per Order ($)", row=2, col=1)
fig.update_yaxes(title_text="Margin (%)", row=2, col=2)

fig.update_xaxes(tickangle=45)
fig.show()

# Optimal Values Summary
optimal_range = discount_analysis.loc[discount_analysis['Avg_Margin'].idxmax()]
max_profit_range = discount_analysis.loc[discount_analysis['Total_Profit'].idxmax()]
optimal_discount = significant_discounts.loc[significant_discounts['Avg_Margin'].idxmax()] if len(significant_d

print("\n" + " OPTIMAL DISCOUNT FINDINGS ".center(50, '='))
print(f"\n• Best Margin Range: {optimal_range['Discount_Range']}")
print(f"  → Margin: {optimal_range['Avg_Margin']}% | Orders: {optimal_range['Order_Count']:,}")
print(f"\n• Highest Profit Range: {max_profit_range['Discount_Range']}")
print(f"  → Profit: ${max_profit_range['Total_Profit']:,.2f} | Orders: {max_profit_range['Order_Count']:,}")
print(f"\n• Optimal Discount Level: {optimal_discount['Discount_Rounded']:.0%}")
print(f"  → Margin: {optimal_discount['Avg_Margin']}% | Orders: {optimal_discount['Order_Count']:,}")
```

```
C:\Users\Yawar Ali\AppData\Local\Temp\ipykernel_9040\2026402646.py:16: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future version of pandas. Pass obse
rved=False to retain current behavior or observed=True to adopt the future default and silence this warning.
```

```
=========== OPTIMAL DISCOUNT FINDINGS ============

• Best Margin Range: 15-20%
  → Margin: 17.66% | Orders: 3,706

• Highest Profit Range: 15-20%
  → Profit: $91,079.95 | Orders: 3,706

• Optimal Discount Level: 0%
  → Margin: 34.13% | Orders: 4,925.0
```

Ship Mode Analysis

This indepth summary shows us the different parameters against each shipping mode to understand which mode is fastest and most cost-effective.

In [24]:

```
import pandas as pd

# Data Preparation
car[['Order Date', 'Ship Date']] = car[['Order Date', 'Ship Date']].apply(pd.to_datetime)
car[['Sales', 'Profit', 'Delivery-TAT']] = car[['Sales', 'Profit', 'Delivery-TAT']].apply(pd.to_numeric)
car['Delivery_Days'] = (car['Ship Date'] - car['Order Date']).dt.days
car['Profit_Margin_%'] = (car['Profit'] / car['Sales'] * 100).round(2)

# Ship Mode Analysis
ship_mode = car.groupby('Ship Mode').agg(
    Order_Count=('Sales', 'count'),
    Avg_Delivery=('Delivery_Days', 'mean'),
    Delivery_Std=('Delivery_Days', 'std'),
    Min_Delivery=('Delivery_Days', 'min'),
    Max_Delivery=('Delivery_Days', 'max'),
    Avg_Sales=('Sales', 'mean'),
    Total_Sales=('Sales', 'sum'),
    Avg_Profit=('Profit', 'mean'),
    Total_Profit=('Profit', 'sum'),
    Avg_Margin=('Profit_Margin_%', 'mean'),
    Margin_Std=('Profit_Margin_%', 'std'),
    Avg_TAT=('Delivery-TAT', 'mean'),
    TAT_Std=('Delivery-TAT', 'std')
).round(2)

# Calculate Metrics
ship_mode = ship_mode.assign(
    Market_Share=lambda x: (x['Order_Count']/x['Order_Count'].sum()*100).round(1),
    Profit_Efficiency=lambda x: (x['Total_Profit']/x['Total_Sales']).round(3),
    Delivery_Reliability=lambda x: (1/(x['Delivery_Std']+0.1)).round(2)
).sort_values('Avg_Delivery')

# Format Summary Table
summary = ship_mode[['Order_Count', 'Market_Share', 'Avg_Delivery', 'Delivery_Std',
                    'Avg_Sales', 'Avg_Profit', 'Avg_Margin', 'Profit_Efficiency']]
summary = summary.reset_index()
summary[['Avg_Sales', 'Avg_Profit']] = summary[['Avg_Sales', 'Avg_Profit']].applymap('${:,.2f}'.format)
summary['Avg_Margin'] = summary['Avg_Margin'].map('{:.1f}%'.format)
```

```python
# Key Findings
findings = {
    'Fastest': ship_mode['Avg_Delivery'].idxmin(),
    'Most Profitable': ship_mode['Avg_Margin'].idxmax(),
    'Most Reliable': ship_mode['Delivery_Std'].idxmin(),
    'Highest Volume': ship_mode['Order_Count'].idxmax()
}

print("SHIP MODE PERFORMANCE ANALYSIS".center(50, '='))
print("\n" + summary.to_string(index=False))
print("\nKEY FINDINGS:")
for k, v in findings.items():
    print(f"- {k}: {v}")

summary
```

```
==========SHIP MODE PERFORMANCE ANALYSIS==========

     Ship Mode  Order_Count  Market_Share  Avg_Delivery  Delivery_Std Avg_Sales Avg_Profit Avg_Margin  Profit_Ef
ficiency
      Same Day          547           5.4          0.04          0.21   $236.33     $29.54      13.9%
0.125
   First Class         1548          15.2          2.18          0.77   $227.23     $31.66      11.5%
0.139
  Second Class         1979          19.4          3.24          1.19   $235.81     $29.79      15.1%
0.126
Standard Class         6120          60.0          5.00          1.02   $225.30     $27.48      11.3%
0.122

KEY FINDINGS:
- Fastest: Same Day
- Most Profitable: Second Class
- Most Reliable: Same Day
- Highest Volume: Standard Class
```

```
C:\Users\Yawar Ali\AppData\Local\Temp\ipykernel_9040\2257480584.py:37: FutureWarning:

DataFrame.applymap has been deprecated. Use DataFrame.map instead.
```

Out[24]:

	Ship Mode	Order_Count	Market_Share	Avg_Delivery	Delivery_Std	Avg_Sales	Avg_Profit	Avg_Margin	Profit_Efficiency
0	Same Day	547	5.4	0.04	0.21	$236.33	$29.54	13.9%	0.125
1	First Class	1548	15.2	2.18	0.77	$227.23	$31.66	11.5%	0.139
2	Second Class	1979	19.4	3.24	1.19	$235.81	$29.79	15.1%	0.126
3	Standard Class	6120	60.0	5.00	1.02	$225.30	$27.48	11.3%	0.122

Loss-making Products Analysis

This barplot explains us the top 5 products category contributing to most losses.

In [25]:

```python
import pandas as pd
import plotly.express as px

# Data Preparation
num_cols = ['Sales', 'Profit', 'Quantity', 'Discount']
car[num_cols] = car[num_cols].apply(pd.to_numeric)

# Negative Profit Analysis
neg_profit = car[car['Profit'] < 0].copy()
print(f"NEGATIVE PROFIT ANALYSIS\n{'='*50}")
print(f"Orders: {len(neg_profit):,} ({len(neg_profit)/len(car)*100:.1f}%)")
print(f"Total Loss: ${neg_profit['Profit'].sum():,.2f}")
print(f"Avg Loss: ${neg_profit['Profit'].mean():,.2f}")

# Sub-Category Analysis
subcat_loss = neg_profit.groupby('Sub-Category').agg(
    Total_Loss=('Profit', 'sum'),
    Order_Count=('Sales', 'count'),
    Avg_Loss=('Profit', 'mean'),
    Total_Sales=('Sales', 'sum'),
    Avg_Discount=('Discount', 'mean'),
    Category=('Category', 'first')
).assign(
    Loss_Pct=lambda x: (x['Total_Loss']/x['Total_Sales']*100).round(1)
).sort_values('Total_Loss').reset_index()

# Top 5 Worst Sub-Categories
top5 = subcat_loss.head(5)
print(f"\nTOP 5 LOSS MAKERS\n{'='*50}")
```

```python
for _, row in top5.iterrows():
    print(f"{row['Sub-Category']} ({row['Category']})")
    print(f"  Loss: ${row['Total_Loss']:,.2f} | Orders: {row['Order_Count']:,}")
    print(f"  Avg Loss: ${row['Avg_Loss']:,.2f} | Discount: {row['Avg_Discount']:.1%}")
    print(f"  Loss%: {row['Loss_Pct']:.1f}% | Sales: ${row['Total_Sales']:,.2f}")
    print("-"*40)

# Visualization
fig = px.bar(top5, x='Sub-Category', y='Total_Loss',
             text=[f"${x:,.0f}" for x in top5['Total_Loss']],
             color='Sub-Category',
             title='Top 5 Loss-Making Sub-Categories')
fig.update_layout(showlegend=False, yaxis_title='Total Loss ($)',
                  plot_bgcolor='white', height=500)
fig.update_yaxes(tickprefix='$', showgrid=True, gridcolor='lightgray')
fig.add_hline(y=0, line_dash="dash", line_color="black")

# Overall Profitability
subcat_profit = car.groupby('Sub-Category').agg(
    Total_Profit=('Profit', 'sum'),
    Order_Count=('Sales', 'count'),
    Category=('Category', 'first')
).reset_index()
unprofitable = subcat_profit[subcat_profit['Total_Profit'] < 0]

print(f"\nOVERALL PROFITABILITY\n{'='*50}")
print(f"Sub-Categories: {len(subcat_profit)}")
print(f"Unprofitable: {len(unprofitable)} ({(len(unprofitable)/len(subcat_profit)*100):.1f}%)")
if not unprofitable.empty:
    print("\nUnprofitable Sub-Categories:")
    for _, row in unprofitable.sort_values('Total_Profit').iterrows():
        print(f"  {row['Sub-Category']}: ${row['Total_Profit']:,.2f}")

fig.show()
```

```
NEGATIVE PROFIT ANALYSIS
==================================================
Orders: 1,901 (18.6%)
Total Loss: $-157,038.93
Avg Loss: $-82.61

TOP 5 LOSS MAKERS
==================================================
Binders (Third Party)
  Loss: $-38,563.49 | Orders: 619
  Avg Loss: $-62.30 | Discount: 73.6%
  Loss%: -106.5% | Sales: $36,200.50
----------------------------------------
Tables (Direct Sale)
  Loss: $-32,503.66 | Orders: 205
  Avg Loss: $-158.55 | Discount: 36.5%
  Loss%: -30.8% | Sales: $105,699.38
----------------------------------------
Machines (Pre Book)
  Loss: $-30,118.67 | Orders: 44
  Avg Loss: $-684.52 | Discount: 58.2%
  Loss%: -41.6% | Sales: $72,456.25
----------------------------------------
Bookcases (Direct Sale)
  Loss: $-12,349.81 | Orders: 111
  Avg Loss: $-111.26 | Discount: 35.5%
  Loss%: -25.6% | Sales: $48,217.33
----------------------------------------
Chairs (Direct Sale)
  Loss: $-10,135.04 | Orders: 238
  Avg Loss: $-42.58 | Discount: 26.1%
  Loss%: -10.8% | Sales: $93,460.17
----------------------------------------

OVERALL PROFITABILITY
==================================================
Sub-Categories: 17
Unprofitable: 3 (17.6%)

Unprofitable Sub-Categories:
  Tables: $-17,753.21
  Bookcases: $-3,632.07
  Supplies: $-1,171.39
```

05- Key Findings and Recommendations

Sales & Profit Analysis

- Negative Profit Orders: `18.6%` of orders are unprofitable, with `$-157,038.93` total losses.
- Worst Sub-Categories: Top 5 loss-making sub-categories (e.g., `Tables: $-17,753.21, Bookcases: $-3,632.07,Supplies: $-1,171.39`) contribute `$-157,038.93` in losses.
- Optimal Discount: Highest profit margin at `15%-20%` discount range. Avoid discounts beyond `35%-40%` as they erode margins.

✅ Recommendations:

- Review pricing strategy for loss-making sub-categories.
- Cap discounts at `15%` to maximize profitability.

Shipping & Delivery Analysis

- Fastest Ship Mode: `Same Day (std 0.2 days)`.
- Most Profitable Ship Mode: `Second Class with 15.1%  margin`.
- Delivery Impact: Longer deliveries(`Standard`) correlate with `11.3% lower profit margins`.

✅ Recommendations:

- Promote `Second Class` to `high-value` customers.
- Improve `logistics` for `slow-delivery` categories.

Customer Segmentation VIP Customers (Top 20): Drive `11.8%` of total sales `($275,371.13)`.

At-Risk Customers: `10.1%` haven't purchased in `93+ days`.

High-Value Segments: `VIP Customers` have the `highest average order value ($784.84)`.

✅ Recommendations:

- Launch `loyalty programs` for `VIP customers`.
- Win back `at-risk customers with targeted discounts`.

Product Performance

- Best Sellers: `Chairs (Direct Sale)` generates `$25,449.75 (8.3% margin)` in profit.
- Low-Margin Items: `Binders (Third Party)` has only `-106.5% margin`.

✅ Recommendations:

- Bundle `low-margin products` with `high-margin` ones.
- `Increase stock` for high-demand, `high-margin` items.

Operational Insights

- Discounts & Profit Trade-off: Orders with `10%-15% discount` have `3% lower margins`.
- Delivery Reliability: `Same Day` has the `lowest variability (0.21 days std)` which eventually `improves customer trust and reduces complaints`.

✅ Recommendations:

- Optimize `discounting` strategy to `balance sales volume & profit`.
- Standardize `shipping methods` for consistency.

Final Strategic Priorities

- `Fix Loss-Makers:` Adjust pricing/discontinue unprofitable products.
- `Retain VIPs:` Personalized offers for top customers.
- `Optimize Shipping:` Balance speed vs. cost.
- `Smart Discounting:` Limit deep discounts to clearance items only.
