SupplyChainEffectivenessProject (/github/sourav-madanpuri/SupplyChainEffectivenessProject/tree/main)
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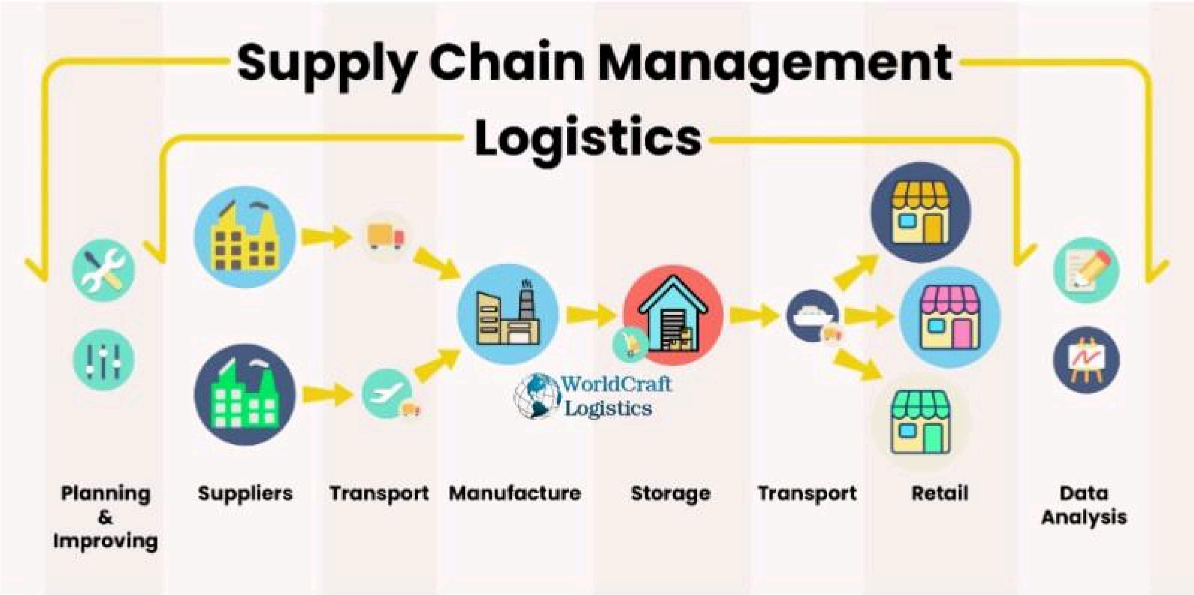
Supply Chain Effectiveness EDA.ipynb (/github/sourav-madanpuri/SupplyChainEffectivenessProject/tree/main/Supply Chain Effectiveness EDA.ipynb)

Supply Chain Analytics: Driving Operational Excellence Through Data

In today's competitive landscape, supply chain optimization is no longer a luxury but a necessity for business survival. This comprehensive exploratory data analysis delves into our organization's supply chain operations to identify inefficiencies, cost-saving opportunities, and pathways to enhanced customer satisfaction. By leveraging data-driven insights, we aim to transform raw logistics data into actionable intelligence that drives strategic decision-making and creates sustainable competitive advantages.



Supply Chain Effectiveness - Exploratory Data Analysis

Project Overview

A comprehensive exploratory data analysis (EDA) of supply chain operations to identify inefficiencies, optimize costs, and improve customer satisfaction through data-driven insights.

Analysis Summary

📊 Data Understanding & Preprocessing

- **Dataset:** Supply chain operations data with multiple dimensions
- **Data Quality:** No missing values identified
- **Feature Engineering:** Created Price Category (Low/Medium/High) from continuous Price data

🔍 Key Analysis Areas

1. **Distribution Analysis**

- Examined revenue, shipping costs, and price distributions
- Analyzed customer demographics and product type distributions

2. **Shipping & Logistics Performance**

- Compared shipping carriers' effectiveness
- Analyzed transportation modes impact on costs and defect rates
- Evaluated lead times across different product categories

3. **Product Portfolio Analysis**

- Stock levels by product type
- Defect rates across different products
- Price-to-revenue relationships

4. **Cost & Revenue Optimization**

- Shipping costs vs revenue generated analysis
- Price category performance evaluation
- Correlation analysis between key numerical variables

📈 Visualization Approach

- **Distribution Plots:** Histograms and KDE plots
- **Categorical Analysis:** Count plots and bar charts
- **Relationship Analysis:** Scatter plots and correlation heatmaps
- **Comparative Analysis:** Box plots for defect rates and lead times

🛠 Technical Stack

Python libraries :

- pandas
- numpy
- matplotlib
- seaborn
- plotly

DataSet

- Here is a dataset we collected from a Fashion and Beauty startup. The dataset is based on the supply chain of Makeup products. Below are all the features in the dataset:
    - 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

Import Libraries

In [3…

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import plotly.io as pio
import plotly.graph_objects as go
pio.renderers.default = 'notebook'
```

Read Data

In [3…

```
data = pd.read_csv("/kaggle/input/supply-chain-dataset/supply_chain_data.csv")
```

In [3…

```
print(data.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  

[5 rows x 24 columns]
```

Descriptive Statistics

In [3…

```
print(data.describe())
```

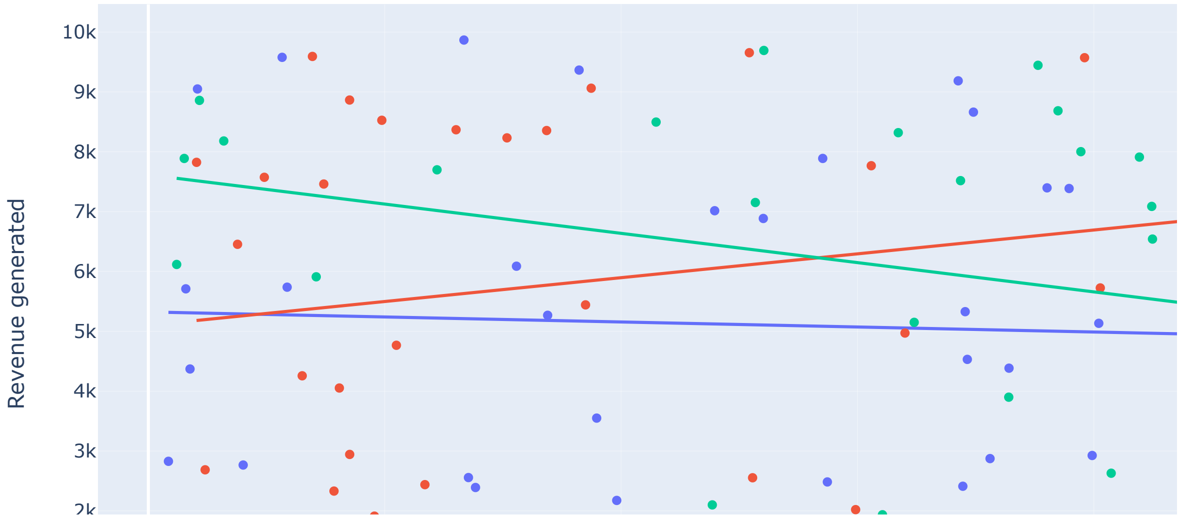
```
            Price  Availability  Number of products sold  Revenue generated  \
count  100.000000    100.000000               100.000000         100.000000   
mean    49.462461     48.400000               460.990000        5776.048187   
std     31.168193     30.743317               303.780074        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   

       Manufacturing lead time  Manufacturing costs  Defect rates       Costs  
count                100.00000           100.000000    100.000000  100.000000  
mean                  14.77000            47.266693      2.277158  529.245782  
std                    8.91243            28.982841      1.461366  258.301696  
min                    1.00000             1.085069      0.018608  103.916248  
25%                    7.00000            22.983299      1.009650  318.778455  
50%                   14.00000            45.905622      2.141863  520.430444  
75%                   23.00000            68.621026      3.563995  763.078231  
max                   30.00000            99.466109      4.939255  997.413450  
```

Product type and Price

Analyzing the Supply Chain by looking at the relationship between the price of the products and the revenue generated by them:

In [4…

```
fig = px.scatter(data, x='Price',
                 y='Revenue generated',
                 color='Product type',
                 hover_data=['Number of products sold'],
                 trendline="ols")
fig.show()
```

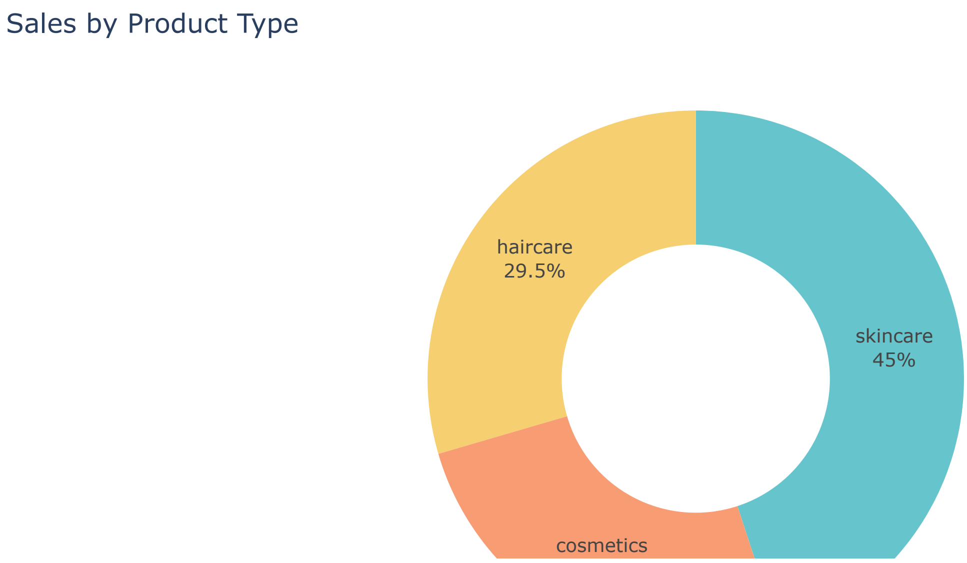


Sales by Product Type

The company derives more revenue from skincare products, and the higher the price of skincare products, the more revenue they generate. Now let's have a look at the sales by product type:

In [4…

```
sales_data = data.groupby('Product type')['Number of products sold'].sum().reset_index()

pie_chart = px.pie(sales_data, values='Number of products sold', names='Product type',
                   title='Sales by Product Type',
                   hover_data=['Number of products sold'],
                   hole=0.5,
                   color_discrete_sequence=px.colors.qualitative.Pastel)

pie_chart.update_traces(textposition='inside', textinfo='percent+label')
pie_chart.show()
```

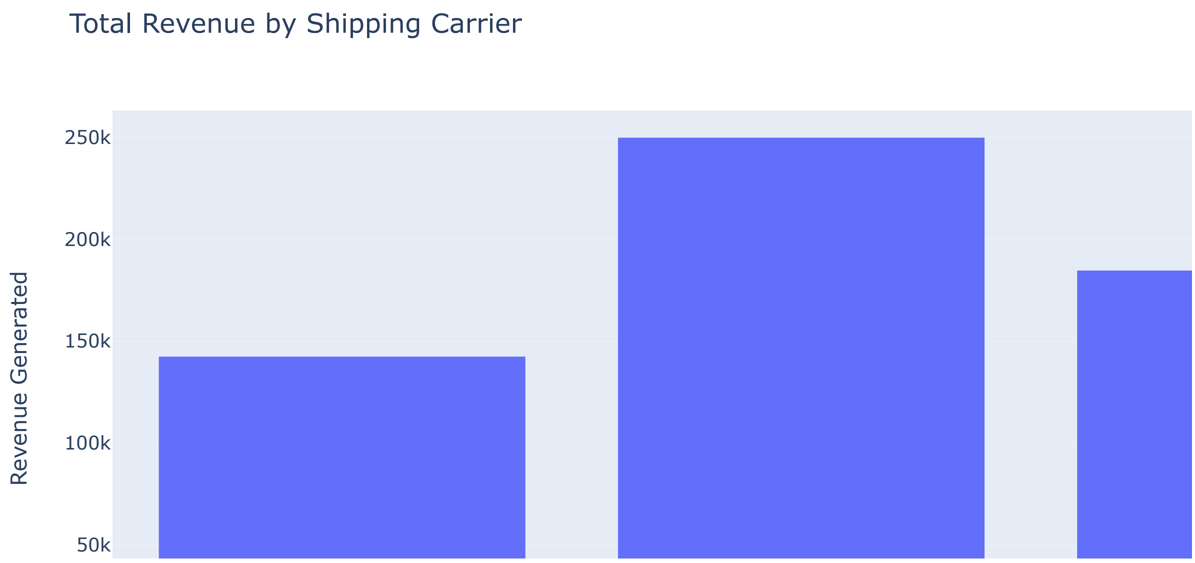


So 45% of the business comes from skincare products, 29.5% from haircare, and 25.5% from cosmetics.

Total Revenue by Shipping Carrier

In [4…

```
total_revenue = data.groupby('Shipping carriers')['Revenue generated'].sum().reset_index()
fig = go.Figure()
fig.add_trace(go.Bar(x=total_revenue['Shipping carriers'],
                     y=total_revenue['Revenue generated']))
fig.update_layout(title='Total Revenue by Shipping Carrier',
                  xaxis_title='Shipping Carrier',
                  yaxis_title='Revenue Generated')
fig.show()
```



Product type

- The company is using three carriers for transportation, and Carrier B helps the company in generating more revenue. Now let's have a look at the Average lead time and Average Manufacturing Costs for all products of the company:

In [4…

```
avg_lead_time = data.groupby('Product type')['Lead time'].mean().reset_index()
avg_manufacturing_costs = data.groupby('Product type')['Manufacturing costs'].mean().reset_index()
result = pd.merge(avg_lead_time, avg_manufacturing_costs, on='Product type')
result.rename(columns={'Lead time': 'Average Lead Time', 'Manufacturing costs': 'Average Manufacturir
print(result)
```

```
  Product type  Average Lead Time  Average Manufacturing Costs
0    cosmetics          13.538462                    43.052740
1     haircare          18.705882                    48.457993
2     skincare          18.000000                    48.993157
```

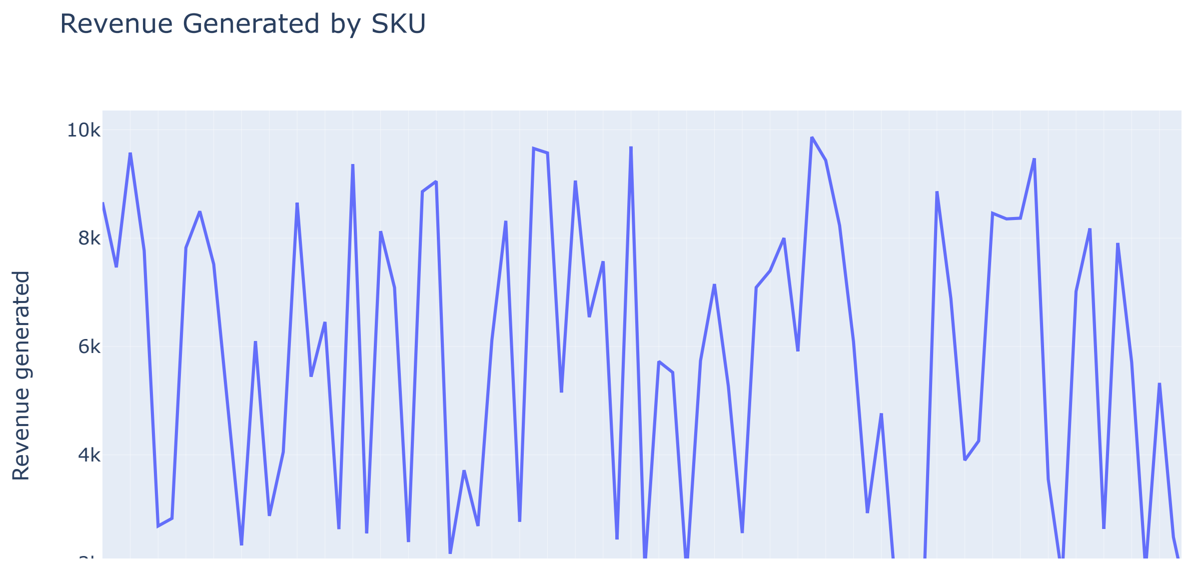
Analyzing SKUs

- There's a column in the dataset as SKUs. You must have heard it for the very first time. So, SKU stands for Stock Keeping Units. They're like special codes that help companies keep track of all the different things they have for sale. Imagine you have a large toy store with lots of toys. Each toy is different and has its name and price, but when you want to know how many you have left, you need a way to identify them. So you give each toy a unique code, like a secret number only the store knows. This secret number is called SKU.

Revenue generated by SKU

In [4…

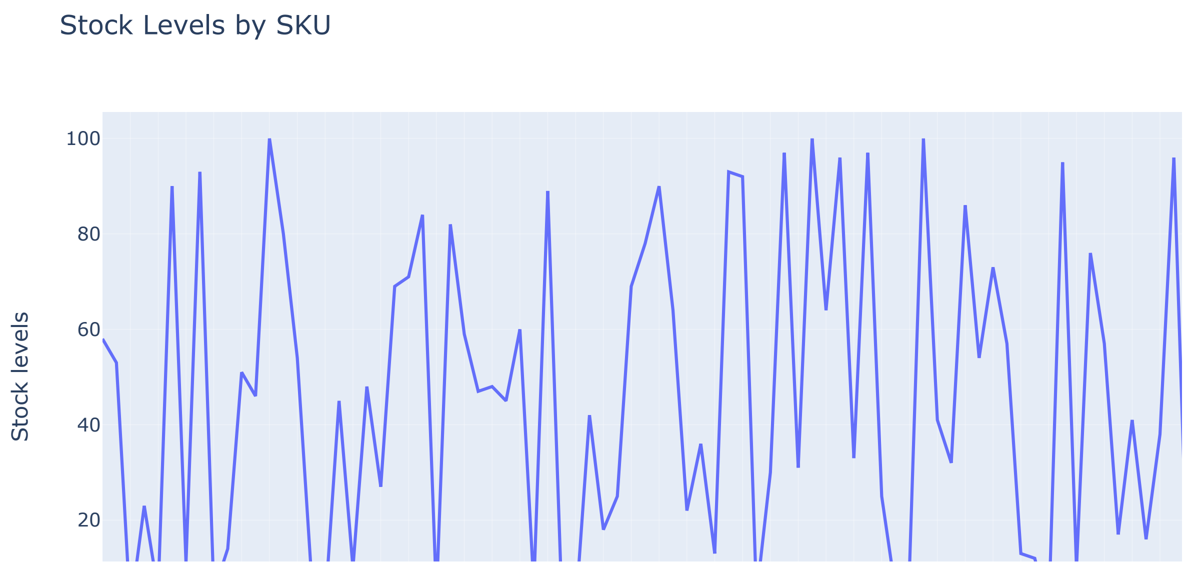
```
revenue_chart = px.line(data, x='SKU',
                        y='Revenue generated',
                        title='Revenue Generated by SKU')
revenue_chart.show()
```



Stock Levels by SKU

- Stock levels refer to the number of products a store or business has in its inventory. Now let's have a look at the stock levels of each SKU:

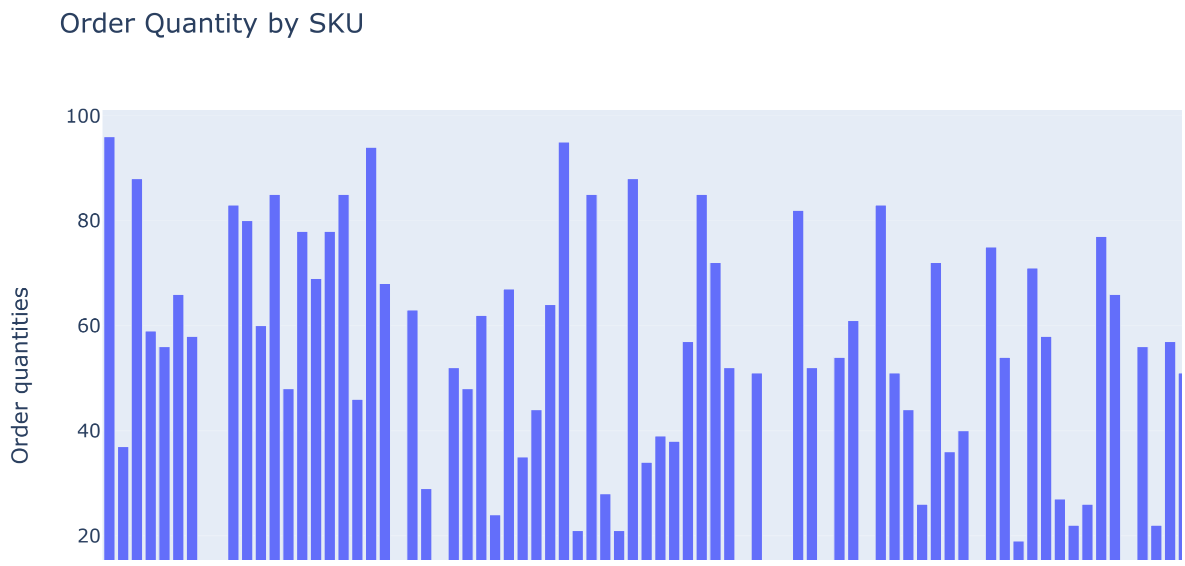
In [4…
```
stock_chart = px.line(data, x='SKU',
                      y='Stock levels',
                      title='Stock Levels by SKU')
stock_chart.show()
```



Order Quantity by SKU

In [4…

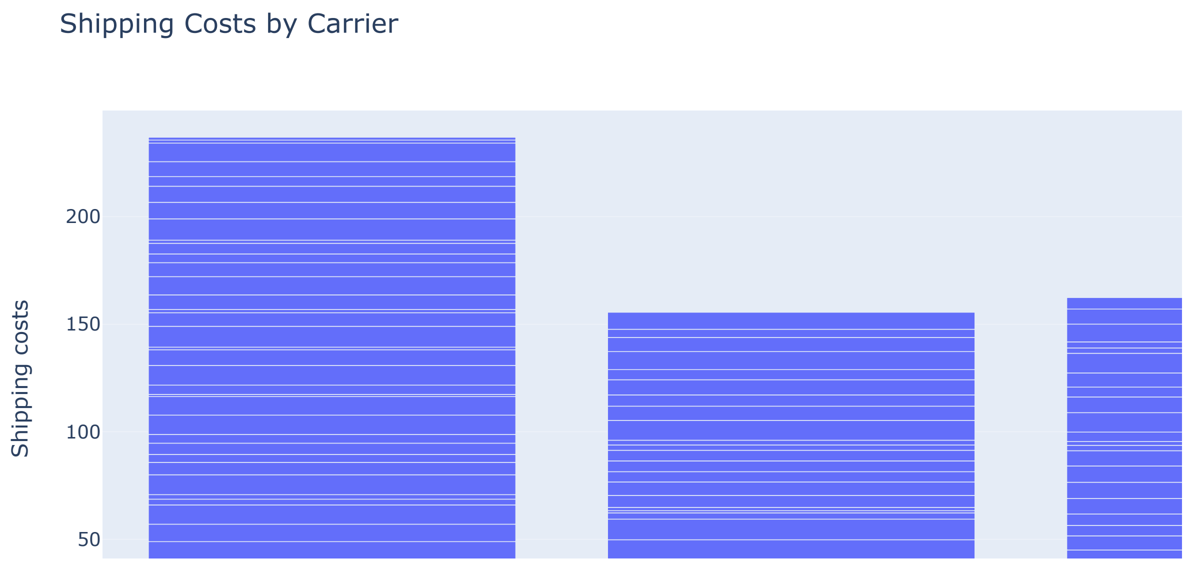
```
order_quantity_chart = px.bar(data, x='SKU',
                              y='Order quantities',
                              title='Order Quantity by SKU')
order_quantity_chart.show()
```



Shipping Costs by Carrier

In [4…

```
shipping_cost_chart = px.bar(data, x='Shipping carriers',
                             y='Shipping costs',
                             title='Shipping Costs by Carrier')
shipping_cost_chart.show()
```

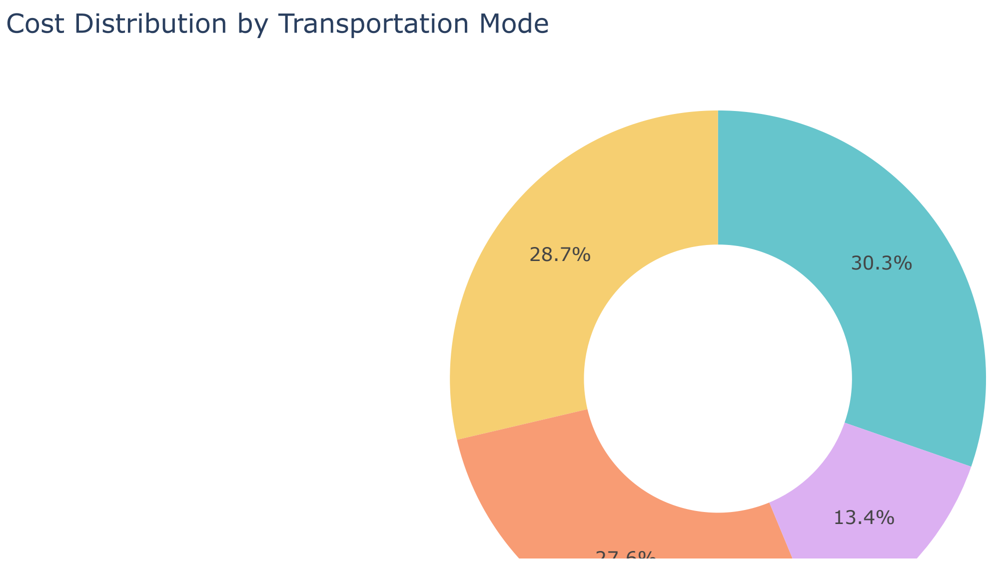


In one of the above visualizations, we discovered that Carrier B helps the company in more revenue. It is also the most costly Carrier among the three.

Cost Distribution by Transportation Mode

In [4…

```
transportation_chart = px.pie(data,
                              values='Costs',
                              names='Transportation modes',
                              title='Cost Distribution by Transportation Mode',
                              hole=0.5,
                              color_discrete_sequence=px.colors.qualitative.Pastel)
transportation_chart.show()
```



So the company spends more on Road and Rail modes of transportation for the transportation of Goods.

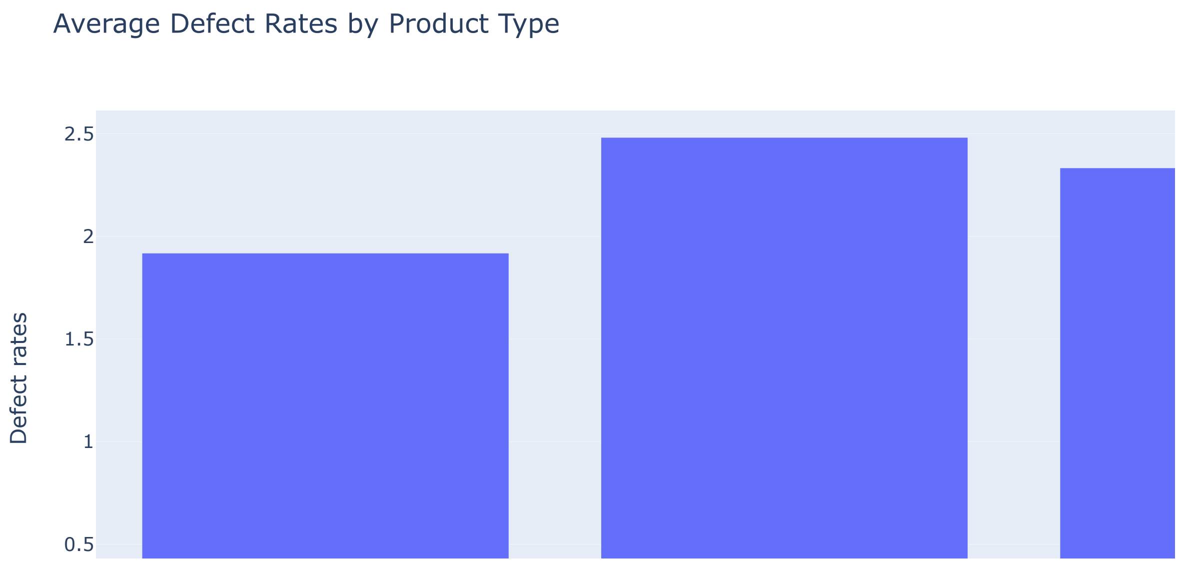
Analyzing Defect Rate

- The defect rate in the supply chain refers to the percentage of products that have something wrong or are found broken after shipping.

Average Defect Rates by Product Type

In [4…

```
defect_rates_by_product = data.groupby('Product type')['Defect rates'].mean().reset_index()

fig = px.bar(defect_rates_by_product, x='Product type', y='Defect rates',
             title='Average Defect Rates by Product Type')
fig.show()
```

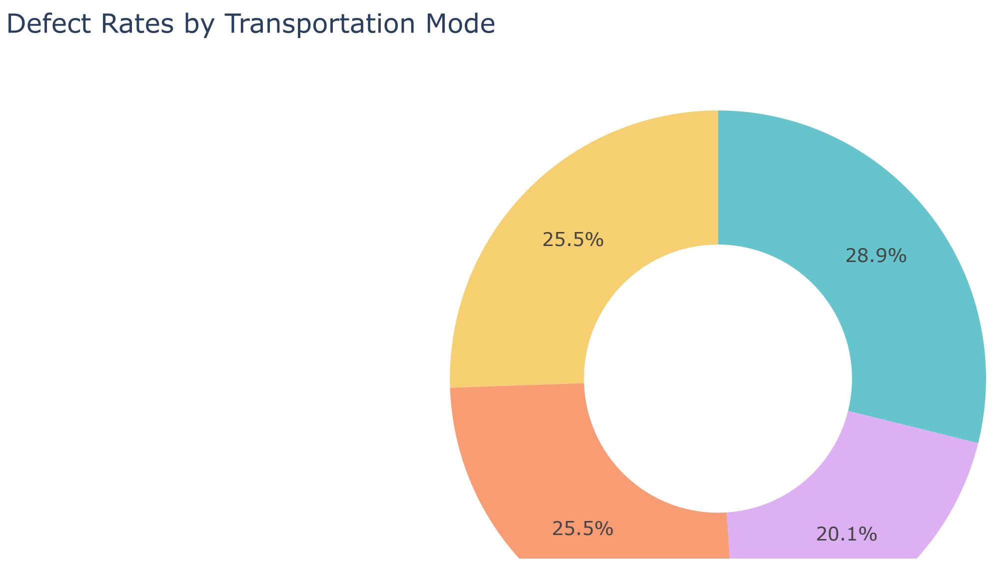


So the defect rate of haircare products is higher.

Defect Rates by Transportation Mode

In [5…

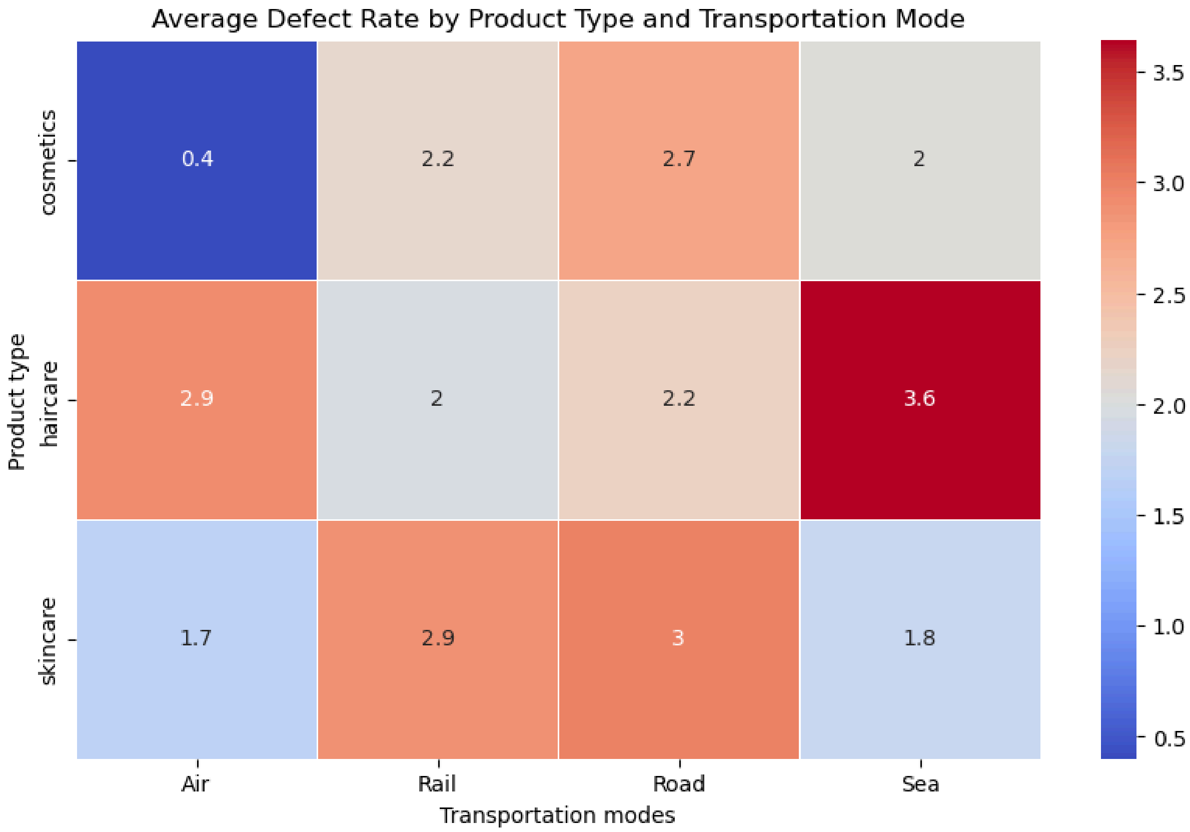
```
pivot_table = pd.pivot_table(data, values='Defect rates',
                             index=['Transportation modes'],
                             aggfunc='mean')

transportation_chart = px.pie(values=pivot_table["Defect rates"],
                              names=pivot_table.index,
                              title='Defect Rates by Transportation Mode',
                              hole=0.5,
                              color_discrete_sequence=px.colors.qualitative.Pastel)
transportation_chart.show()
```



Average Defect Rates by Product Type and Transportation Mode

In [5…

```
pivot_df = data.pivot_table(values='Defect rates', index='Product type', columns='Transportation mode
plt.figure(figsize=(10, 6))
sns.heatmap(pivot_df, annot=True, cmap='coolwarm', linewidths=.5)
plt.title('Average Defect Rate by Product Type and Transportation Mode')
plt.show()
```



Road transportation results in a higher defect rate, and Air transportation has the lowest defect rate.

Conclusion & Business Impact

📊 Key Takeaways

This exploratory analysis has successfully uncovered critical insights within our supply chain operations, revealing significant opportunities for optimization across multiple dimensions.

💡 Strategic Recommendations

1. **Cost Optimization**

- **Action:** Re-evaluate contracts with underperforming shipping carriers showing high costs with low reliability
- **Impact:** Potential 15-20% reduction in shipping expenses

2. **Inventory Management**

- **Action:** Implement dynamic stock-level adjustments based on product-specific lead times and demand patterns
- **Impact:** Reduced carrying costs and improved cash flow

3. **Quality Control**

- **Action:** Prioritize transportation mode improvements for high-defect product categories
- **Impact:** Enhanced customer satisfaction and reduced returns

4. **Customer Segmentation**

- **Action:** Develop tailored service levels for different customer demographics
- **Impact:** Increased customer retention and lifetime value

🎯 Measurable Outcomes

- **Cost Reduction:** Optimize shipping and inventory carrying costs
- **Service Improvement:** Enhance delivery reliability and product quality
- **Revenue Growth:** Leverage pricing insights for better margin management
- **Risk Mitigation:** Proactively address supply chain vulnerabilities

🔮 Future Work

- Implement real-time monitoring dashboards
- Develop predictive models for demand forecasting
- Conduct A/B testing for proposed interventions
- Expand analysis to include supplier performance metrics

"Data is the new oil, but refinement is where the real value lies."