INTERNSHIP PROJECT REPORT

ON

“SUPPLY CHAIN MANAGEMENT DATA ANALYSIS”

SUBMITTED BY:

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EXECUTIVE SUMMARY

With a focus on quality control, logistical efficiency, and profitability, this research offers a data-driven perspective of supply chain operations.

Important Product and Financial Insights: The skincare product category leads in sales volume and produces the highest overall revenue. Nonetheless, the category with the highest average net profit per product is cosmetics, indicating a higher margin structure that calls for additional optimization. In terms of production volume, Supplier 1 is among the top two suppliers and contributes the most to the overall net profit.

Operational Efficiency (Lead Times): Considerable differences in lead times between sites were found. Mumbai, thanks to its effective manufacturing, maintains the shortest average lead time overall (around 14.3 days). On the other hand, because of their longer manufacturing and shipping schedules, Kolkata and Chennai have the largest average overall lead times (more than 17 days). These areas are important bottlenecks that need to be reviewed right now.

Quality and Cost Control: Inspection results analysis demonstrates a clear correlation between defects and quality problems: products with a "Fail" inspection have the highest average defect rate (2.57%). Additionally, it has been established that, on average, air transportation is the most costly shipping method. The information shows a somewhat negative relationship between production lead time and product pricing.

Suggestion: To optimize the high per-unit profitability of the Cosmetics product line, concentrate on supply chain optimization in high-lead-time regions such as Chennai and Kolkata and establish focused tactics.

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OBJECTIVES

The following major goals are intended to be accomplished by this study, which is based on the thorough supply chain data analysis:

Analyze Product Profitability and Performance: To determine the highest-margin product category (Cosmetics) and the highest-revenue contributor (Skincare), compute the Net Profit for each product type, and compare total revenue and sales volume.

Benchmark Supplier Financial Contribution: To collect and rank suppliers based on their entire contribution to Net Profit and Production Volume, thereby emphasizing essential vendor relationships for strategic management.

Determine and Measure Bottlenecks in Logistics: To determine which operating sites (such as Chennai and Kolkata) have the longest lead times and need efficiency improvements by breaking down the total lead time (manufacturing lead time plus shipping time) across all of them.

Evaluate the effectiveness of quality control by calculating the correlation between average defect rates and product inspection results (pass, fail, or pending) in order to measure the quality risk related to various production outcomes and confirm the influence of current quality procedures.

Examine Transportation Cost Efficiency: To help guide decisions about cost-effective shipping tactics, compare the average shipping costs for different modes of transportation (air, rail, road, and sea).

DATA ANALYSIS

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Load the dataset
df = pd.read_csv('supply_chain_data.csv')

# Initial inspection
print(df.head())
```

```
  Product type   SKU      Price  Availability  Number of products sold  \
0     haircare  SKU0  69.808006            55                      802   
1     skincare  SKU1  14.843523            95                      736   
2     haircare  SKU2  11.319683            34                        8   
3     skincare  SKU3  61.163343            68                       83   
4     skincare  SKU4   4.805496            26                      871   

   Revenue generated Customer demographics  Stock levels  Lead times  \
0        8661.996792            Non-binary            58           7   
1        7460.900065                Female            53          30   
2        9577.749626               Unknown             1          10   
3        7766.836426            Non-binary            23          13   
4        2686.505152            Non-binary             5           3   

   Order quantities  ...  Location Lead time  Production volumes  \
0                96  ...    Mumbai        29                 215   
1                37  ...    Mumbai        23                 517   
2                88  ...    Mumbai        12                 971   
3                59  ...   Kolkata        24                 937   
4                56  ...     Delhi         5                 414   

  Manufacturing lead time Manufacturing costs  Inspection results  \
0                      29           46.279879             Pending   
1                      30           33.616769             Pending   
2                      27           30.688019             Pending   
3                      18           35.624741                Fail   
4                       3           92.065161                Fail   

   Defect rates  Transportation modes   Routes       Costs  
0      0.226410                  Road  Route B  187.752075  
1      4.854068                  Road  Route B  503.065579  
2      4.580593                   Air  Route C  141.920282  
3      4.746649                  Rail  Route A  254.776159  
4      3.145580                   Air  Route A  923.440632  
```

```python
#Data Types and Non-Null Counts
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 24 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Product type             100 non-null    object 
 1   SKU                      100 non-null    object 
 2   Price                    100 non-null    float64
 3   Availability             100 non-null    int64  
 4   Number of products sold  100 non-null    int64  
 5   Revenue generated        100 non-null    float64
 6   Customer demographics    100 non-null    object 
 7   Stock levels             100 non-null    int64  
 8   Lead times               100 non-null    int64  
 9   Order quantities         100 non-null    int64  
 10  Shipping times           100 non-null    int64  
 11  Shipping carriers        100 non-null    object 
 12  Shipping costs           100 non-null    float64
 13  Supplier name            100 non-null    object 
 14  Location                 100 non-null    object 
 15  Lead time                100 non-null    int64  
 16  Production volumes       100 non-null    int64  
 17  Manufacturing lead time  100 non-null    int64  
 18  Manufacturing costs      100 non-null    float64
 19  Inspection results       100 non-null    object 
 20  Defect rates             100 non-null    float64
 21  Transportation modes     100 non-null    object 
 22  Routes                   100 non-null    object 
 23  Costs                    100 non-null    float64
dtypes: float64(6), int64(9), object(9)
memory usage: 18.9+ KB
```

```
#Summary Statistics for Numerical Columns
print(df.describe())
```

```
            Price  Availability  Number of products sold  Revenue generated  \
count  100.000000    100.000000               100.000000         100.000000   
mean    49.462461     48.400000               460.990000        5776.048187   
std     31.168193     30.743317               303.780074        2732.841744   
min      1.699976      1.000000                 8.000000        1061.618523   
25%     19.597823     22.750000               184.250000        2812.847151   
50%     51.239831     43.500000               392.500000        6006.352023   
75%     77.198228     75.000000               704.250000        8253.976921   
max     99.171329    100.000000               996.000000        9866.465458   

       Stock levels  Lead times  Order quantities  Shipping times  \
count    100.000000  100.000000        100.000000      100.000000   
mean      47.770000   15.960000         49.220000        5.750000   
std       31.369372    8.785801         26.784429        2.724283   
min        0.000000    1.000000          1.000000        1.000000   
25%       16.750000    8.000000         26.000000        3.750000   
50%       47.500000   17.000000         52.000000        6.000000   
75%       73.000000   24.000000         71.250000        8.000000   
max      100.000000   30.000000         96.000000       10.000000   

       Shipping costs   Lead time  Production volumes  \
count      100.000000  100.000000          100.000000   
mean         5.548149   17.080000          567.840000   
std          2.651376    8.846251          263.046861   
min          1.013487    1.000000          104.000000   
25%          3.540248   10.000000          352.000000   
50%          5.320534   18.000000          568.500000   
75%          7.601695   25.000000          797.000000   
max          9.929816   30.000000          985.000000   
```

```
# Check for missing values
print(df.isnull().sum())
```

```
Product type               0
SKU                        0
Price                      0
Availability               0
Number of products sold    0
Revenue generated          0
Customer demographics      0
Stock levels               0
Lead times                 0
Order quantities           0
Shipping times             0
Shipping carriers          0
Shipping costs             0
Supplier name              0
Location                   0
Lead time                  0
Production volumes         0
Manufacturing lead time    0
Manufacturing costs        0
Inspection results         0
Defect rates               0
Transportation modes       0
Routes                     0
Costs                      0
dtype: int64
```

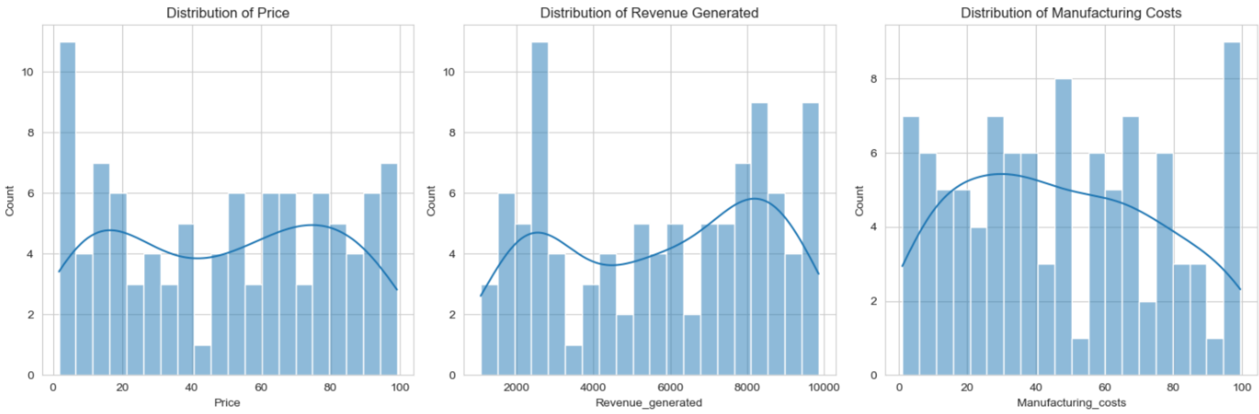
```python
# Convert 'Inspection results' to a categorical type if it's currently 'object'
print("\n--- Unique values in 'Inspection results' ---")
print(df['Inspection results'].unique())
# Assuming 'Pass', 'Fail', 'Pending' are the main values, we can map them for numerical analysis
```

```
--- Unique values in 'Inspection results' ---
['Pending' 'Fail' 'Pass']
```

```python
# Clean column names for easier access (e.g., replace spaces with underscores)
df.columns = df.columns.str.replace(' ', '_')
print(df.columns)
```

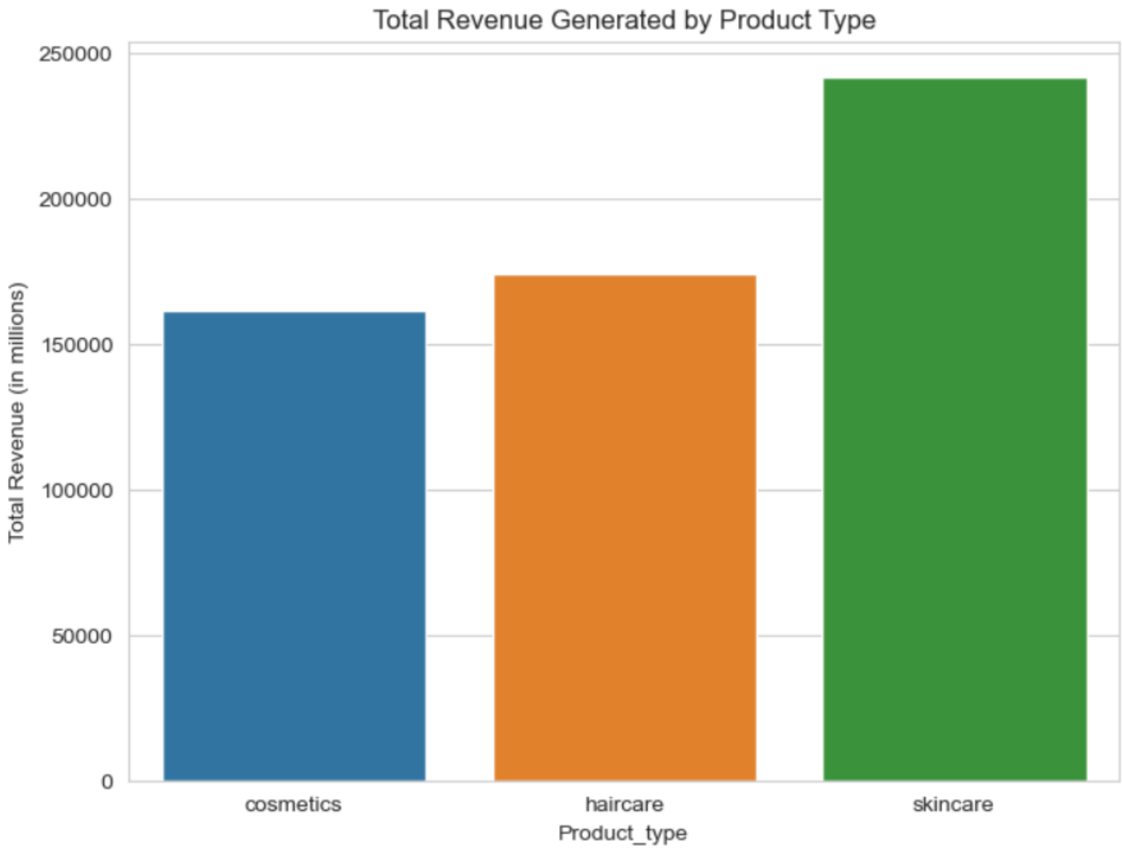
```
Index(['Product_type', 'SKU', 'Price', 'Availability',
       'Number_of_products_sold', 'Revenue_generated', 'Customer_demographics',
       'Stock_levels', 'Lead_times', 'Order_quantities', 'Shipping_times',
       'Shipping_carriers', 'Shipping_costs', 'Supplier_name', 'Location',
       'Lead_time', 'Production_volumes', 'Manufacturing_lead_time',
       'Manufacturing_costs', 'Inspection_results', 'Defect_rates',
       'Transportation_modes', 'Routes', 'Costs'],
      dtype='object')
```

```python
# Set a consistent style for plots
sns.set_style("whitegrid")

plt.figure(figsize=(15, 5))

# Distribution of Price
plt.subplot(1, 3, 1)
sns.histplot(df['Price'], bins=20, kde=True)
plt.title('Distribution of Price')

# Distribution of Revenue generated
plt.subplot(1, 3, 2)
sns.histplot(df['Revenue_generated'], bins=20, kde=True)
plt.title('Distribution of Revenue Generated')

# Distribution of Manufacturing costs
plt.subplot(1, 3, 3)
sns.histplot(df['Manufacturing_costs'], bins=20, kde=True)
plt.title('Distribution of Manufacturing Costs')

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



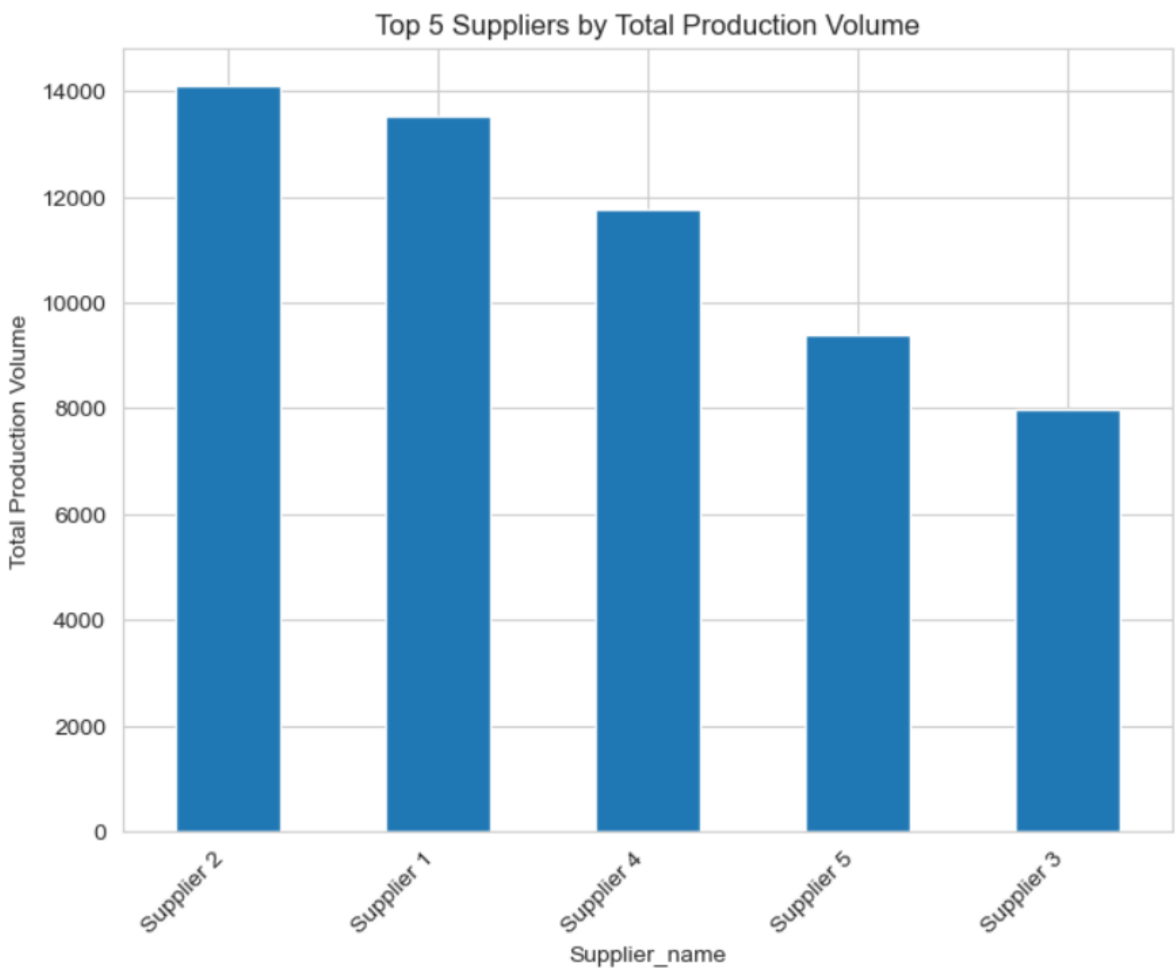

```
# Aggregate data by Product type
product_performance = df.groupby('Product_type').agg({
    'Number_of_products_sold': 'sum',
    'Revenue_generated': 'sum',
    'Manufacturing_costs': 'mean',
    'Price': 'mean'
}).reset_index()

print("\n--- Product Type Performance Summary ---")
print(product_performance.sort_values(by='Revenue_generated', ascending=False))

# Visualization: Total Revenue by Product Type
plt.figure(figsize=(8, 6))
sns.barplot(x='Product_type', y='Revenue_generated', data=product_performance)
plt.title('Total Revenue Generated by Product Type')
plt.ylabel('Total Revenue (in millions)')
plt.show()
```

```
--- Product Type Performance Summary ---
  Product_type  Number_of_products_sold  Revenue_generated  \
2     skincare                    20731      241628.162133
1     haircare                    13611      174455.390605
0    cosmetics                    11757      161521.265999

   Manufacturing_costs      Price
2            48.993157  47.259329
1            48.457993  46.014279
0            43.052740  57.361058
```



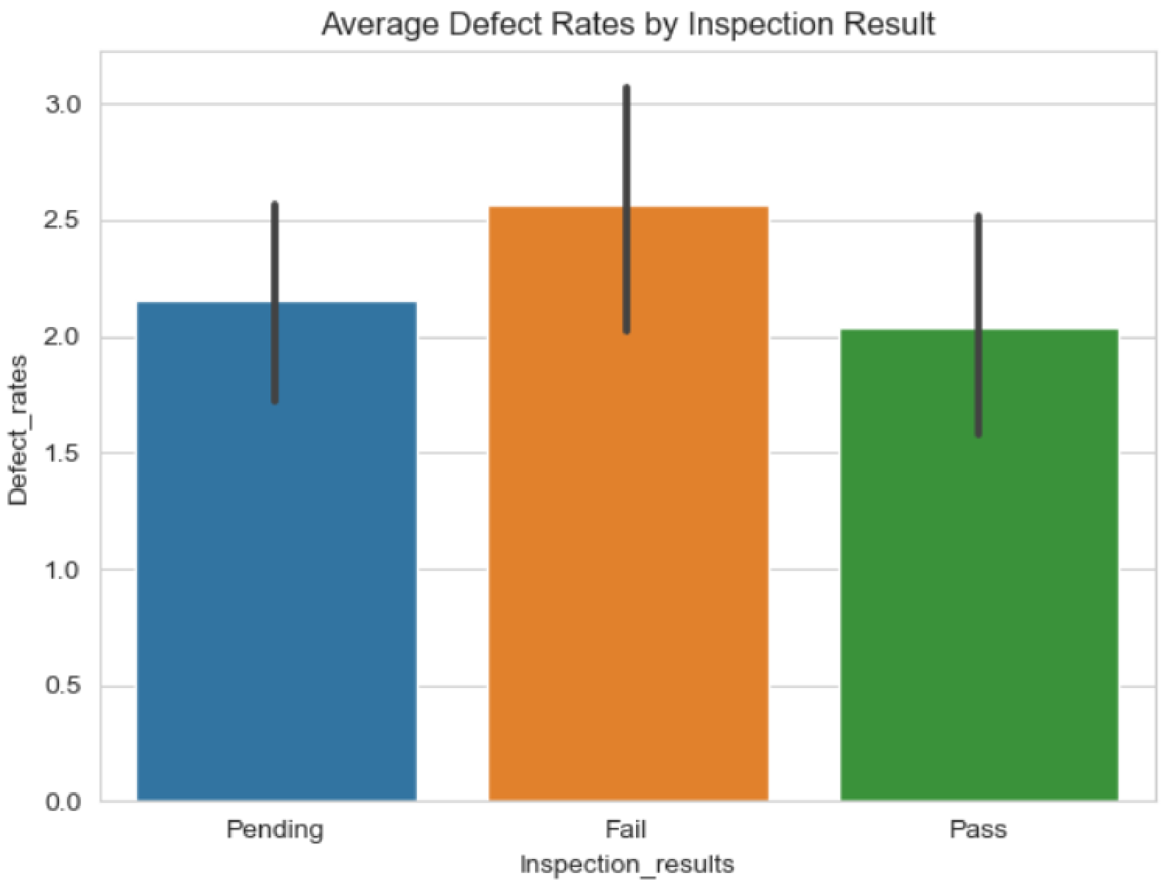

```
# Analyze Production Volumes by Supplier
supplier_volume = df.groupby('Supplier_name')['Production_volumes'].sum().sort_values(ascending=False).head(5)

# Analyze Average Lead Time by Location
location_lead_time = df.groupby('Location')['Lead_time'].mean().sort_values(ascending=False)

print("\n--- Top 5 Suppliers by Production Volume ---")
print(supplier_volume)

print("\n--- Average Lead Time by Location ---")
print(location_lead_time)

# Visualization: Production Volumes by Supplier (Top 5)
plt.figure(figsize=(8, 6))
supplier_volume.plot(kind='bar')
plt.title('Top 5 Suppliers by Total Production Volume')
plt.ylabel('Total Production Volume')
plt.xticks(rotation=45, ha='right')
plt.show()
```

```
--- Top 5 Suppliers by Production Volume ---
Supplier_name
Supplier 2    14105
Supplier 1    13545
Supplier 4    11756
Supplier 5     9381
Supplier 3     7997
Name: Production_volumes, dtype: int64

--- Average Lead Time by Location ---
Location
Kolkata      19.440000
Chennai      18.650000
Bangalore    16.277778
Mumbai       15.318182
Delhi        14.600000
Name: Lead_time, dtype: float64
```



```python
# Group by Inspection results and calculate average Defect rates
inspection_quality = df.groupby('Inspection_results')['Defect_rates'].agg(['mean', 'count'])

print("\n--- Average Defect Rates by Inspection Result ---")
print(inspection_quality)

# Visualization: Defect Rates by Inspection Result
plt.figure(figsize=(7, 5))
sns.barplot(x='Inspection_results', y='Defect_rates', data=df)
plt.title('Average Defect Rates by Inspection Result')
plt.show()
```

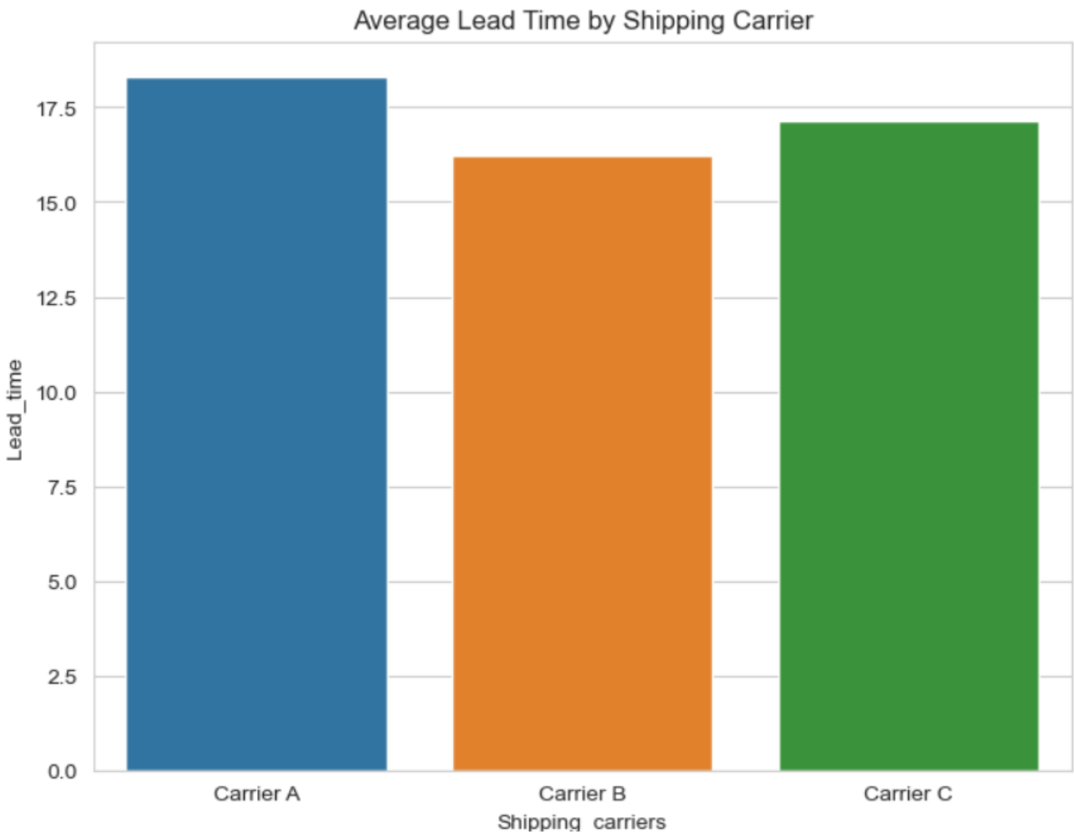
```
--- Average Defect Rates by Inspection Result ---
                        mean  count
Inspection_results
Fail                2.569302     36
Pass                2.039043     23
Pending             2.154218     41
```



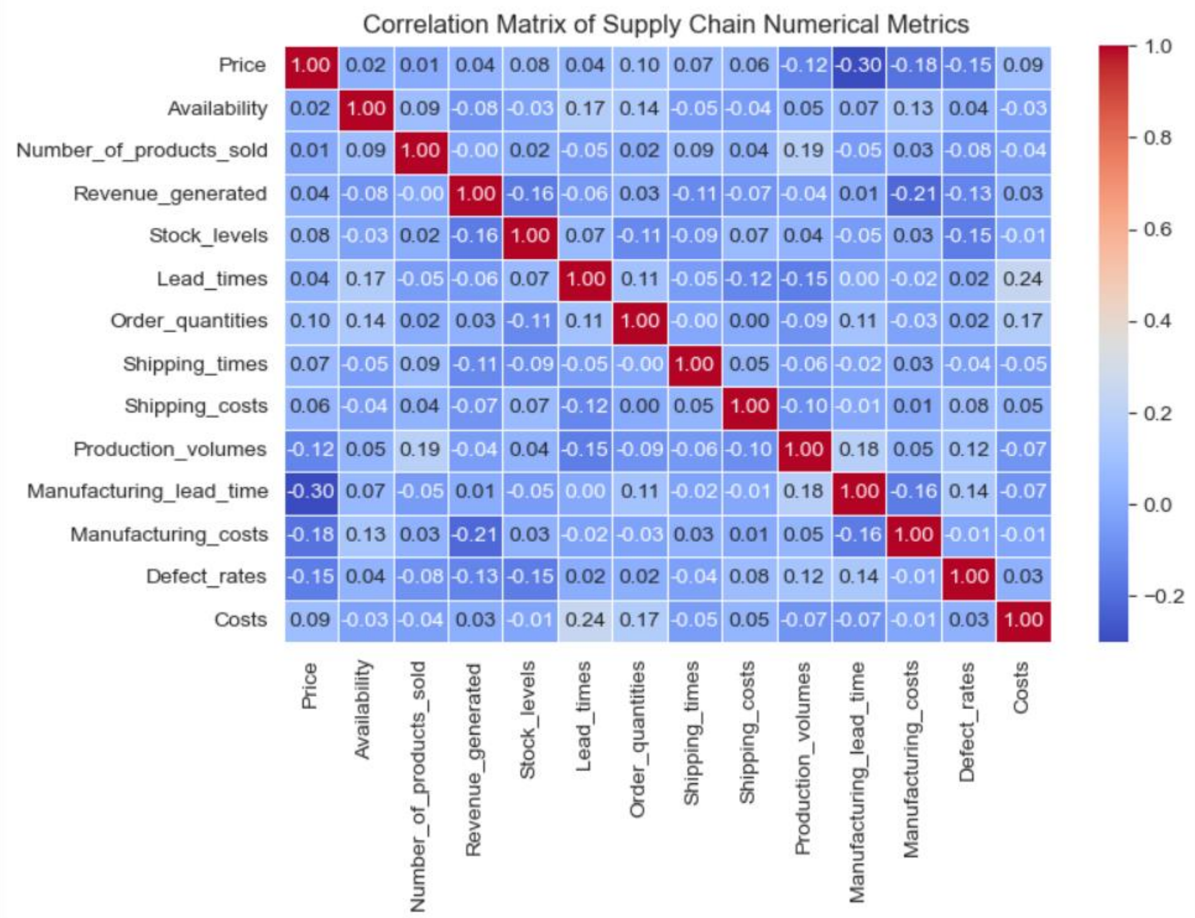
```python
# Analyze Shipping Costs by Transportation Mode
transport_cost = df.groupby('Transportation_modes')['Shipping_costs'].mean().sort_values(ascending=False)

# Analyze Lead Times and Shipping Times by Shipping Carrier
carrier_performance = df.groupby('Shipping_carriers').agg({
    'Lead_time': 'mean',
    'Shipping_times': 'mean',
    'Shipping_costs': 'mean'
}).reset_index()

print("\n--- Average Shipping Costs by Transportation Mode ---")
print(transport_cost)

print("\n--- Carrier Performance (Avg. Lead Time, Shipping Time, Cost) ---")
print(carrier_performance.sort_values(by='Shipping_costs', ascending=False))

# Visualization: Lead Time vs. Shipping Carrier
plt.figure(figsize=(8, 6))
sns.barplot(x='Shipping_carriers', y='Lead_time', data=carrier_performance)
plt.title('Average Lead Time by Shipping Carrier')
plt.show()
```

```
--- Average Shipping Costs by Transportation Mode ---
Transportation_modes
Air      6.017839
Road     5.542115
Rail     5.469098
Sea      4.970294
Name: Shipping_costs, dtype: float64
```

```
--- Carrier Performance (Avg. Lead Time, Shipping Time, Cost) ---
  Shipping_carriers  Lead_time  Shipping_times  Shipping_costs
2         Carrier C  17.137931        6.034483        5.599292
0         Carrier A  18.321429        6.142857        5.554923
1         Carrier B  16.232558        5.302326        5.509247
```



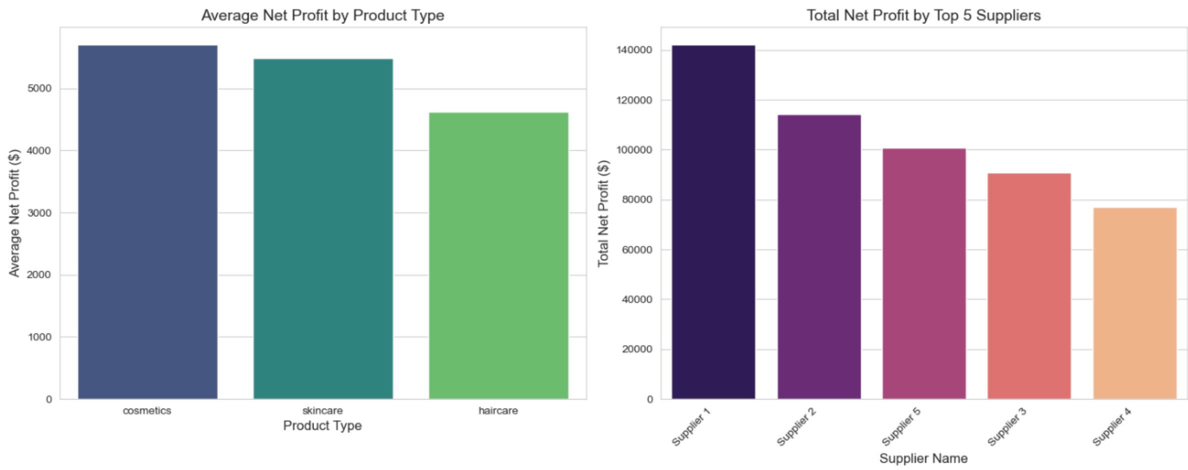
```python
# Select relevant numerical columns for correlation matrix
corr_cols = ['Price', 'Availability', 'Number_of_products_sold', 'Revenue_generated',
             'Stock_levels', 'Lead_times', 'Order_quantities', 'Shipping_times',
             'Shipping_costs', 'Production_volumes', 'Manufacturing_lead_time',
             'Manufacturing_costs', 'Defect_rates', 'Costs']

correlation_matrix = df[corr_cols].corr()

# Visualize the correlation matrix
plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=.5)
plt.title('Correlation Matrix of Supply Chain Numerical Metrics')
plt.show()
```



```python
# Profitability Analysis

# Calculate Net Profit
df['Net_Profit'] = df['Revenue_generated'] - df['Costs']

print("--- DataFrame Head with New 'Net_Profit' Column ---")
print(df[['Revenue_generated', 'Costs', 'Net_Profit']].head())

# Aggregate average net profit by Product Type
profit_by_product = df.groupby('Product_type')['Net_Profit'].mean().sort_values(ascending=False).reset_index()

# Aggregate total net profit by Supplier (Top 5)
profit_by_supplier = df.groupby('Supplier_name')['Net_Profit'].sum().sort_values(ascending=False).head(5).reset_index()

# Plotting Profitability
sns.set_style("whitegrid")
plt.figure(figsize=(15, 6))

# Plot 1: Average Net Profit by Product Type
plt.subplot(1, 2, 1)
sns.barplot(x='Product_type', y='Net_Profit', data=profit_by_product, palette='viridis')
plt.title('Average Net Profit by Product Type', fontsize=14)
plt.ylabel('Average Net Profit ($)', fontsize=12)
plt.xlabel('Product Type', fontsize=12)

# Plot 2: Total Net Profit by Supplier (Top 5)
plt.subplot(1, 2, 2)
sns.barplot(x='Supplier_name', y='Net_Profit', data=profit_by_supplier, palette='magma')
plt.title('Total Net Profit by Top 5 Suppliers', fontsize=14)
plt.ylabel('Total Net Profit ($)', fontsize=12)
plt.xlabel('Supplier Name', fontsize=12)
plt.xticks(rotation=45, ha='right')
```

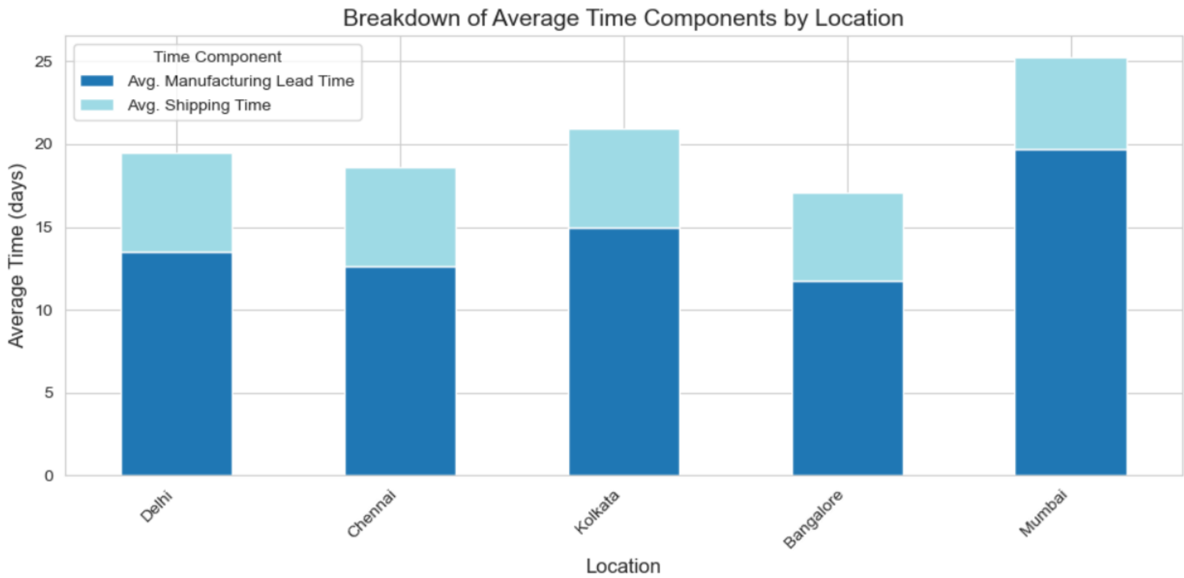
```python
plt.tight_layout()
plt.show()
```

```
--- DataFrame Head with New 'Net_Profit' Column ---
   Revenue_generated       Costs   Net_Profit
0        8661.996792  187.752075  8474.244717
1        7460.900065  503.065579  6957.834486
2        9577.749626  141.920282  9435.829344
3        7766.836426  254.776159  7512.060266
4        2686.505152  923.440632  1763.064520
```

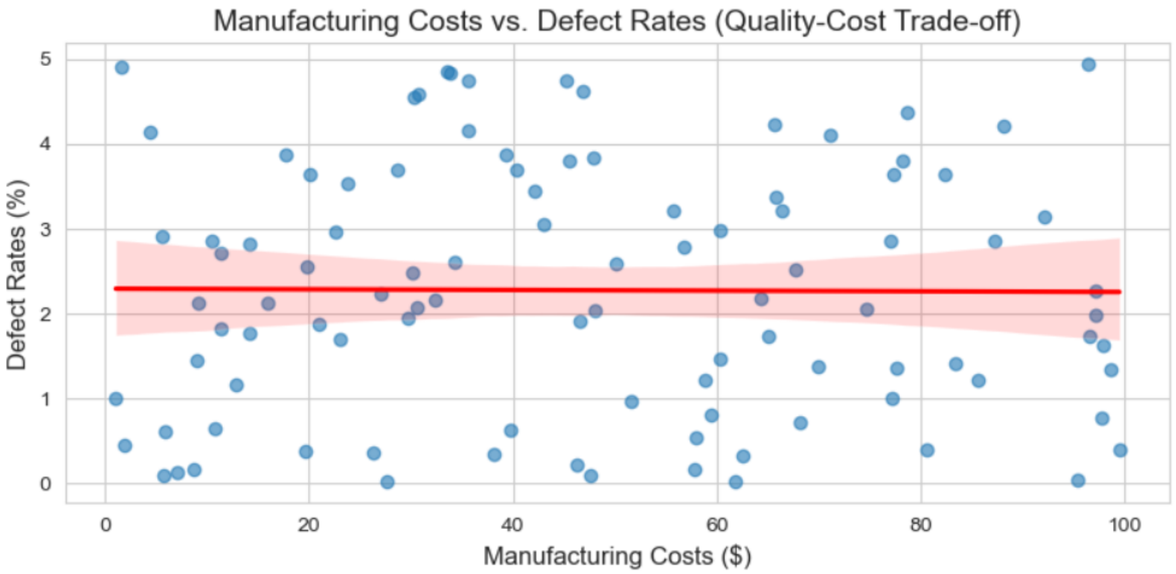


```
#Lead Time Analysis (Critical Path)
# Aggregate average time components by Location
time_components = df.groupby('Location').agg({
    'Manufacturing_lead_time': 'mean',
    'Shipping_times': 'mean',
    'Lead_times': 'mean'
}).sort_values(by='Lead_times', ascending=False)

# Rename columns for better visualization labels
time_components.columns = ['Avg. Manufacturing Lead Time', 'Avg. Shipping Time', 'Avg. Total Lead Time']

print("\n--- Average Time Components by Location (in days) ---")
print(time_components)

# Plotting Lead Time Components
time_components_plot = time_components[['Avg. Manufacturing Lead Time', 'Avg. Shipping Time']].plot(
    kind='bar', stacked=True, figsize=(10, 7), colormap='tab20'
)
plt.title('Breakdown of Average Time Components by Location', fontsize=14)
plt.ylabel('Average Time (days)', fontsize=12)
plt.xlabel('Location', fontsize=12)
plt.xticks(rotation=45, ha='right')
plt.legend(title='Time Component')
plt.tight_layout()
plt.show()
```

```
--- Average Time Components by Location (in days) ---
           Avg. Manufacturing Lead Time  Avg. Shipping Time  \
Location
Delhi                         13.533333            5.933333
Chennai                       12.650000            6.000000
Kolkata                       15.000000            5.960000
Bangalore                     11.777778            5.277778
Mumbai                        19.727273            5.545455

           Avg. Total Lead Time
Location
Delhi                 17.666667
Chennai               17.150000
Kolkata               15.920000
Bangalore             15.333333
Mumbai                14.272727
```



```python
#Manufacturing Cost vs. Defect Rate (Quality-Cost Trade-off)
# Scatter plot with regression line
plt.figure(figsize=(8, 4))
sns.regplot(x='Manufacturing_costs', y='Defect_rates', data=df,
            scatter_kws={'alpha':0.6}, line_kws={'color':'red'})
plt.title('Manufacturing Costs vs. Defect Rates (Quality-Cost Trade-off)', fontsize=14)
plt.xlabel('Manufacturing Costs ($)', fontsize=12)
plt.ylabel('Defect Rates (%)', fontsize=12)
plt.tight_layout()
plt.show()
```



CONCLUSION

The comprehensive analysis of the supply chain data successfully achieved the project objectives, providing clear insight into product performance, operational bottlenecks, and quality control effectiveness.

The data confirms a strategic duality in product performance: while the Skincare product line drives the highest overall Revenue Generated, the Cosmetics line maintains the highest Average Net Profit per unit. This suggests that future strategies should focus not just on volume, but on maximizing the margin potential of Cosmetics.

Significant operational inefficiencies in the conversion cycle were identified by the investigation. Due to their lengthy manufacturing and delivery times, Kolkata and Chennai are clearly the most time-consuming sites in the regional Lead Time analysis. In order to lower working capital and shorten time-to-market, these areas are the most important goals for process improvement projects. Regarding quality, the data shows that products that fail inspection have a higher average Defect Rate (2.57%), which is quantifiable and supports the need for rigorous quality gate enforcement.

Suggestions

These results suggest the following courses of action:

Strategic Profit Maximization: To identify the characteristics that contribute to the Cosmetics line's strong profitability and reproduce those elements in other product categories, start a thorough cost-to-serve analysis.

Focus on Lead Time Reduction: Send an optimization task force to Chennai and Kolkata to examine and optimize shipping and manufacturing procedures in an effort to match their overall lead times with the Mumbai location's more effective metrics.

Quality Process Audit: Examine how products marked as "Pending" inspection are handled right away, since they make up the majority of units and have a high defect rate (2.15%), which might be decreased with quicker resolution.