Exploratory Data Analysis on FedEx Delivery Operations

This notebook performs a complete EDA. It includes data cleaning, univariate/bivariate analyses, geographic & operational insights, and business recommendations.

Setup

In [2]:
```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# Display options
pd.set_option('display.max_columns', None)
```

Load the dataset & first look

In [3]:
```
# Load the CSV
df = pd.read_csv("/Users/shivalimuthukumar/Desktop/fedex_deliveries

display(df.head())

# Basic structure
print("Rows, Columns:", df.shape)
display(df.dtypes)
```

	ShipmentID	Origin	Destination	Pickup_Date	Delivery_Date	Delivery_Status	Distance_
0	SHP100000	Seattle	New York	2025-03-10	2025-03-18 04:48:00	In Transit	37
1	SHP100001	Detroit	Los Angeles	2025-08-30	2025-09-04 09:36:00	Delivered	28
2	SHP100002	Phoenix	San Diego	2025-01-07	2025-01-10 02:24:00	Delivered	12
3	SHP100003	Miami	San Francisco	2024-09-29	2024-10-04 21:36:00	Delivered	30
4	SHP100004	Seattle	Miami	2025-07-29	2025-07-31 16:48:00	Delivered	12

```
Rows, Columns: (5000, 12)

ShipmentID                  object
Origin                      object
Destination                 object
Pickup_Date         datetime64[ns]
Delivery_Date       datetime64[ns]
Delivery_Status             object
Distance_KM                float64
Shipment_Mode               object
Weight_KG                  float64
Cost_USD                   float64
Customer_Segment            object
Delay_Reason                object
dtype: object
```

Part A: Data Understanding & Cleaning

1) Identify missing values & plan to handle them

In [5]:
```
# Count missing values per column
missing_counts = df.isna().sum().sort_values(ascending=False)
display(missing_counts.to_frame('Missing_Count'))

# Strategy:
# - Numerical (Weight_KG, Cost_USD, Distance_KM): fill with median.
# - Categorical (Shipment_Mode, Delay_Reason): fill with mode.
# - Dates are already present by generation; if missing, dropping t
```

	Missing_Count
Delay_Reason	2950
Weight_KG	97
Cost_USD	88
Distance_KM	50
Shipment_Mode	26
ShipmentID	0
Origin	0
Destination	0
Pickup_Date	0
Delivery_Date	0
Delivery_Status	0
Customer_Segment	0

2) Handle missing values (imputation)

In [6]:
```python
# Impute numeric with median
for col in ["Weight_KG","Cost_USD","Distance_KM"]:
    med = df[col].median()
    df[col] = df[col].fillna(med)

# Impute categorical with mode
for col in ["Shipment_Mode","Delay_Reason"]:
    mode_val = df[col].mode(dropna=True)[0]
    df[col] = df[col].fillna(mode_val)

# Verify no remaining missing values
display(df.isna().sum())
```

```
ShipmentID          0
Origin              0
Destination         0
Pickup_Date         0
Delivery_Date       0
Delivery_Status     0
Distance_KM         0
Shipment_Mode       0
Weight_KG           0
Cost_USD            0
Customer_Segment    0
Delay_Reason        0
dtype: int64
```

3) Convert dates & create `Delivery_Time_Days`

In [7]:
```
# Dates already parsed via read_csv
df['Pickup_Date'] = pd.to_datetime(df['Pickup_Date'])
df['Delivery_Date'] = pd.to_datetime(df['Delivery_Date'])

# Delivery time in days
df['Delivery_Time_Days'] = (df['Delivery_Date'] - df['Pickup_Date']
df['Delivery_Time_Days'] = df['Delivery_Time_Days'].round(1)

display(df[['Pickup_Date','Delivery_Date','Delivery_Time_Days']].he
```

	Pickup_Date	Delivery_Date	Delivery_Time_Days
0	2025-03-10	2025-03-18 04:48:00	8.2
1	2025-08-30	2025-09-04 09:36:00	5.4
2	2025-01-07	2025-01-10 02:24:00	3.1
3	2024-09-29	2024-10-04 21:36:00	5.9
4	2025-07-29	2025-07-31 16:48:00	2.7

Part B: Univariate and Bivariate Analysis

Distribution of `Delivery_Time_Days` & Average Delivery Time

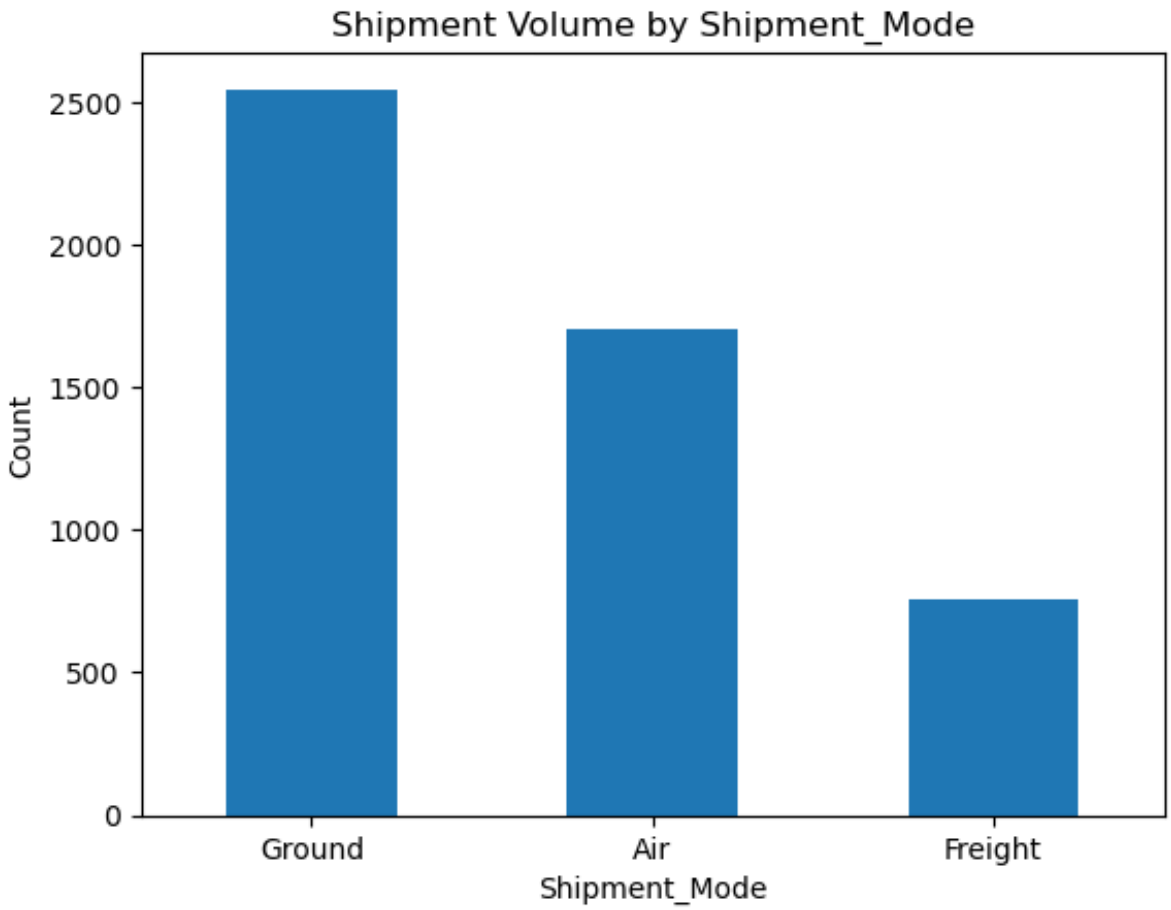
In [8]:
```
avg_time = df['Delivery_Time_Days'].mean()
print(f"Average delivery time (days): {avg_time:.2f}")

plt.figure()
plt.hist(df['Delivery_Time_Days'], bins=30)
plt.title('Distribution of Delivery_Time_Days')
plt.xlabel('Days')
plt.ylabel('Frequency')
plt.show()
```

```
Average delivery time (days): 4.72
```

Shipment volume by `Shipment_Mode`

In [9]:
```
mode_counts = df['Shipment_Mode'].value_counts().sort_values(ascend
display(mode_counts.to_frame('Count'))

plt.figure()
mode_counts.plot(kind='bar')
plt.title('Shipment Volume by Shipment_Mode')
plt.xlabel('Shipment_Mode')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.show()
```

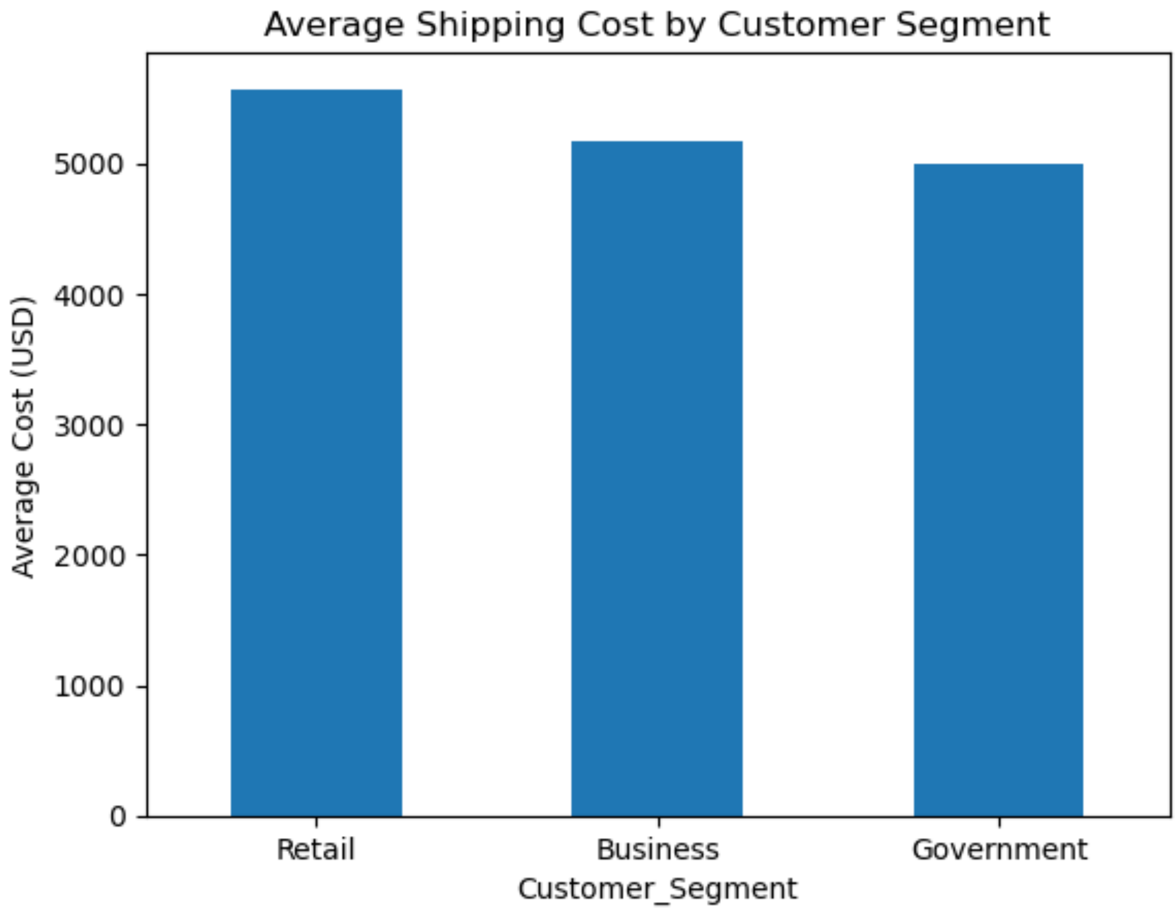
Shipment_Mode	Count
Ground	2544
Air	1701
Freight	755



Average shipping cost per `Customer_Segment`

In [10]:
```
avg_cost_segment = df.groupby('Customer_Segment')['Cost_USD'].mean(
display(avg_cost_segment.to_frame('Avg_Cost_USD').round(2))

plt.figure()
avg_cost_segment.plot(kind='bar')
plt.title('Average Shipping Cost by Customer Segment')
plt.xlabel('Customer_Segment')
plt.ylabel('Average Cost (USD)')
plt.xticks(rotation=0)
plt.show()
```

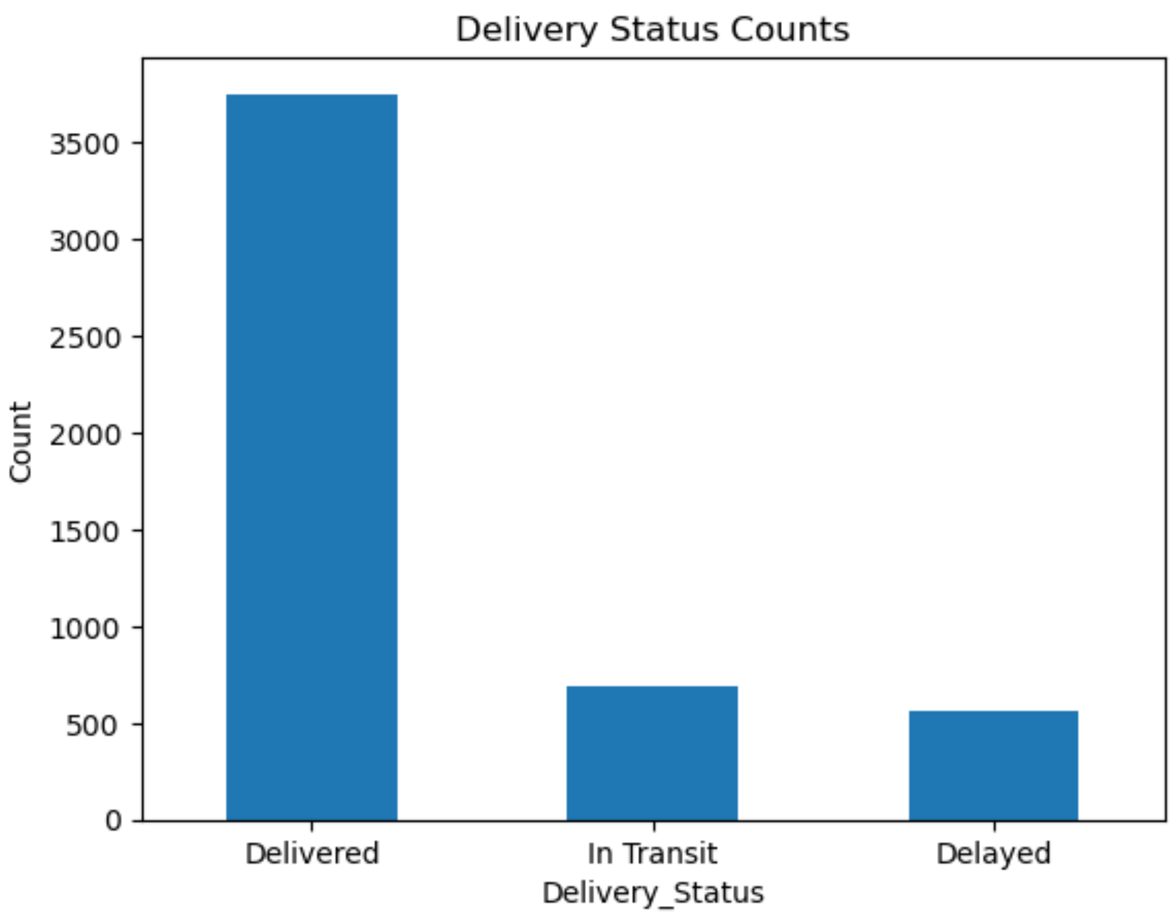
	Avg_Cost_USD
Customer_Segment	
Retail	5570.10
Business	5165.63
Government	5001.36



Delivery status counts

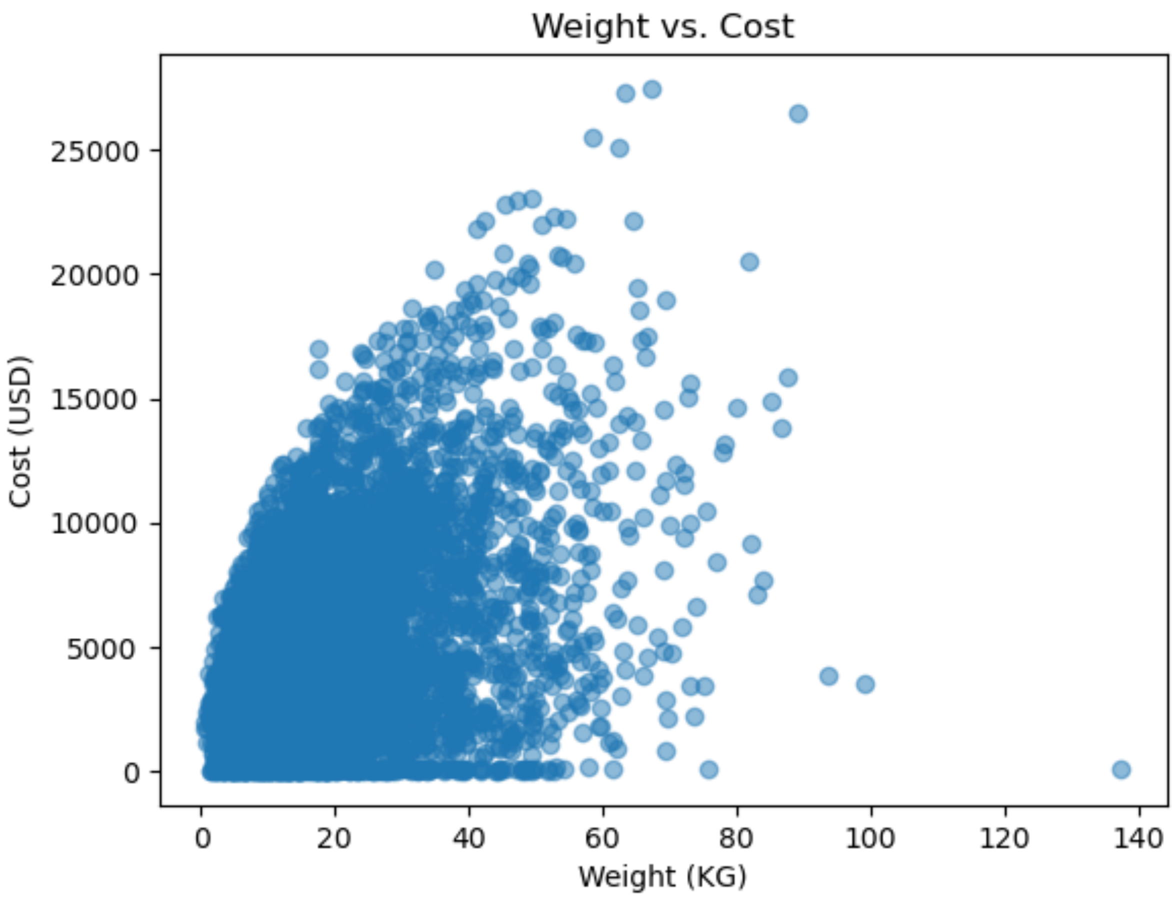
In [11]:
```
status_counts = df['Delivery_Status'].value_counts()
display(status_counts.to_frame('Count'))

plt.figure()
status_counts.plot(kind='bar')
plt.title('Delivery Status Counts')
plt.xlabel('Delivery_Status')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.show()
```

Delivery_Status	Count
Delivered	3753
In Transit	688
Delayed	559



Relationship between `Weight_KG` and `Cost_USD`

In [12]:
```
plt.figure()
plt.scatter(df['Weight_KG'], df['Cost_USD'], alpha=0.5)
plt.title('Weight vs. Cost')
plt.xlabel('Weight (KG)')
plt.ylabel('Cost (USD)')
plt.show()
```



Part C: Geographic and Operational Insights

Top 5 city pairs (Origin–Destination) by shipment frequency

In [13]:
```
pair_counts = (
    df.groupby(['Origin','Destination'])
      .size()
      .sort_values(ascending=False)
      .head(5)
      .rename('Count')
)
display(pair_counts)
```

```
Origin         Destination
San Francisco  Houston        28
Seattle        Charlotte      26
Boston         Boston         26
Detroit        Miami          26
Boston         Seattle        25
Name: Count, dtype: int64
```

Delivery delays by `Shipment_Mode` (stacked bar of status within mode)

In [14]:
```
ct = pd.crosstab(df['Shipment_Mode'], df['Delivery_Status'])
display(ct)

plt.figure()
ct.plot(kind='bar', stacked=True)
plt.title('Delivery Status Distribution by Shipment Mode')
plt.xlabel('Shipment_Mode')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.legend(title='Delivery_Status')
plt.show()
```

Delivery_Status	Delayed	Delivered	In Transit
Shipment_Mode			
Air	172	1317	212
Freight	89	534	132
Ground	298	1902	344

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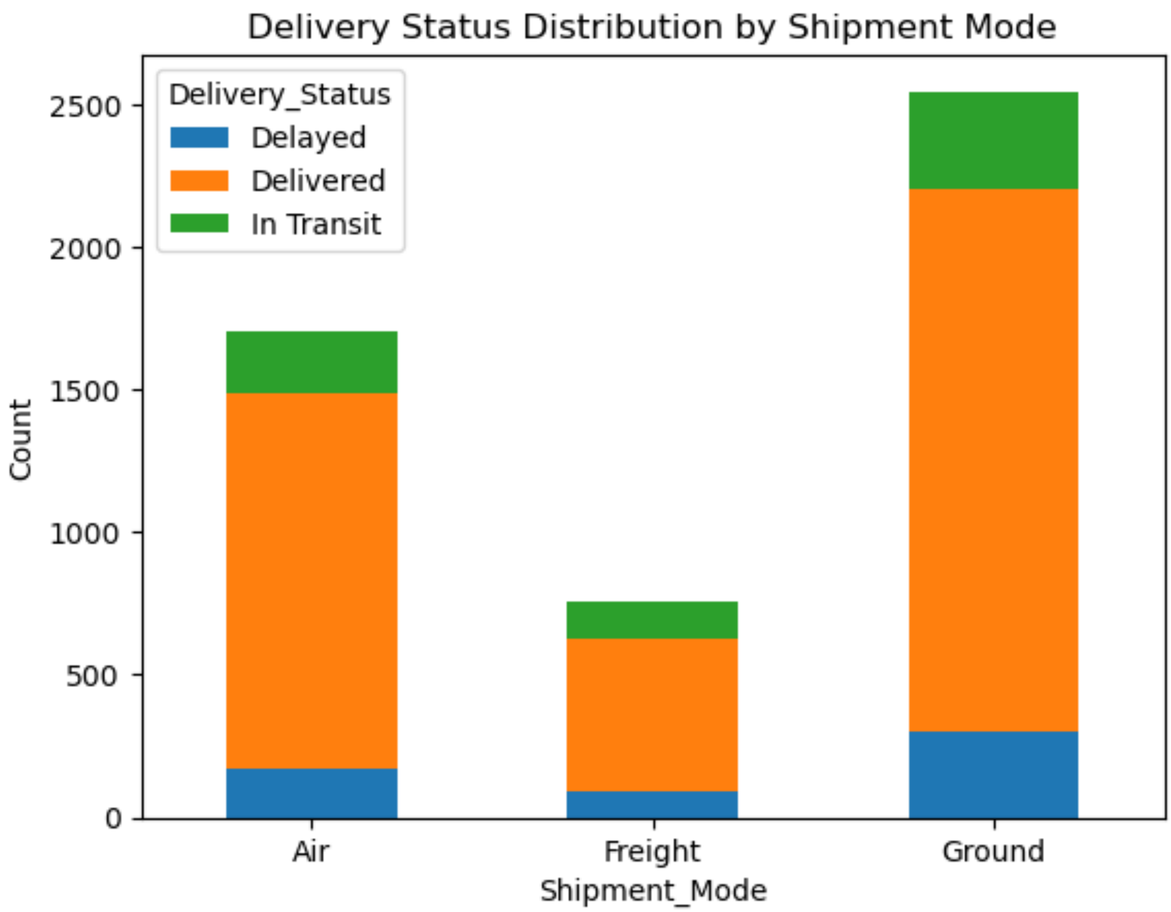
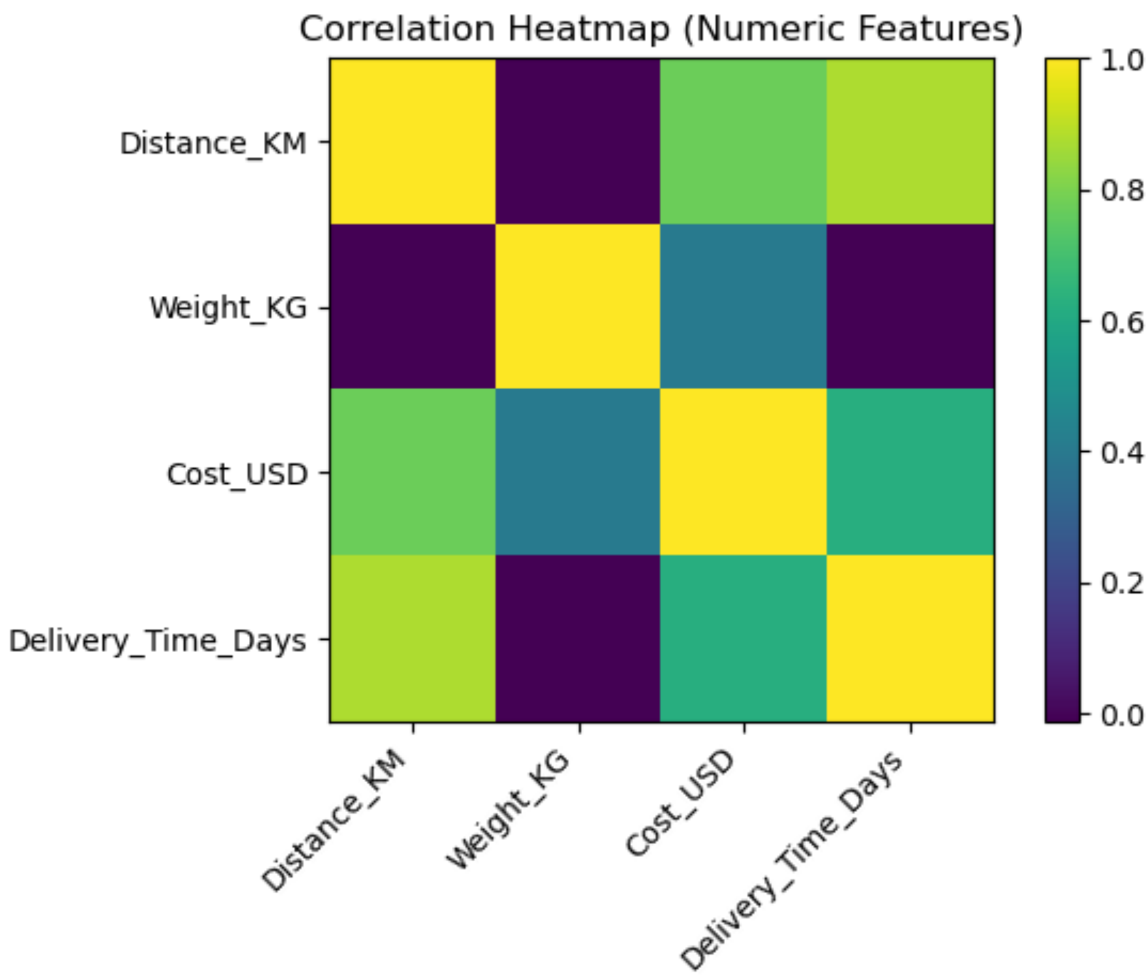


Correlation heatmap of numeric features

In [15]:
```
numeric_cols = ['Distance_KM','Weight_KG','Cost_USD','Delivery_Time_
corr = df[numeric_cols].corr()

import numpy as np
plt.figure()
plt.imshow(corr, interpolation='nearest')
plt.title('Correlation Heatmap (Numeric Features)')
plt.xticks(range(len(numeric_cols)), numeric_cols, rotation=45, ha=
plt.yticks(range(len(numeric_cols)), numeric_cols)
plt.colorbar()
plt.tight_layout()
plt.show()

display(corr.round(3))
```



	Distance_KM	Weight_KG	Cost_USD	Delivery_Time_Days
Distance_KM	1.000	-0.012	0.772	0.875
Weight_KG	-0.012	1.000	0.402	-0.009

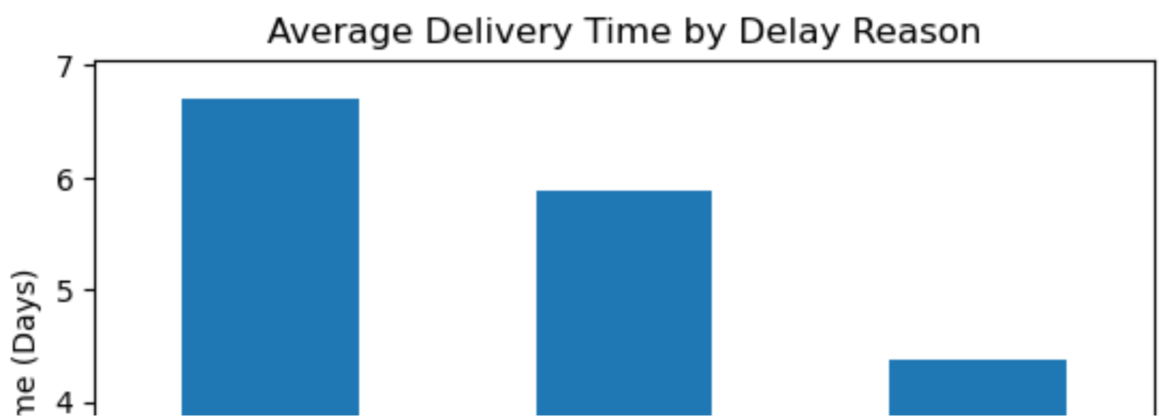
Cost_USD	0.772	0.402	1.000	0.623
Delivery_Time_Days	0.875	-0.009	0.623	1.000

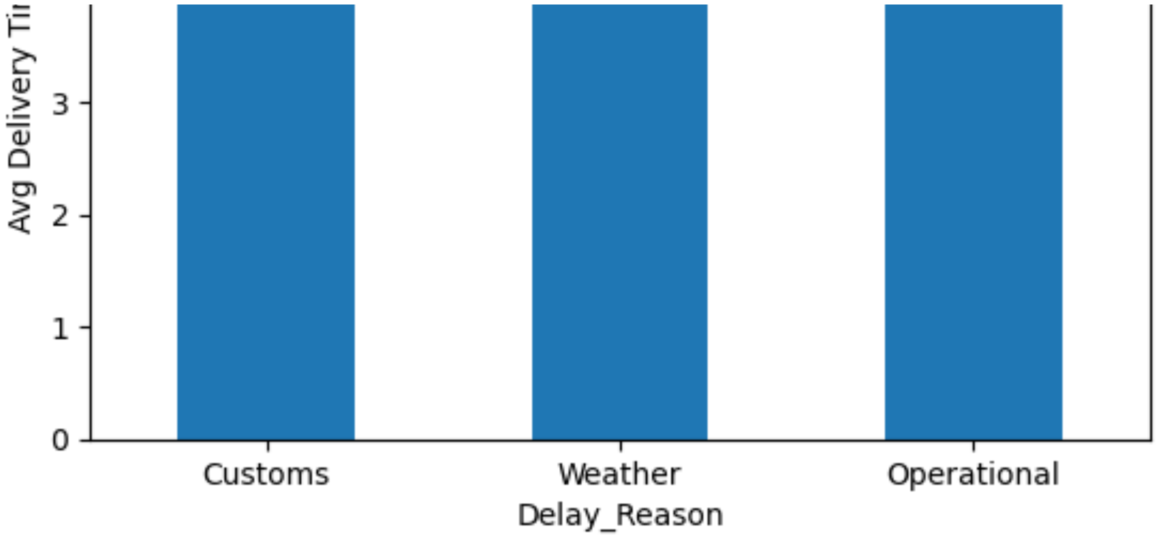
Most common `Delay_Reason` and its impact on `Delivery_Time_Days`

In [16]:
```
delay_counts = df['Delay_Reason'].value_counts()
display(delay_counts.to_frame('Count'))

impact = df.groupby('Delay_Reason')['Delivery_Time_Days'].mean().so
display(impact.to_frame('Avg_Delivery_Time_Days').round(2))

plt.figure()
impact.plot(kind='bar')
plt.title('Average Delivery Time by Delay Reason')
plt.xlabel('Delay_Reason')
plt.ylabel('Avg Delivery Time (Days)')
plt.xticks(rotation=0)
plt.show()
```

	Count
Delay_Reason	
Operational	4002
Weather	751
Customs	247

	Avg_Delivery_Time_Days
Delay_Reason	
Customs	6.71
Weather	5.88
Operational	4.37

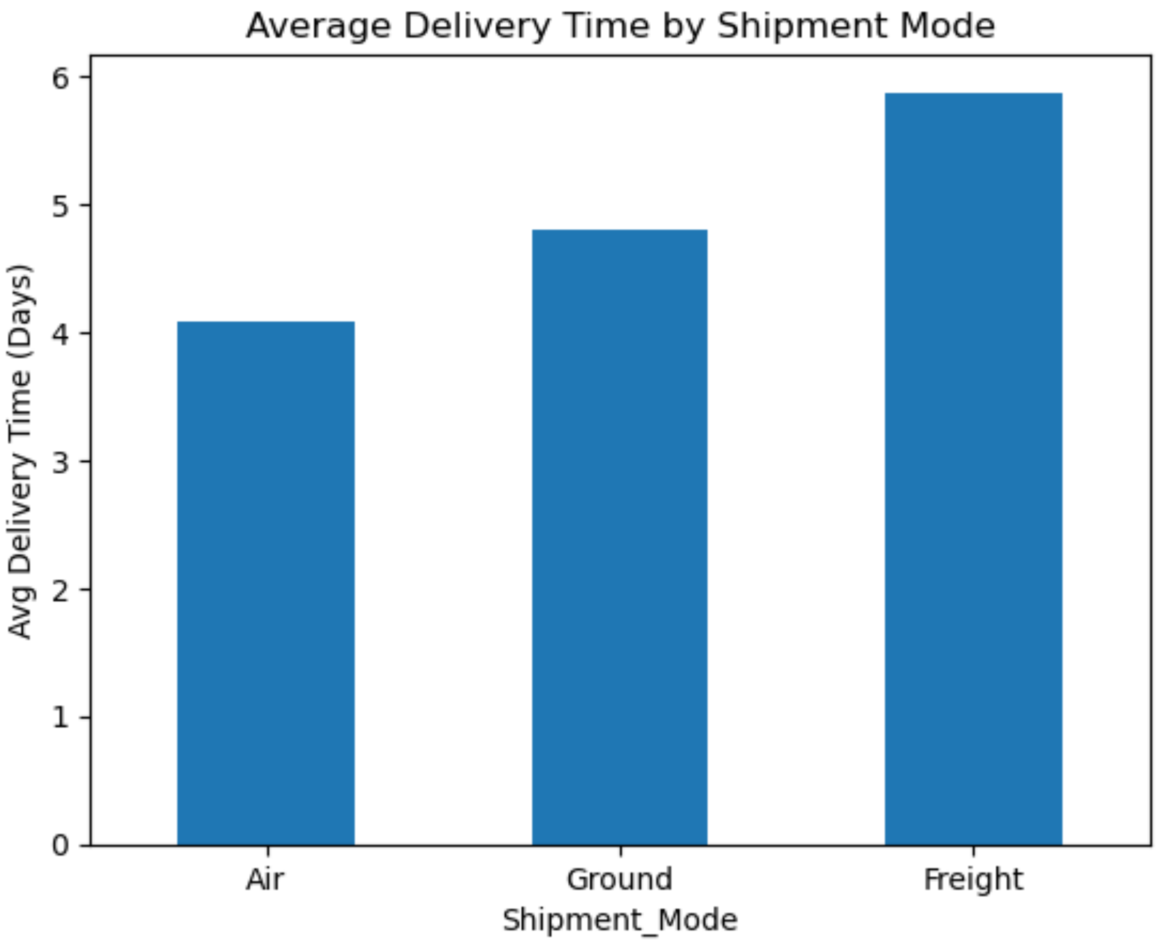




Compare average delivery times between `Shipment_Mode`s

In [17]:
```
avg_time_by_mode = df.groupby('Shipment_Mode')['Delivery_Time_Days'
display(avg_time_by_mode.to_frame('Avg_Delivery_Time_Days').round(2

plt.figure()
avg_time_by_mode.plot(kind='bar')
plt.title('Average Delivery Time by Shipment Mode')
plt.xlabel('Shipment_Mode')
plt.ylabel('Avg Delivery Time (Days)')
plt.xticks(rotation=0)
plt.show()
```

	Avg_Delivery_Time_Days
Shipment_Mode	
Air	4.08
Ground	4.80
Freight	5.87



Part D: Business Recommendations

Based on the above analyses:

1. **Operational Inefficiencies:** If certain delay reasons (e.g., *Customs* or *Operational*) correlate with longer delivery times, prioritize root-cause fixes (pre-clearance for customs, capacity planning for operations).
2. **Shipment Mode Allocation:** For short distances (e.g., < 500 KM), **Ground** can offer comparable delivery times at lower cost versus **Air**; consider routing rules accordingly.
3. **Cost Reduction Strategies:** For high-cost segments (e.g., heavy + long-distance via Air), implement **mode downgrade** eligibility with SLAs, and negotiate **business-segment contracts**.
4. **Customer Satisfaction:** Trigger **proactive notifications** for Weather/Customs delays with revised ETAs; offer coupons or fee waivers for severe delays.

Save the cleaned dataset

In [18]:
```
clean_path = '/Users/shivalimuthukumar/Desktop/fedex_deliveries_cle
df.to_csv(clean_path, index=False)
print('Saved cleaned file ->', clean_path)
```

```
Saved cleaned file -> /Users/shivalimuthukumar/Desktop/fedex_deliv
eries_cleaned.csv
```