Supply Chain

June 26, 2025

1 Supply Chain Management

1.1 Project Overview

This project aims to perform a comprehensive analysis of a supply chain dataset to uncover key business insights and performance metrics across various operational dimensions. The dataset includes product information, sales performance, customer demographics, supplier data, manufacturing costs, transportation details, and quality control outcomes.

The objective of this analysis is to identify patterns, trends, and potential areas for optimization in the supply chain. Insights gained from this study will support data-driven decision-making in areas such as pricing strategy, inventory management, supplier evaluation, logistics planning, and quality assurance.

1.2 Dataset Overview

The dataset includes the following key features:

- **Product Information:** Product type, SKU, price, availability, and stock levels.
- **Sales & Revenue:** Number of products sold and total revenue generated.
- **Customer Demographics:** Gender and identity segments contributing to sales.
- **Manufacturing Data:** Production volumes and associated manufacturing costs.
- **Logistics & Transportation:** Shipping carriers, transportation modes, routes, and transportation costs.
- **Supplier Details:** Supplier name and location.
- **Quality Control:** Inspection results and defect rates.

1.3 Key Analytical Goals

- Measure sales and revenue performance by product type and customer demographics.
- Examine pricing effectiveness and its impact on product sales.
- Evaluate supplier contributions and manufacturing cost efficiency.

- Analyze transportation modes and routes in relation to shipping costs.
- Investigate quality metrics including inspection outcomes and defect rates.
- Compare performance metrics across different regional locations.

1.3.1 Load Required libraries

[2]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

1.3.2 Load Data From CSV File

[3]:
```python
# Load csv file
df = pd.read_csv("supply_chain_data.csv")
df.head(10)
```

[3]:
```
  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
5     haircare  SKU5   1.699976            87                      147
6     skincare  SKU6   4.078333            48                       65
7    cosmetics  SKU7  42.958384            59                      426
8    cosmetics  SKU8  68.717597            78                      150
9     skincare  SKU9  64.015733            35                      980

   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
5        2828.348746            Non-binary            90          27
6        7823.476560                  Male            11          15
7        8496.103813                Female            93          17
8        7517.363211                Female             5          10
9        4971.145988               Unknown            14          27

   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
5                 66  …  Bangalore        10                  104
6                 58  …    Kolkata        14                  314
7                 11  …  Bangalore        22                  564
8                 15  …     Mumbai        13                  769
9                 83  …    Chennai        29                  963

  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
5                      17           56.766476                Fail
6                      24            1.085069             Pending
7                       1           99.466109                Fail
8                       8           11.423027             Pending
9                      23           47.957602             Pending

   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
5      2.779194                  Road  Route A  235.461237
6      1.000911                   Sea  Route A  134.369097
7      0.398177                  Road  Route C  802.056312
8      2.709863                   Sea  Route B  505.557134
9      3.844614                  Rail  Route B  995.929461

[10 rows x 24 columns]
```

1.3.3 Data Inspection

[4]:
```
# Get all columns name
df.columns
```

[4]:
```
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')
```

[5]:
```
#Drop un-usefull columns and update main data frame
df.drop(['Lead times','Lead time','Shipping times','Manufacturing lead␣
↪time'],axis=1,inplace=True)
```

[19]:
```
# get dataframe infomations like data type, counts and non-null
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 20 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   Order quantities         100 non-null    int64
 9   Shipping carriers        100 non-null    object
 10  Shipping costs           100 non-null    float64
 11  Supplier name            100 non-null    object
 12  Location                 100 non-null    object
 13  Production volumes       100 non-null    int64
 14  Manufacturing costs      100 non-null    float64
 15  Inspection results       100 non-null    object
 16  Defect rates             100 non-null    float64
 17  Transportation modes     100 non-null    object
 18  Routes                   100 non-null    object
 19  Costs                    100 non-null    float64
dtypes: float64(6), int64(5), object(9)
memory usage: 15.8+ KB
```

[20]:
```
# Check null value in dataframe
df.isnull().sum()
```

[20]:
```
Product type               0
SKU                        0
Price                      0
Availability               0
Number of products sold    0
Revenue generated          0
Customer demographics      0
Stock levels               0
Order quantities           0
Shipping carriers          0
```

```
Shipping costs           0
Supplier name            0
Location                 0
Production volumes       0
Manufacturing costs      0
Inspection results       0
Defect rates             0
Transportation modes     0
Routes                   0
Costs                    0
dtype: int64
```

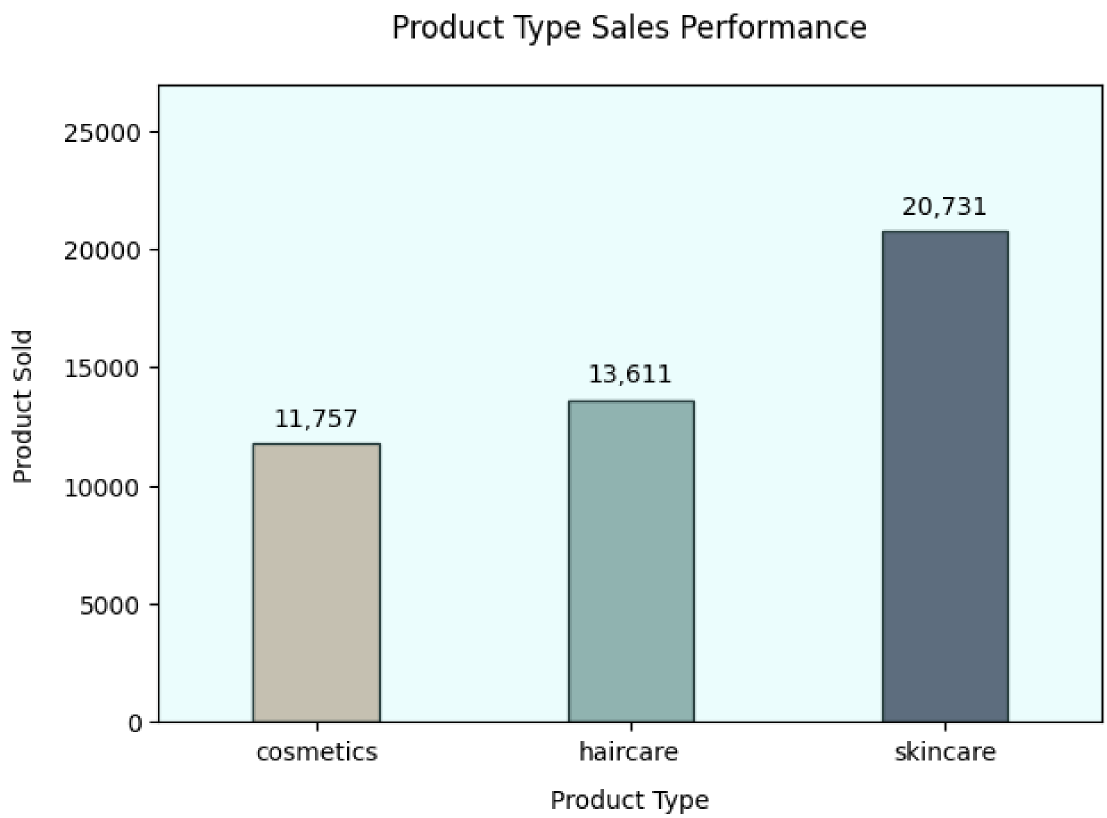
[8]:
```python
# get descriptive statistics of a dataframe like the central tendency,
↪dispersion, and shape of a distribution
df.describe()
```

[8]:
```
            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  Order quantities  Shipping costs  Production volumes  \
count    100.000000        100.000000      100.000000          100.000000
mean      47.770000         49.220000        5.548149          567.840000
std       31.369372         26.784429        2.651376          263.046861
min        0.000000          1.000000        1.013487          104.000000
25%       16.750000         26.000000        3.540248          352.000000
50%       47.500000         52.000000        5.320534          568.500000
75%       73.000000         71.250000        7.601695          797.000000
max      100.000000         96.000000        9.929816          985.000000

       Manufacturing costs  Defect rates       Costs
count           100.000000    100.000000  100.000000
mean             47.266693      2.277158  529.245782
std              28.982841      1.461366  258.301696
min               1.085069      0.018608  103.916248
25%              22.983299      1.009650  318.778455
50%              45.905622      2.141863  520.430444
75%              68.621026      3.563995  763.078231
max              99.466109      4.939255  997.413450
```

2 Exploratory Analysis

2.0.1 Product Type Sales Performance

[21]:
```
# set chart style properties
plt.margins(0.3)

# Aggregate total Number of products sold by product type
sold = df.groupby('Product type')['Number of products sold'].sum().
 ↪reset_index().sort_values(by='Number of products sold')

# create barplot
ax = sns.barplot(data = sold,
                 x = "Product type",
                 y = "Number of products sold",
                 palette = ['#c8c2ae','#8ab9b5','#586d83'],
                 hue = "Product type",
                 errorbar = None,
                 width = 0.4,
                 edgecolor="#2b4141")

# set barplot properties
ax.set_facecolor("#ebfdfd")
ax.set_title('Product Type Sales Performance',y=1.05)
ax.set_xlabel('Product Type',labelpad=10)
ax.set_ylabel('Product Sold',labelpad=10)

# set sales value on lagend
for container in ax.containers:
    ax.bar_label(container,
                 fmt='{:,.0f}',
                 padding=5)

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



The bar chart illustrates the total number of units sold for three product type: **cosmetics, haircare, and skincare**.

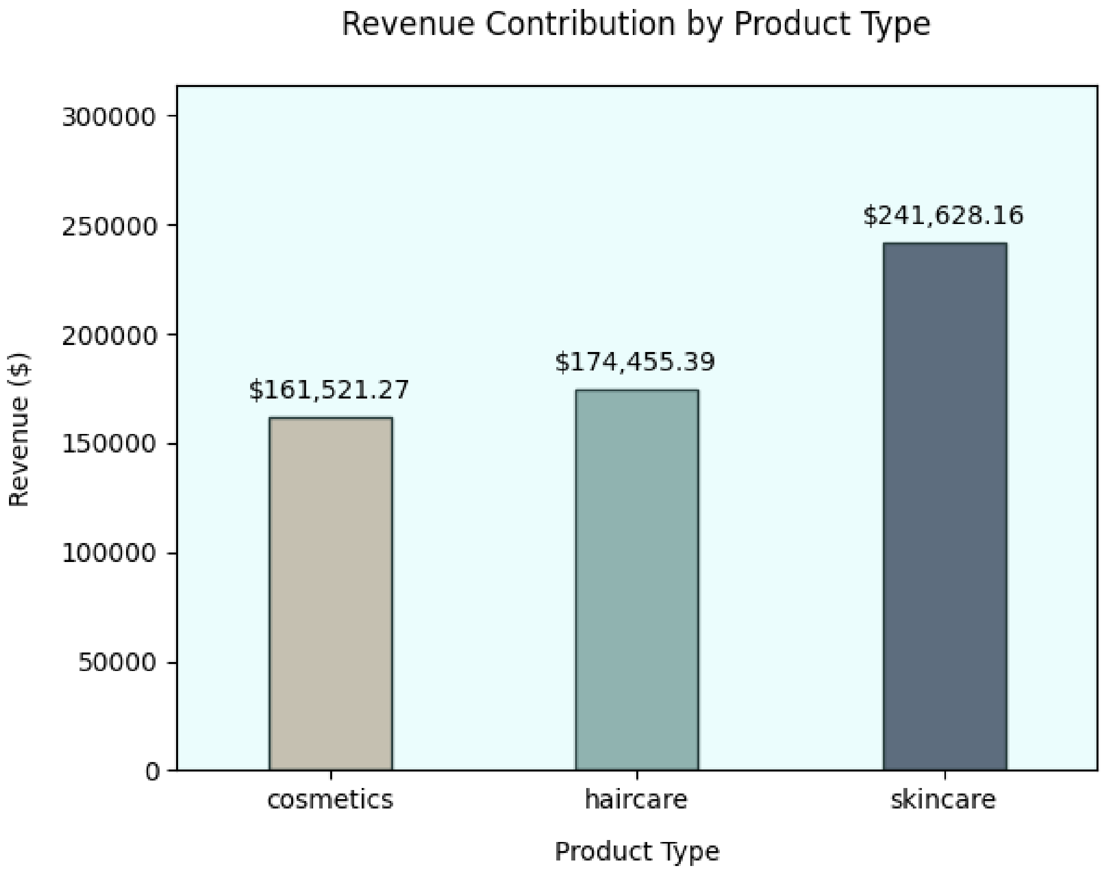
- **Skincare** products achieved the highest sales volume, with **20,731** units sold, indicating strong consumer demand in this category.
- **Haircare** followed with **13,611** units sold, showing moderate market performance.
- **Cosmetics** registered the lowest sales among the three, with **11,757** units sold.

This data highlights a clear consumer preference for skincare products, significantly outperforming both haircare and cosmetics. The insights suggest potential for increased investment or marketing focus on the skincare category to further leverage its market traction. and For both Haircare and Cosmetics, a dual approach of strategic niche identification and aggressive, targeted promotions is crucial for revenue growth.

2.0.2 Revenue Contribution by Product Type

[10]:
```
# set chart style properties
plt.margins(0.3)

# Aggregate total Revenue generated by product type
```

```python
revenue = df.groupby('Product type')['Revenue generated'].sum().reset_index().
↪sort_values(by='Revenue generated')

# create barplot
ax = sns.barplot(data = revenue,
                 x = "Product type",
                 y = "Revenue generated",
                 palette = ['#c8c2ae','#8ab9b5','#586d83'],
                 hue = "Product type",
                 errorbar = None,
                 width = 0.4,
                 edgecolor="#2b4141")

# set barplot properties
ax.set_facecolor("#ebfdfd")
ax.set_title('Revenue Contribution by Product Type',y=1.05)
ax.set_xlabel('Product Type',labelpad=10)
ax.set_ylabel('Revenue ($)',labelpad=10)

# set cost value on lagend
for container in ax.containers:
    ax.bar_label(container,
                 fmt='${:,.2f}',
                 padding=5)

plt.show()
```



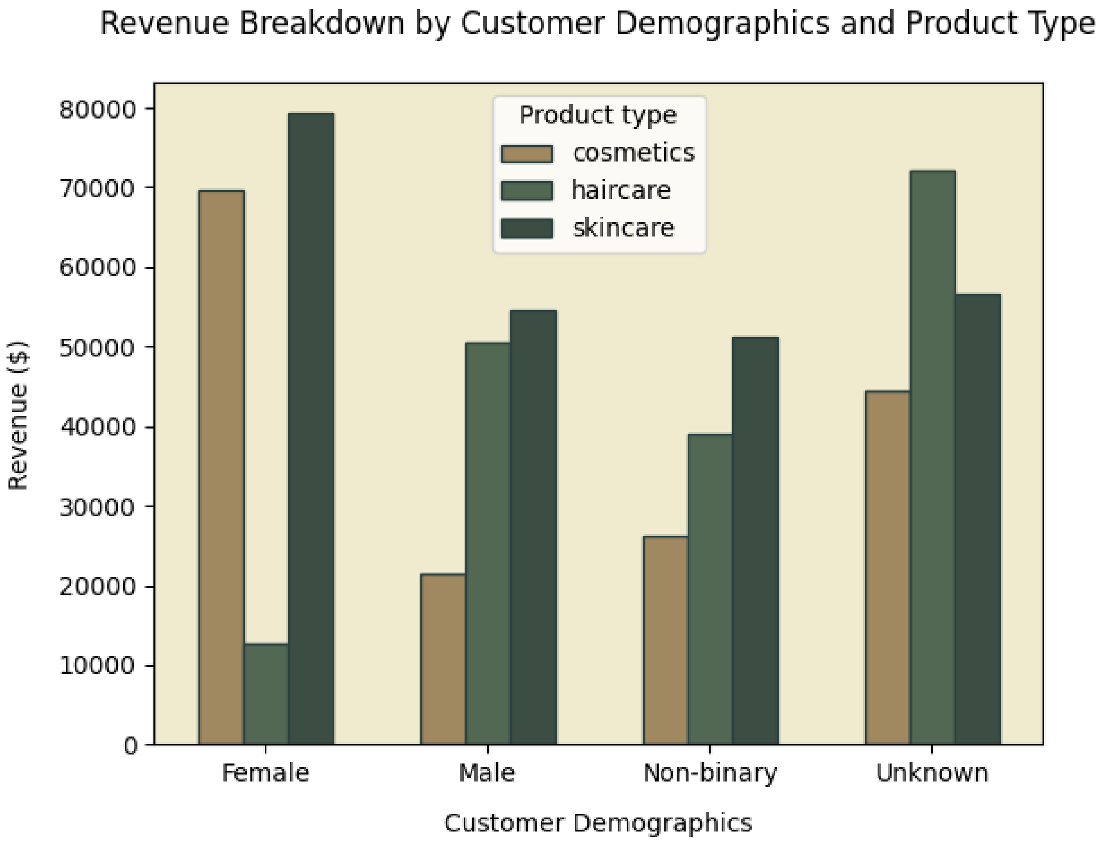
The bar chart presents a clear picture of revenue distribution across three key product types: **cosmetics, haircare, and skincare**.

- **Skincare** products stand out, generating the highest revenue at **$241,628.16** , which indicates robust consumer interest.
- **Haircare** products secured the second spot with **$174,455.39**, reflecting a solid market presence.
- **Cosmetics** recorded the lowest revenue at **$161,521.27**.

We've observed that skincare product sales and their corresponding revenue are dominant, surpassing both haircare and cosmetic categories. The insights suggest potential for increased investment or marketing focus on the skincare category to further leverage its market traction. and For both Haircare and Cosmetics, a dual approach of strategic niche identification and aggressive, targeted promotions is crucial for revenue growth.

2.0.3 Revenue Breakdown by Customer Demographics and Product Type

[11]:
```
# Aggregate total Revenue generated by Customer demographics and product type
revenue = df.groupby(['Customer demographics','Product type'])['Revenue␣
↪generated'].sum().reset_index()

# create barplot
ax = sns.barplot(data = revenue,
                 x = "Customer demographics",
                 y = "Revenue generated",
                 palette = ['#AA8B56','#4E6C50','#395144'],
                 hue = "Product type",
                 errorbar = None,
                 width = 0.6,
                 edgecolor="#2b4141")

# set barplot properties
ax.set_facecolor("#F0EBCE")
ax.set_title('Revenue Breakdown by Customer Demographics and Product Type',y=1.
↪05)
ax.set_xlabel('Customer Demographics',labelpad=10)
ax.set_ylabel('Revenue ($)',labelpad=10)

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



This clustered bar chart breaks down revenue by customer demographics (Female, Male, Non-binary, Unknown) across three product types: **Cosmetics, Haircare, and Skincare**.

- **Female** customers are the primary revenue drivers, especially for Skincare and Cosmetics.
- **Male** customers show higher revenue in Skincare and Haircare compared to cosmetics.
- **Non-binary** and **Unknown** demographics contribute lower, but still noticeable, revenue across all categories, with Skincare being generally higher.

Overall, Skincare consistently generates high revenue across all known demographics, while Cosmetics is strong with Female customers and Haircare has a broader appeal.

The insights suggest to prioritize female-centric marketing for Cosmetics and Skincare and male marketing for Skincare. Capitalize on haircare's universal appeal by marketing it to a diverse customer base.

2.0.4 Relationship Between Price And Number Of Product Sold

[12]:
```
# set chart style properties
plt.figure(figsize=(10, 8))

# create scatterplot
```

```
ax = sns.scatterplot(data=df,
                     x='Price',
                     y='Number of products sold',
                     hue='Product type',
                     palette=['#FF7D29','#5F8D4E','#E63E6D'],)

# move scatterplot lagend to center bottom
sns.move_legend(ax,
                "lower center",
                bbox_to_anchor=(0.5, -0.20),
                ncol=3,
                title='Product type',
                frameon=True,
)

# set scatterplot properties
ax.set_title('Relationship Between Price And Number Of Product Sold',y=1.05)
ax.set_ylabel('Number Of Products Sold',labelpad=10)
ax.set_xlabel('Price ($)',labelpad=10)

plt.grid(True)
plt.tight_layout()
plt.show()

print(f"The correlation between Price and number of product sold is:␣
 ↪{df['Price'].corr(df['Number of products sold']):.4f}")
```


```
The correlation between Price and number of product sold is: 0.0057
```

This scatter plots chart shows the relationship between price and the number of products sold across three product types: **Cosmetics, Haircare, and Skincare**.

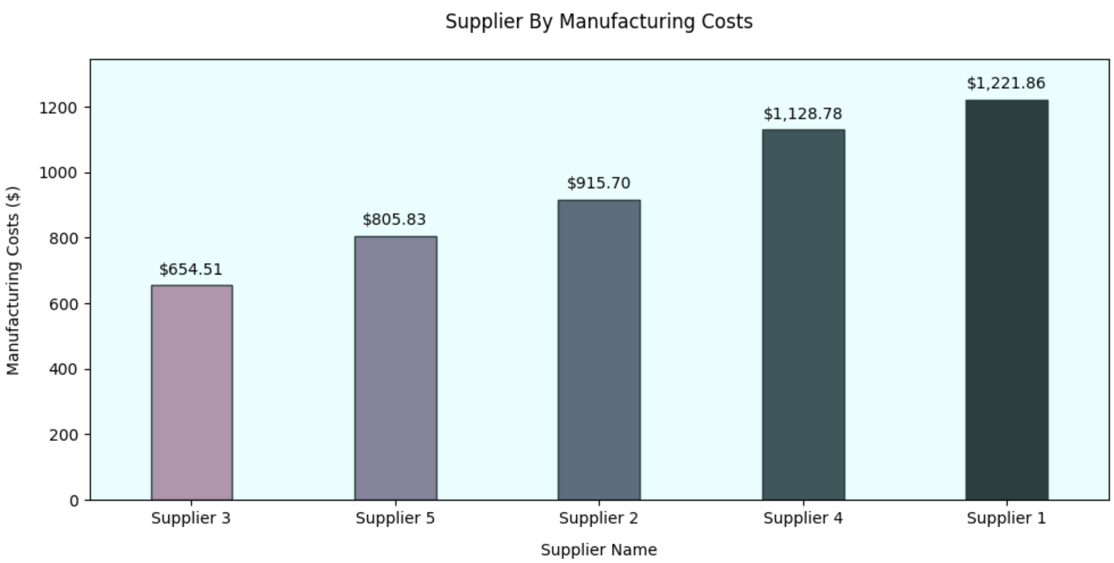
The absence of a clear, strong correlation between price and the number of products sold for any of the three product types indicates that price alone is not the primary determinant of sales volume.

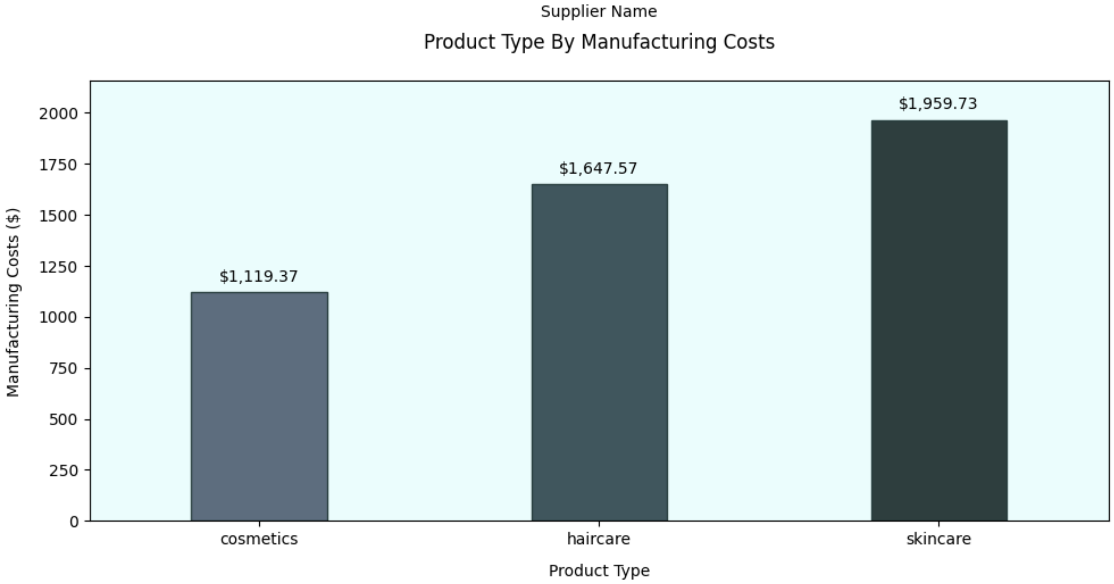
2.0.5 Manufacturing Cost Breakdown by Supplier and Product

[31]:
```
# set chart style properties
plt.figure(figsize = (10,10))

# set chart grid properties
plt.subplot(2,1,1)

# set chart style properties
plt.margins(0.1)

# Aggregate total Manufacturing costs by Supplier name
```

```python
manufacturing_cost_supplier = df.groupby('Supplier name')['Manufacturing␣
↪costs'].sum().reset_index().sort_values(by="Manufacturing costs")

# create barplot
ax = sns.barplot(manufacturing_cost_supplier,
                 x = 'Supplier name',
                 y = 'Manufacturing costs',
                 palette = ['#b392b1','#82809f','#586d83','#3b5862','#2b4141'],
                 hue = "Supplier name",
                 errorbar = None,
                 width = 0.4,
                 edgecolor="#2b4141")

# set barplot properties
ax.set_facecolor("#ebfdfd")
ax.set_title('Supplier By Manufacturing Costs',y=1.05)
ax.set_xlabel('Supplier Name',labelpad=10)
ax.set_ylabel('Manufacturing Costs ($)',labelpad=10)

# set cost value on lagend
for container in ax.containers:
    ax.bar_label(container,
                 fmt='${:,.2f}',
                 padding=5)

# set chart grid properties
plt.subplot(2,1,2)

# set chart style properties
plt.subplots_adjust(hspace=0.4)
plt.margins(0.1)

# Aggregate total Manufacturing costs by Product type
manufacturing_cost_product = df.groupby('Product type')['Manufacturing costs'].
↪sum().reset_index().sort_values(by="Manufacturing costs")

# create barplot
ax = sns.barplot(manufacturing_cost_product,
                 x = 'Product type',
                 y = 'Manufacturing costs',
                 palette = ['#586d83','#3b5862','#2b4141'],
                 hue = "Product type",
                 errorbar = None,
                 width = 0.4,
                 edgecolor="#2b4141")

# set barplot properties
```

```
ax.set_facecolor("#ebfdfd")
ax.set_title('Product Type By Manufacturing Costs',y=1.05)
ax.set_xlabel('Product Type',labelpad=10)
ax.set_ylabel('Manufacturing Costs ($)',labelpad=10)

# set cost value on lagend
for container in ax.containers:
    ax.bar_label(container,
                 fmt='${:,.2f}',
                 padding=5)

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





1. First bar chart compares the average manufacturing costs for different suppliers.
   - **Supplier 1** incurs the highest manufacturing cost at **$1,221.86** , followed by **Supplier 4**.
   - **Supplier 3** has the lowest average cost at **$654.51** .

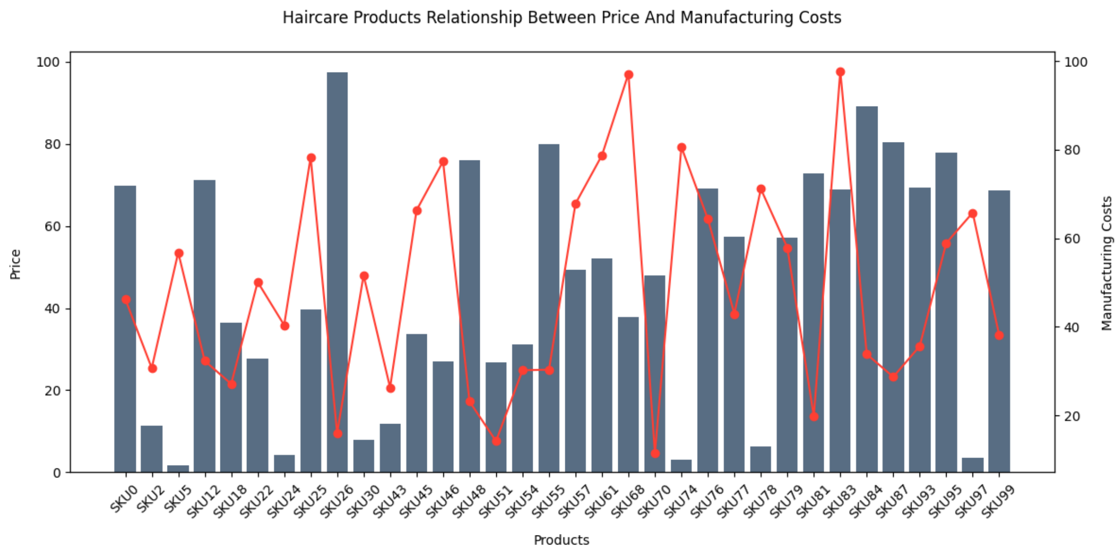
Consider shifting more production to Supplier 3 if quality and capacity meet requirements. and negotiation with Supplier 1 and 4 to reduce cost

2. Second chart shows average manufacturing cost by product category
   - **Skincare** has the highest manufacturing cost: **$1,959.73**
   - **Haircare** follows: **$1,647.57**
   - **Cosmetics** are the least costly to produce: **$1,119.37**

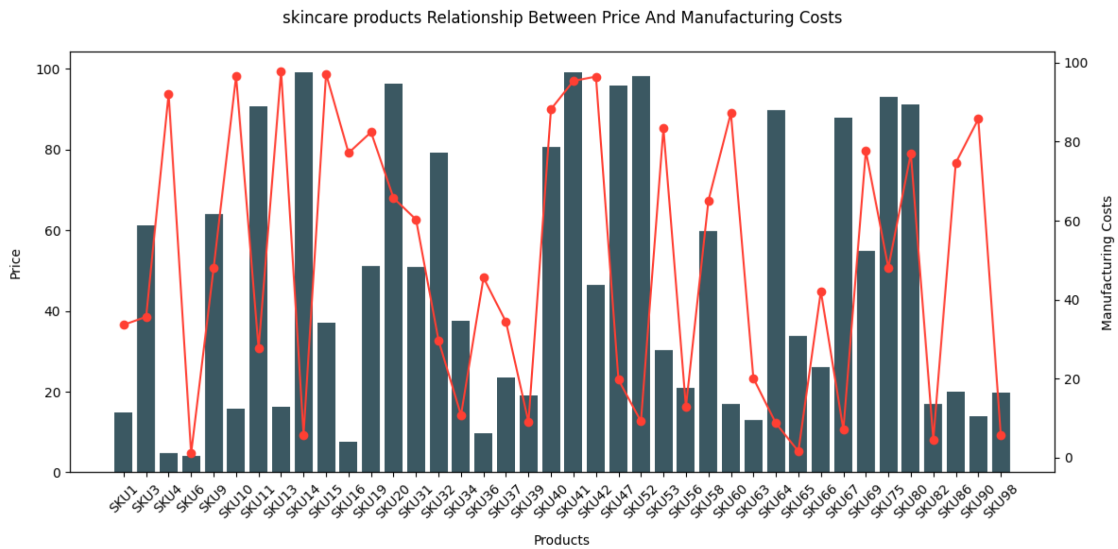
Skincare and haircare products require significantly higher investment. Consider pricing strategies to ensure profit margins.Investigate if high manufacturing cost in skincare is justified by revenue or perceived value.

2.0.6 Price Vs Manufacturing Cost

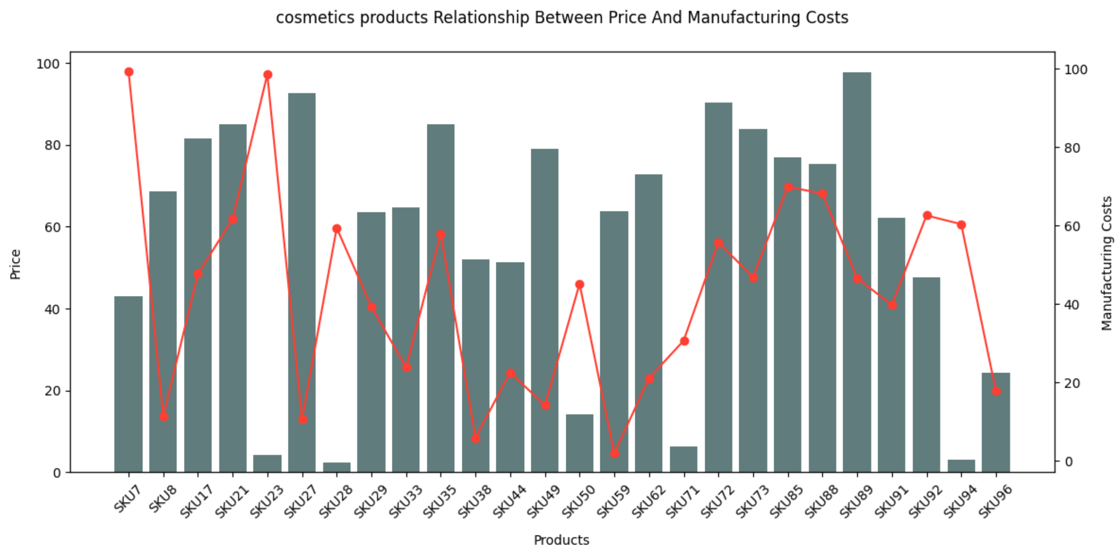
[22]:
```python
# get all data, where Product type is haircare
product = df[df['Product type'] == "haircare"]

# set chart style properties
fig, ax1 = plt.subplots(figsize=(12, 6))

# twinx for second y axis on same chart
ax2 = ax1.twinx()

# create barplot
ax1.bar(product['SKU'], product['Price'],color="#586d83")

# plot second chart
ax2.plot(product['SKU'], product['Manufacturing costs'], 'o-', color="#FF3F33" )

# set chart properties
ax1.set_xlabel('Products',labelpad=10)
ax1.tick_params(axis='x', labelbottom=True,rotation=45)
ax1.set_ylabel('Price',labelpad=10)
ax2.set_ylabel('Manufacturing Costs',labelpad=10)

plt.title('Haircare Products Relationship Between Price And Manufacturing␣
 ↪Costs',y=1.05)
fig.tight_layout(h_pad=10)
plt.show()
```



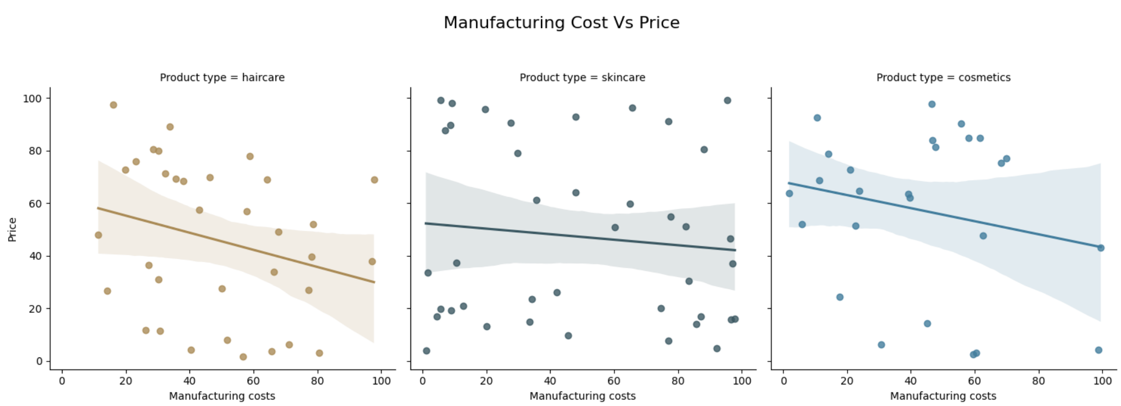
[23]:
```
# get all data, where Product type is skincare
product = df[df['Product type'] == "skincare"]

# set chart style properties
fig, ax1 = plt.subplots(figsize=(12, 6))

# twinx for second y axis on same chart
ax2 = ax1.twinx()

# create barplot
ax1.bar(product['SKU'], product['Price'],color="#3b5862")

# plot second chart
ax2.plot(product['SKU'], product['Manufacturing costs'], 'o-', color="#FF3F33" )

# set chart properties
ax1.set_xlabel('Products',labelpad=10)
ax1.tick_params(axis='x', labelbottom=True,rotation=45)
ax1.set_ylabel('Price',labelpad=10)
ax2.set_ylabel('Manufacturing Costs',labelpad=10)

plt.title('skincare products Relationship Between Price And Manufacturing␣
↪Costs',y=1.05)
fig.tight_layout(h_pad=10)
plt.show()
```



[24]:
```
# get all data, where Product type is skincare
product = df[df['Product type'] == "cosmetics"]

# set chart style properties
fig, ax1 = plt.subplots(figsize=(12, 6))

# twinx for second y axis on same chart
ax2 = ax1.twinx()

# create barplot
ax1.bar(product['SKU'], product['Price'],color="#617c7c")

# plot second chart
ax2.plot(product['SKU'], product['Manufacturing costs'], 'o-', color="#FF3F33" )

# set chart properties
ax1.set_xlabel('Products',labelpad=10)
ax1.tick_params(axis='x', labelbottom=True,rotation=45)
ax1.set_ylabel('Price',labelpad=10)
ax2.set_ylabel('Manufacturing Costs',labelpad=10)

plt.title('cosmetics products Relationship Between Price And Manufacturing␣
 ↪Costs',y=1.05)
fig.tight_layout(h_pad=10)
plt.show()
```



[148]:
```
# create lmplot
ax = sns.lmplot(df,
                x="Manufacturing costs",
                y="Price",
                hue="Product type",
                col="Product type",
                palette = ['#AA8B56','#3b5862','#427D9D'])

fig = ax.fig
fig.suptitle('Products Relationship Between Price And Manufacturing Costs',␣
 ↪fontsize=16,y=1.05)

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



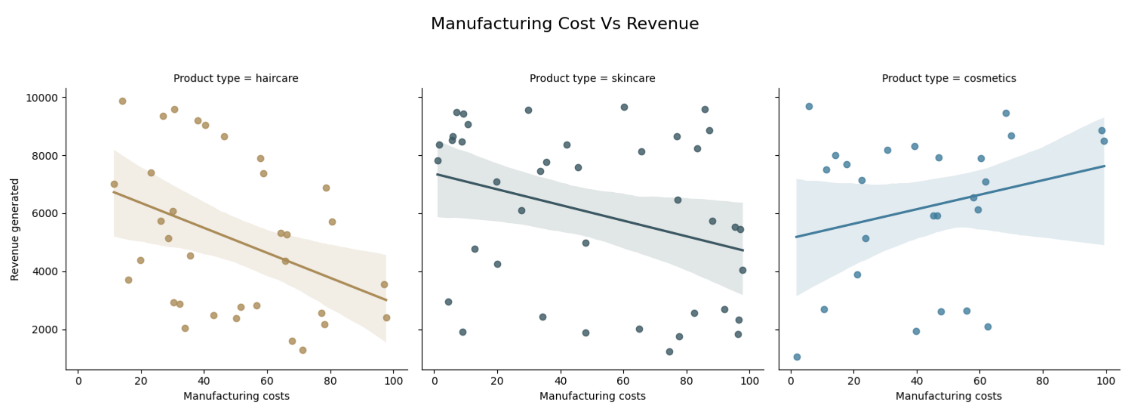
This charts displays the relationship between price and manufacturing costs across three product types: **Cosmetics, Haircare, and Skincare**.

- There is a large disparity between price and cost.
- There's no immediately obvious strong positive or negative correlation between price and manufacturing costs across all SKUs.
- Some low-priced items have high costs, and vice versa.

Consider a review of SKUs with high cost but low price – potential margin loss. Optimize pricing or reduce manufacturing cost on underperforming SKUs. improve pricing strategy

2.0.7 Manufacturing Cost vs Revenue

[25]:
```
# create lmplot
ax = sns.lmplot(df,
                x="Manufacturing costs",
                y="Revenue generated",
                hue="Product type",
                col="Product type",
                palette = ['#AA8B56','#3b5862','#427D9D'])

fig = ax.fig
fig.suptitle('Manufacturing Cost Vs Revenue', fontsize=16,y=1.05)

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



This scatter plots chart shows the relationship between manufacturing costs and revenue generated across three product types: **Cosmetics, Haircare, and Skincare**.

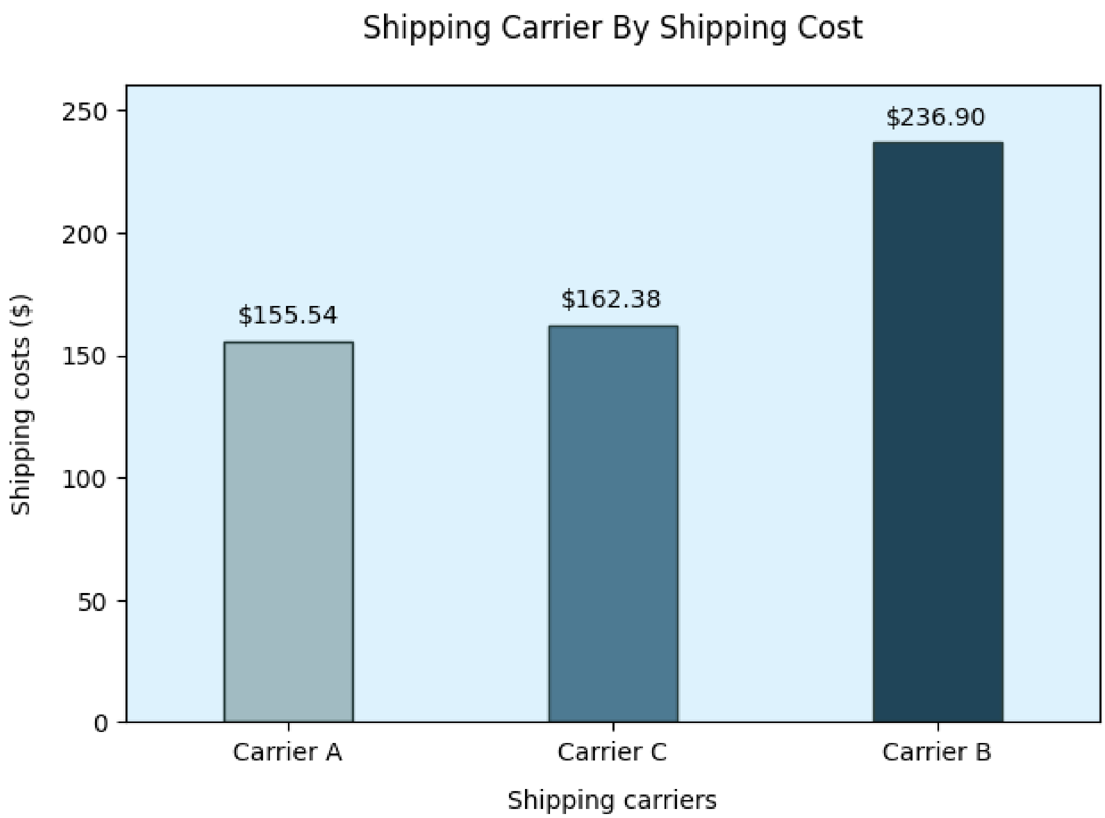
- **Haircare:** There appears to be a moderate to strong negative correlation between manufacturing costs and revenue generated. As manufacturing costs increase, the revenue generated tends to decrease.

- **Skincare:** There appears to be a weak to moderate negative correlation between manufacturing costs and revenue generated. it's not as steep as haircare, and there's more scatter in the data points.
- **Cosmetics:** There appears to be a weak to moderate positive correlation between manufacturing costs and revenue generated. This indicates that for cosmetics, products with higher manufacturing costs tend to generate higher revenue, although the relationship isn't very strong.

For haircare and skincare, the data strongly suggests a need to critically evaluate high-cost products. Are their high manufacturing costs justified by market performance. while Cosmetics is more aligned with the idea that investing in product quality can lead to slightly better market performance.

2.0.8 Shipping Carrier By Shipping Cost

[28]:
```
# Aggregate total Shipping costs by Shipping carriers
shipping_cost = df.groupby('Shipping carriers')['Shipping costs'].sum().
↪reset_index().sort_values(by="Shipping costs")

# set chart style properties
plt.margins(0.1)

# create barplot
ax = sns.barplot(shipping_cost,
                 x = 'Shipping carriers',
                 y = 'Shipping costs',
                 palette = ['#9BBEC8','#427D9D','#164863'],
                 hue = "Shipping carriers",
                 errorbar = None,
                 width = 0.4,
                 edgecolor="#2b4141")

# set barplot properties
ax.set_facecolor("#DDF2FD")
ax.set_title('Shipping Carrier By Shipping Cost',y=1.05)
ax.set_xlabel('Shipping carriers',labelpad=10)
ax.set_ylabel('Shipping costs ($)',labelpad=10)

# set sales value on lagend
for container in ax.containers:
    ax.bar_label(container,
                 fmt='${:,.2f}',
                 padding=5)

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



This bar chart displays the average shipping costs associated with three different shipping carriers: **Carrier A, Carrier C, Carrier B**.

- **Carrier A** has an average shipping cost of **$155.54**.
- **Carrier C** has a slightly higher average shipping cost of **$162.38**.
- **Carrier B** is significantly more expensive, with an average shipping cost of **$236.90**.

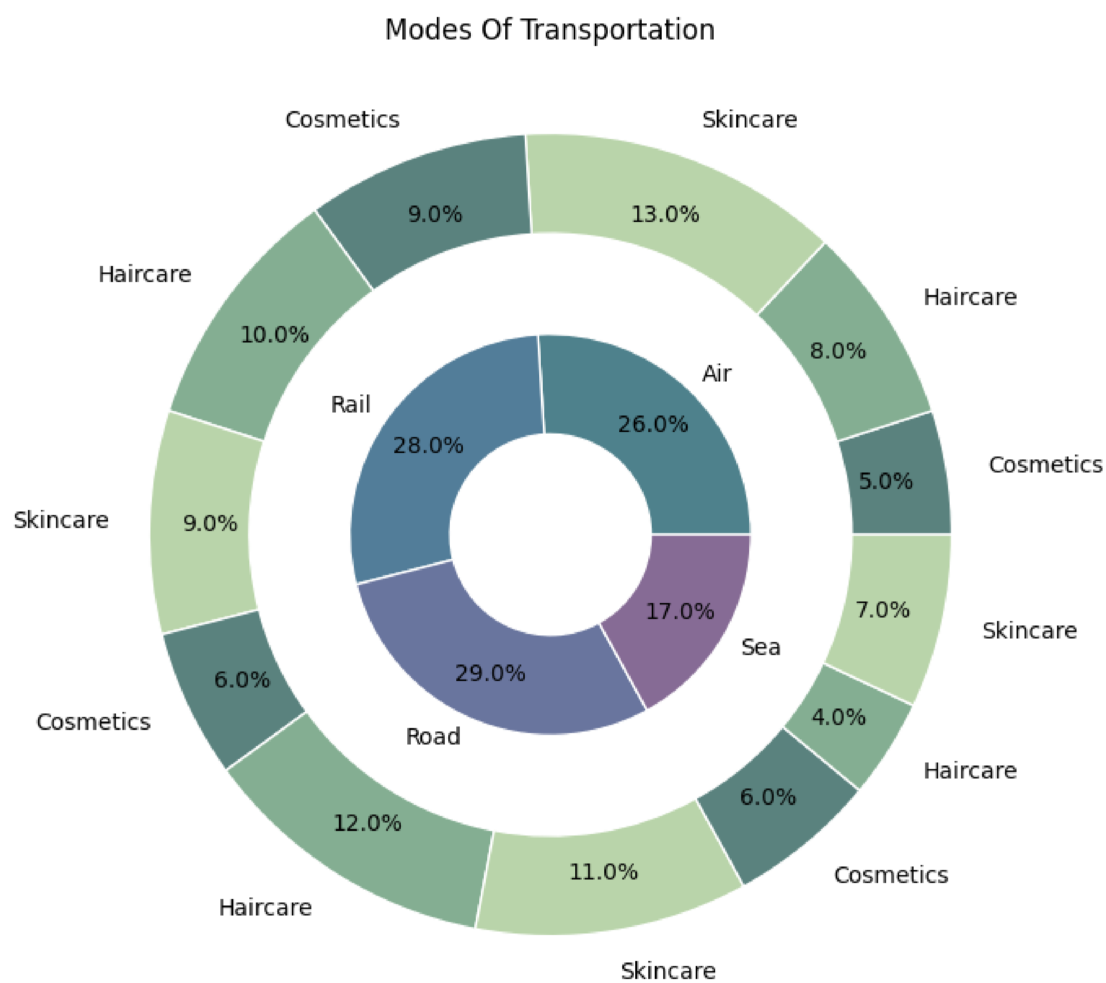
Based solely on shipping cost, **Carrier A is the most cost-effective option**, followed closely by Carrier C. Carrier B is considerably more expensive than the other two.

The insights suggest Prioritize Carrier A for Cost Savings and use Carrier C as secondry option. Investigate the Discrepancy with Carrier B

2.0.9 Modes Of Transportation

[155]:
```
# Aggregate value counts of Transportation modes by product type
transportation = df.groupby(['Transportation modes','Product␣
 ↪type'])['Transportation modes'].value_counts().reset_index()

# set chart style properties
fig, ax = plt.subplots(figsize=(7, 7))
```

```
# Outer pie chart data
wedges_outer, texts_outer, autotexts_outer = ax.pie(transportation['count'],
                                                    radius=1.2,
                                                   ␣
 ↪labels=transportation['Product type'].str.title(),
                                                    autopct='%1.1f%%',
                                                    pctdistance=0.85,
                                                   ␣
 ↪colors=['#5A827E','#84AE92','#B9D4AA'],
                                                    wedgeprops=dict(width=0.3,␣
 ↪edgecolor='w'))

# Inner pie chart data
wedges_inner, texts_inner, autotexts_inner = ax.pie(transportation.
 ↪groupby(['Transportation modes'])['count'].sum(),
                                                    radius=0.6,
                                                   ␣
 ↪labels=transportation['Transportation modes'].unique(),
                                                    autopct='%1.1f%%',
                                                    pctdistance=0.75,
                                                   ␣
 ↪colors=['#4e818c','#527d99','#69759e','#866b95'],
                                                    wedgeprops=dict(width=0.3,␣
 ↪edgecolor='w'))

plt.title('Modes Of Transportation', y=1.05)
plt.axis('equal')
plt.show()
```



This is a donut chart that illustrates the breakdown of transportation modes for three product types: **Cosmetics, Haircare, and Skincare**. The inner ring shows the overall distribution of major transportation modes, while the outer ring provides a more granular view, showing the percentage contribution of each product type within each mode of transport

Overall Modes of Transportation - Road: Accounts for the largest share at **29.0%**.

- **Rail:** Is a close second at **28.0%**.
- **Air:** Represents **26.0%**.
- **Sea:** Is the smallest portion at **17.0%**.

This shows land-based transport Road and Rail is dominant, followed closely by air, with sea transport being the least utilized.

Product Type Distribution with in Transportation - Haircare: primarily transported by road (12.0%), with rail (10.0%) and air (8.0%) also significantly utilized, while sea transport accounts for the smallest portion (4.0%)..

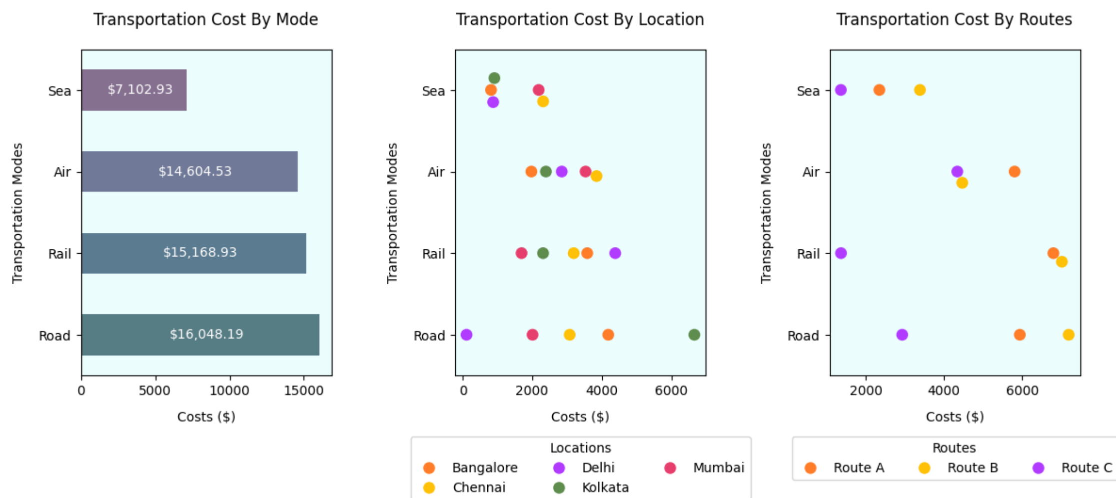
- **Skincare:** Air transport is utilized most frequently (13.0%), followed by road (11.0%) and rail (9.0%), with sea transport being the least used (7.0%).
- **Cosmetics:** Products relies mostly on rail transport (9.0%), followed by road and sea (6.0%), air transport is used the least (4.0%).

2.0.10 Transportation Costs Relationship With Mode And Location

[32]:
```
# set chart style properties
plt.figure(figsize=(12,6))

# set chart grid properties
plt.subplot(1,3,1)

# Aggregate total costs sold by Transportation modes
mode_cost = df.groupby(['Transportation modes'])['Costs'].sum().reset_index().
 ↪sort_values(by="Costs")

# create barplot
ax = sns.barplot(mode_cost,
            x='Costs',
            y='Transportation modes',
            hue='Transportation modes',
            palette=['#866b95','#69759e','#527d99','#4e818c'],
            width=.5
           )

# set cost value on lagend
for container in ax.containers:
    ax.bar_label(container,
                 fmt='${:,.2f}',
                 padding=5,
                 label_type="center",
                 color='white')

# set barplot properties
ax.set_facecolor("#ebfdfd")
ax.set_title('Transportation Cost By Mode',y=1.05)
ax.set_ylabel('Transportation Modes',labelpad=10)
ax.set_xlabel('Costs ($)',labelpad=10)

# set chart grid properties
plt.subplot(1,3,2)

# Aggregate total costs sold by Transportation modes and location
cost = df.groupby(['Transportation modes','Location'])['Costs'].sum().
 ↪reset_index()
```

```
# create swarmplot
ax = sns.swarmplot(data=cost,
                   x="Costs",
                   y="Transportation modes",
                   hue="Location",
                   size=9,
                   palette=['#FF7D29','#FFC107','#B13BFF','#5F8D4E','#E63E6D'],
                   order=mode_cost['Transportation modes'])

# move scatterplot lagend to center bottom
sns.move_legend(ax,
                "lower center",
                bbox_to_anchor=(0.5, -0.40,),
                ncol=3,
                title='Locations',
                frameon=True,
)

# set swarmplot properties
ax.set_facecolor("#ebfdfd")
ax.set_title('Transportation Cost By Location',y=1.05)
ax.set_ylabel('Transportation Modes',labelpad=10)
ax.set_xlabel('Costs ($)',labelpad=10)

# set chart grid properties
plt.subplot(1,3,3)

# Aggregate total costs sold by Transportation modes and routes
cost = df.groupby(['Transportation modes','Routes'])['Costs'].sum().
 ↪reset_index()

# create swarmplot
ax = sns.swarmplot(data=cost,
                   x="Costs",
                   y="Transportation modes",
                   hue="Routes",
                   size=9,
                   palette=['#FF7D29','#FFC107','#B13BFF'],
                   order=mode_cost['Transportation modes'])

# move scatterplot lagend to center bottom
sns.move_legend(
    ax, "lower center",
    bbox_to_anchor=(0.5, -0.34),
    ncol=3,
    title='Routes',
    frameon=True,
```

```
)

# set swarmplot properties
ax.set_facecolor("#ebfdfd")
ax.set_title('Transportation Cost By Routes',y=1.05)
ax.set_ylabel('Transportation Modes',labelpad=10)
ax.set_xlabel('Costs ($)',labelpad=10)

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



1. **Transportation Cost By Mode:**

- **Road** transport incurs the highest cost **$16,048.19**, followed closely by **Rail $15,168.93**, then **Air $14,604.53**, and **Sea** is the least expensive mode **7,102.93**.

2. Transportation Cost By Location: This plot shows transportation costs by mode for five different locations **Bangalore, Chennai, Delhi, Kolkata, Mumbai**.

- Sea transport is consistently cheapest across all visible locations.
- Road, Rail, and Air costs vary significantly by location. Kolkata appears to have higher costs for Road and Rail, while Delhi and Bangalore show higher costs for Air.

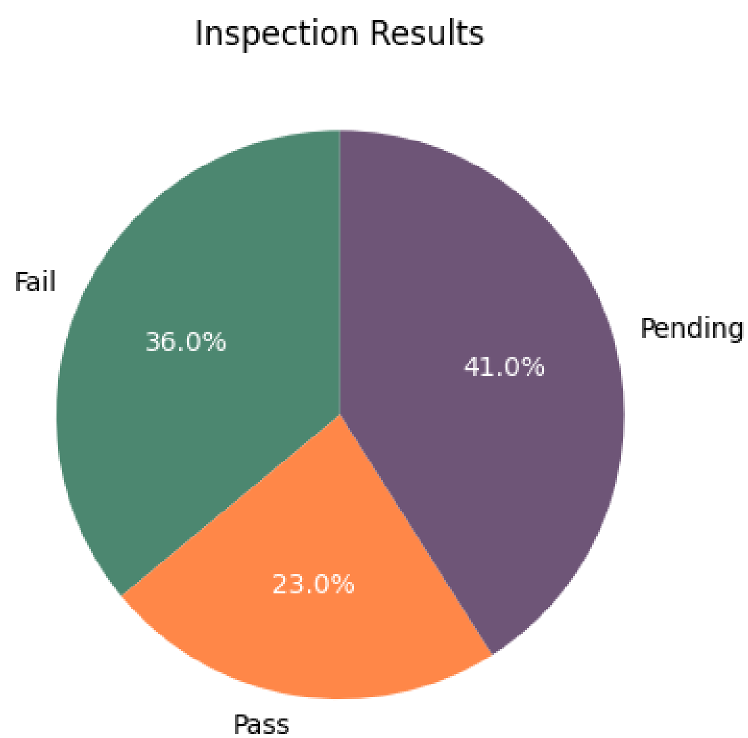
3. Transportation Cost By Routes: This plot shows transportation costs by mode for three different routes **Route A, Route B, Route C**.

- Sea transport is consistently low cost for the routes shown.
- Air transport costs vary across routes, with Route B appearing to be the most expensive for Air.
- Rail and Road costs also show variability depending on the route. Route C appears to have higher Rail costs, and Route A and C show higher Road costs.

Prioritize Sea transport where feasible to minimize costs.

2.0.11 Inspection Results

[158]:
```
# Aggregate value counts of Inspection results
inspection_results = df.groupby(['Inspection results'])['Inspection results'].
↪value_counts().reset_index()

# create pie chart
wedges, texts, autotexts = plt.pie(inspection_results['count'],
                                   labels=inspection_results['Inspection␣
↪results'],
                                   autopct='%1.1f%%',
                                   startangle=90,
                                   colors=['#4c8770','#ff8748','#6e5577'])

# set pie chart properties
for autotext in autotexts:
    autotext.set_color('white')

plt.title('Inspection Results')
plt.show()
```



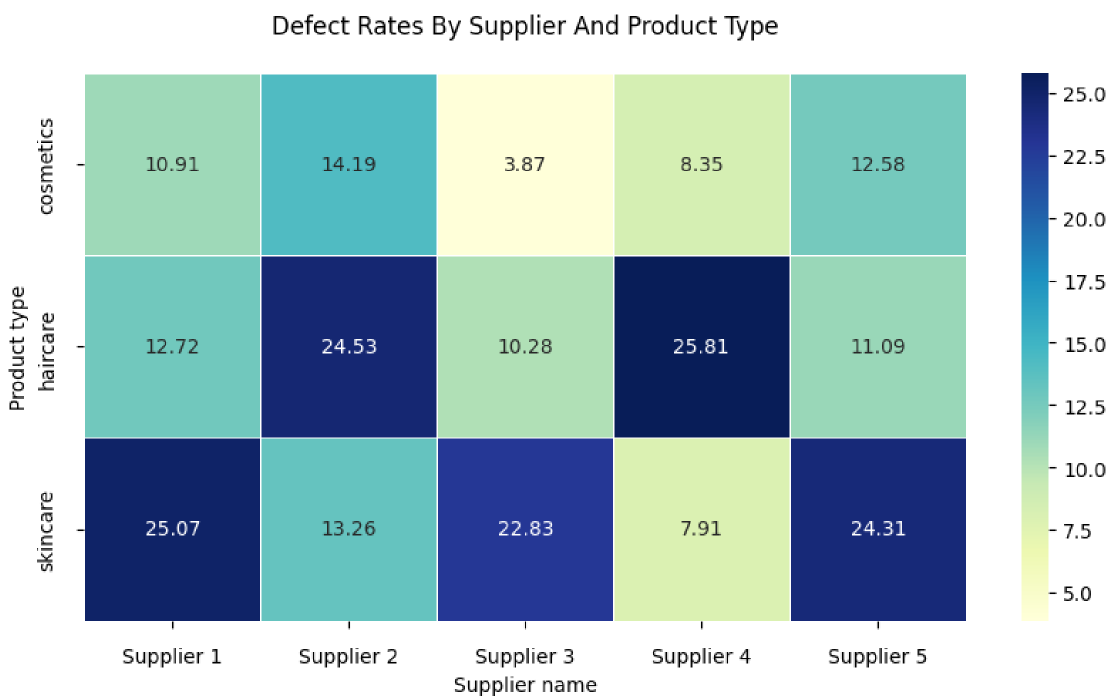
This pie chart displays the distribution of inspection results for products. It categorizes results into **Pending, Fail, and Pass,** showing the percentage each category represents out of the total.

- **Pending:** The largest slice, accounting for **41.0%** of all inspection results. This means nearly half of the inspections are still awaiting a final outcome.
- **Fail:** A significant portion, representing **36.0%** of the results. This indicates that more than one-third of the products inspected did not meet quality standards.
- **Pass:** The smallest slice, at **23.0%**. This means less than a quarter of the products inspected successfully passed.

The inspection results present a critical concern regarding product quality and the efficiency of the inspection process.Prioritize a thorough investigation into the reasons for the high failure rate and reduce the pending rate to get faster feedback on product quality.

2.0.12 Defect Rates By Supplier And Product Type

[157]:
```
# # Aggregate total Defect rates by Supplier name and Product type
defect_rate = df.groupby(['Supplier name','Product type'])['Defect rates'].
 ↪sum().reset_index()

# set chart style properties
plt.figure(figsize=(10, 5))

# create heatmap
ax = sns.heatmap(defect_rate.pivot(index = 'Product type',
                            columns = 'Supplier name',
                            values = 'Defect rates'),
                            annot=True,
                            cmap="YlGnBu",
                            fmt=".2f",
                            linewidths=.5,)

plt.title('Defect Rates By Supplier And Product Type', y=1.05)
ax.tick_params(axis='both',pad=10)
plt.show()
```



This heatmap displays the defect rates three product types **Cosmetics, Haircare, and Skincare** across various suppliers **Supplier 1, Supplier 2, Supplier 3, Supplier 4, Supplier 5**. The color intensity indicates the magnitude of the defect rate, with darker blue representing higher defect rates and lighter yellow representing lower defect rates. The exact defect rate is also displayed as a numerical value within each cell.

Defect rates vary significantly across suppliers and product types. There isn't one single best or worst supplier across all product categories.

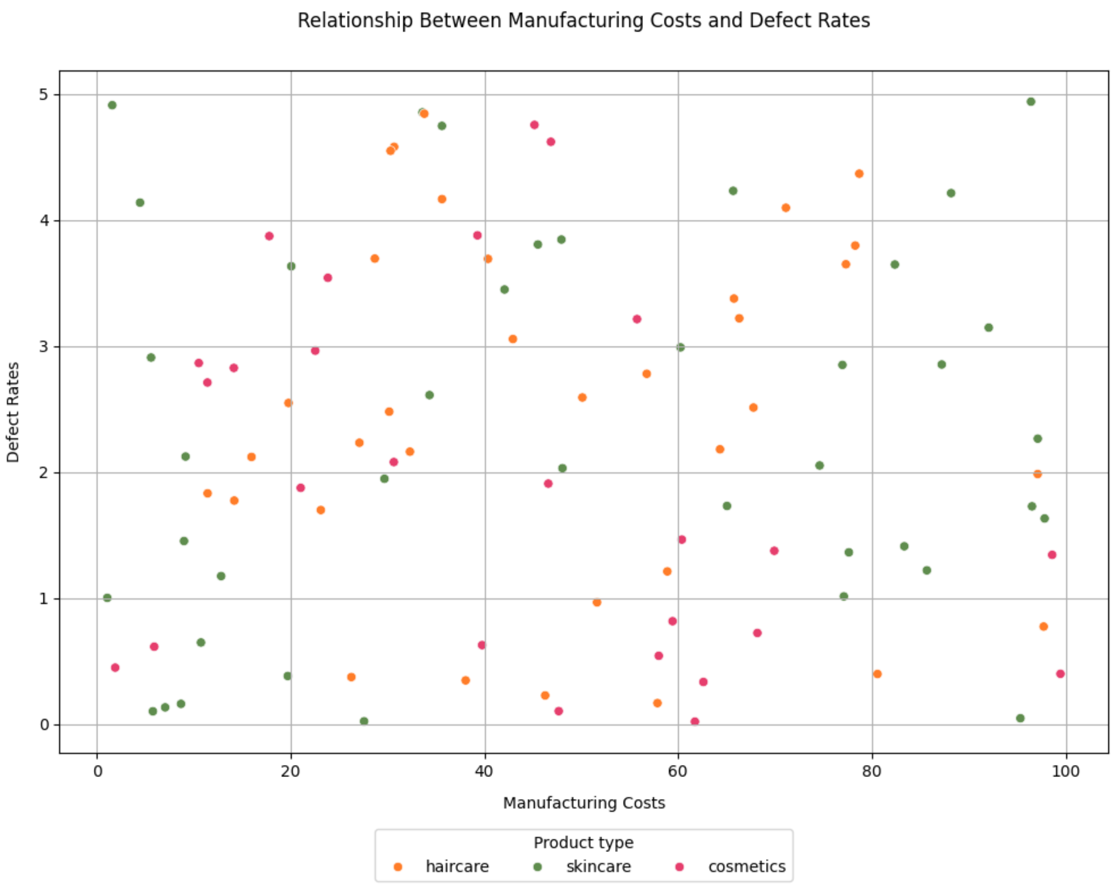
- **Supplier 3** consistently delivers low defect rates for both **Cosmetics and Haircare**.
- **Supplier 4** is excellent for Skincare but performs poorly for **Haircare**.
- **Supplier 1, 2, and 5** show fluctuating performance, often having high defect rates for at least one product type. **Supplier 1 and 5** are particularly problematic for **Skincare**.

The defect rate data clearly shows that supplier performance is highly dependent on the specific product type. There is no single supplier that consistently offers the lowest defect rates across all product categories. This necessitates a diversified and strategic approach to supplier management.

2.0.13 Relationship Between Manufacturing Costs and Defect Rates

[159]:
```
# set chart style properties
plt.figure(figsize=(10, 8))

# create scatterplot
ax = sns.scatterplot(data=df,
```

```
                x="Manufacturing costs",
                y="Defect rates",
                hue="Product type",
                palette=['#FF7D29','#5F8D4E','#E63E6D'])

# move scatterplot lagend to center bottom
sns.move_legend(ax,
                "lower center",
                bbox_to_anchor=(0.5, -0.20),
                ncol=3,
                title='Product type',
                frameon=True,)

plt.title("Relationship Between Manufacturing Costs and Defect Rates",y=1.05)
plt.xlabel("Manufacturing Costs",labelpad=10)
plt.ylabel("Defect Rates",labelpad=10)
plt.grid(True)
plt.tight_layout()
plt.show()

print(f"The correlation between Price and number of product sold is:␣
↪{df['Manufacturing costs'].corr(df['Defect rates']):.4f}")
```



```
The correlation between Price and number of product sold is: -0.0078
```

This scatter plot displays the relationship between manufacturing cost and defect rates accross three product types: **Cosmetics, Haircare, and Skincare**

There doesn't appear to be a strong, clear correlation (either positive or negative) between manufacturing costs and defect rates across all product types. The data points are widely scattered.

2.0.14 Location-Based Performance Variance Comparison

[166]:
```python
regional_performance = df.groupby('Location').agg({
    'Price':'mean',
    'Revenue generated': 'mean',
    'Defect rates': 'mean',
    'Shipping costs': 'mean',
    'Costs': 'mean'
}).round(2)
print(regional_performance)
```

```
           Price  Revenue generated  Defect rates  Shipping costs   Costs
Location
Bangalore  38.03            5700.10          2.09            5.75  586.71
Chennai    68.15            5957.14          2.64            4.69  621.75
Delhi      46.27            5401.85          2.23            5.07  548.24
Kolkata    49.45            5483.10          2.29            5.76  491.27
Mumbai     44.01            6261.59          2.12            6.25  428.34
```

2.1 Recommendations

- **Prioritize Skincare:** Leverage Skincare's dominant sales volume and revenue by increasing investment and marketing focus.
- **Targeted Growth for Haircare & Cosmetics:** Implement strategic niche identification and aggressive, targeted promotions for both Haircare and Cosmetics to drive revenue growth.
- **Demographic-Specific Marketing:** Focus female-centric marketing on Cosmetics and Skincare, male-centric marketing on Skincare, and capitalize on Haircare's broader demographic appeal.
- **Optimize Pricing & Profitability:** Review pricing strategies beyond cost-plus, especially for products with high manufacturing costs but low prices/revenue, to ensure healthy profit margins.
- **Address High Defect Rates Urgently:** Conduct immediate root cause analysis for the alarming 36% inspection failure rate and implement corrective actions.
- **Streamline Inspections:** Address the 41% pending inspection backlog to gain faster insights into product quality and reduce delays.

- **Strategic Supplier Management:** Allocate suppliers based on their product-specific strengths (e.g., Supplier 3 for Cosmetics/Haircare, Supplier 4 for Skincare) and engage underperforming suppliers for improvement. Leverage Supplier 3's low manufacturing costs and negotiate with higher-cost suppliers (Supplier 1 and 4).
- **Optimize Transportation Costs:** Prioritize Carrier A for shipping due to its cost-effectiveness, investigate Carrier B's higher costs, and maximize the use of Sea transport where feasible.
- **Route and Location-Based Logistics:** Develop tailored transportation strategies considering varying costs across locations and routes, particularly scrutinizing high-cost Air routes.