supply chain analysis

October 20, 2024

1 importing the necessary Python libraries and the dataset:

[190]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import linear_model
import pylab as pl
from sklearn.metrics import r2_score
```

[223]:
```
df = pd.read_csv('C:\\Users\\AQ\\Downloads\\supply_chain_data.csv')
```

[72]:
```
df.head()
```

[72]:
```
  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]
```

[ ]:

2 Statistics for Numerical Columns

[73]:

```
df.describe().T
```

[73]:

```
                         count         mean          std          min  \
Price                    100.0    49.462461    31.168193     1.699976
Availability             100.0    48.400000    30.743317     1.000000
Number of products sold  100.0   460.990000   303.780074     8.000000
Revenue generated        100.0  5776.048187  2732.841744  1061.618523
Stock levels             100.0    47.770000    31.369372     0.000000
Lead times               100.0    15.960000     8.785801     1.000000
Order quantities         100.0    49.220000    26.784429     1.000000
Shipping times           100.0     5.750000     2.724283     1.000000
Shipping costs           100.0     5.548149     2.651376     1.013487
Lead time                100.0    17.080000     8.846251     1.000000
Production volumes       100.0   567.840000   263.046861   104.000000
Manufacturing lead time  100.0    14.770000     8.912430     1.000000
Manufacturing costs      100.0    47.266693    28.982841     1.085069
Defect rates             100.0     2.277158     1.461366     0.018608
Costs                    100.0   529.245782   258.301696   103.916248

                                 25%          50%          75%          max
Price                      19.597823    51.239830    77.198228    99.171329
Availability               22.750000    43.500000    75.000000   100.000000
Number of products sold   184.250000   392.500000   704.250000   996.000000
Revenue generated        2812.847151  6006.352023  8253.976920  9866.465458
Stock levels               16.750000    47.500000    73.000000   100.000000
Lead times                  8.000000    17.000000    24.000000    30.000000
Order quantities           26.000000    52.000000    71.250000    96.000000
Shipping times              3.750000     6.000000     8.000000    10.000000
Shipping costs              3.540248     5.320534     7.601695     9.929816
```

```
Lead time                     10.000000    18.000000    25.000000    30.000000
Production volumes           352.000000   568.500000   797.000000   985.000000
Manufacturing lead time        7.000000    14.000000    23.000000    30.000000
Manufacturing costs           22.983299    45.905622    68.621026    99.466109
Defect rates                   1.009650     2.141863     3.563995     4.939255
Costs                        318.778455   520.430444   763.078231   997.413450
```

3 Check for missing values in each column

[188]:
```python
categorical_cols = [
    'Product type','Customer demographics', 'Shipping carriers',
    'Supplier name', 'Location', 'Inspection results', 'Transportation modes',␣
 ↪'Routes'
]
for col in categorical_cols:
    print(f"\nDistribution of {col}:\n", df[col].value_counts())
```

```
Distribution of Product type:
 Product type
skincare     40
haircare     34
cosmetics    26
Name: count, dtype: int64

Distribution of Customer demographics:
 Customer demographics
Unknown       31
Female        25
Non-binary    23
Male          21
Name: count, dtype: int64

Distribution of Shipping carriers:
 Shipping carriers
Carrier B    43
Carrier C    29
Carrier A    28
Name: count, dtype: int64

Distribution of Supplier name:
 Supplier name
Supplier 1    27
Supplier 2    22
Supplier 5    18
Supplier 4    18
Supplier 3    15
```

```
Name: count, dtype: int64

Distribution of Location:
 Location
Kolkata      25
Mumbai       22
Chennai      20
Bangalore    18
Delhi        15
Name: count, dtype: int64

Distribution of Inspection results:
 Inspection results
Pending    41
Fail       36
Pass       23
Name: count, dtype: int64

Distribution of Transportation modes:
 Transportation modes
Road    29
Rail    28
Air     26
Sea     17
Name: count, dtype: int64

Distribution of Routes:
 Routes
Route A    43
Route B    37
Route C    20
Name: count, dtype: int64
```

[78]:
```
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
None
```

[74]:
```python
df.isnull().sum()
```

[74]:
```
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
```

```
[80]: print(df.drop_duplicates(inplace=True))
```

```
None
```

3.0.1 A new column titled 'Inventory Turnover' has been added to the dataset to assess inventory management effectiveness.

```
[87]: df['Inventory Turnover'] = df['Number of products sold'] / df['Stock levels']
      print(df)
```

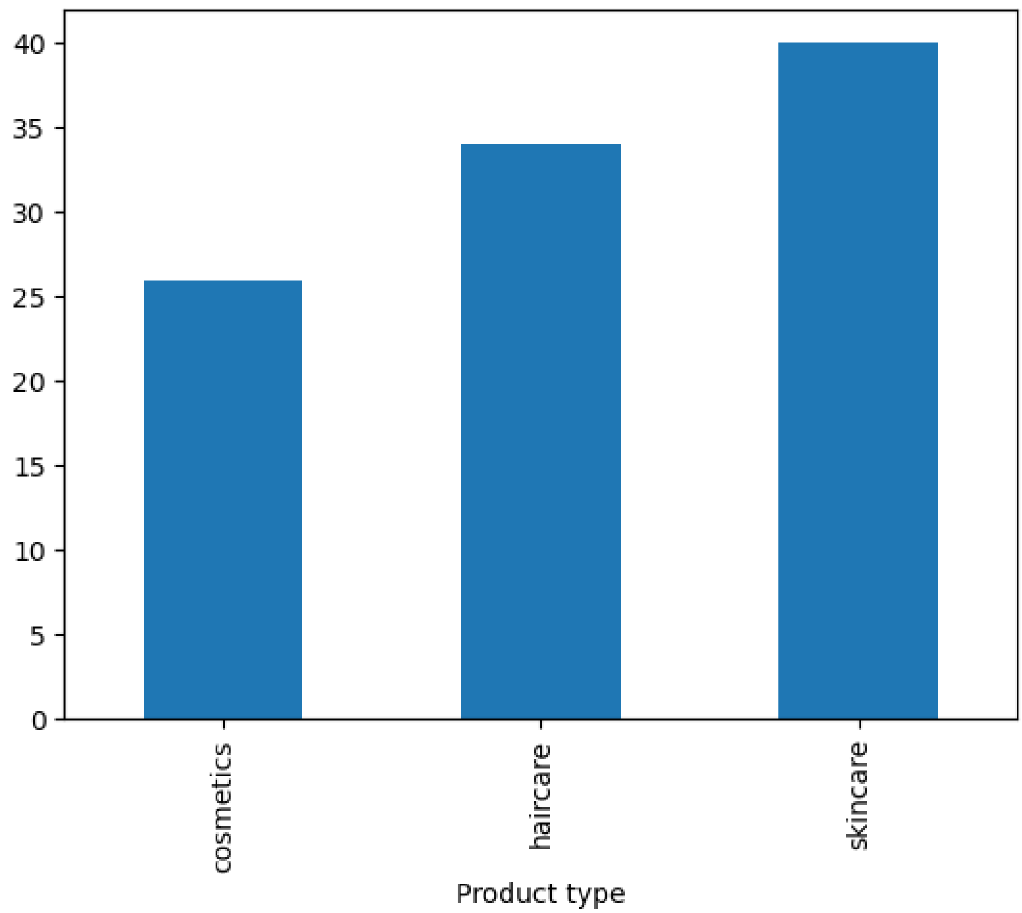
```
   Product type    SKU      Price  Availability  Number of products sold  \
0      haircare   SKU0  69.808006            55                      802
1      skincare   SKU1  14.843523            95                      736
2      haircare   SKU2  11.319683            34                        8
3      skincare   SKU3  61.163343            68                       83
4      skincare   SKU4   4.805496            26                      871
..          …      …        …           …                      …
95     haircare  SKU95  77.903927            65                      672
96    cosmetics  SKU96  24.423131            29                      324
97     haircare  SKU97   3.526111            56                       62
98     skincare  SKU98  19.754605            43                      913
99     haircare  SKU99  68.517833            17                      627

    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
..                …                     …           …         …
95        7386.363944               Unknown            15          14
96        7698.424766            Non-binary            67           2
97        4370.916580                  Male            46          19
98        8525.952560                Female            53           1
99        9185.185829               Unknown            55           8

    Order quantities  …  Lead time Production volumes  \
0                 96  …         29                 215
1                 37  …         23                 517
2                 88  …         12                 971
3                 59  …         24                 937
4                 56  …          5                 414
..               …  …       …                 …
95                26  …         18                 450
96                32  …         28                 648
97                 4  …         10                 535
98                27  …         28                 581
99                59  …         29                 921
```

```
    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
..                      …                   …                  …
95                       26           58.890686            Pending
96                       28           17.803756            Pending
97                       13           65.765156               Fail
98                        9            5.604691            Pending
99                        2           38.072899               Fail

    Defect rates  Transportation modes   Routes       Costs Inventory Turnover
0       0.226410                  Road  Route B  187.752075          13.827586
1       4.854068                  Road  Route B  503.065579          13.886792
2       4.580593                   Air  Route C  141.920282           8.000000
3       4.746649                  Rail  Route A  254.776159           3.608696
4       3.145580                   Air  Route A  923.440632         174.200000
..           …                   …      …         …                 …
95      1.210882                   Air  Route A  778.864241          44.800000
96      3.872048                  Road  Route A  188.742141           4.835821
97      3.376238                  Road  Route A  540.132423           1.347826
98      2.908122                  Rail  Route A  882.198864          17.226415
99      0.346027                  Rail  Route B  210.743009          11.400000

[100 rows x 25 columns]
```

4 Deep Exploratory Analysis

[90]:
```python
df.groupby(['Product type'])['Product type'].count().plot(kind='bar')
print(df.groupby(['Product type'])['Product type'].count())
```

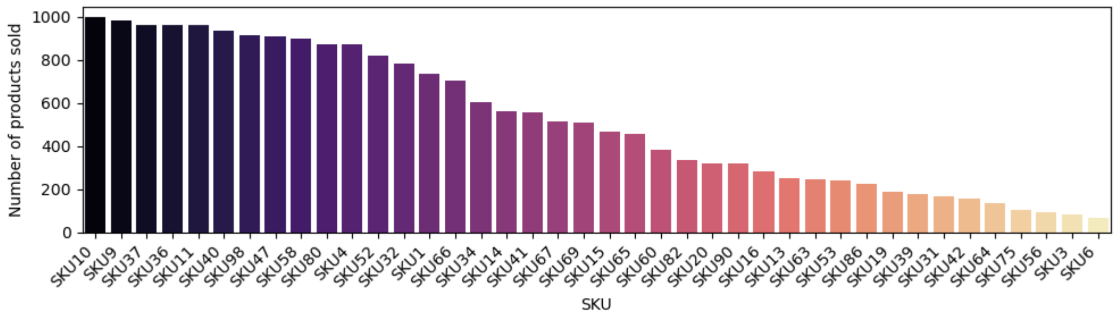
```
Product type
cosmetics    26
haircare     34
skincare     40
Name: Product type, dtype: int64
```



5 Analyzing SKUs

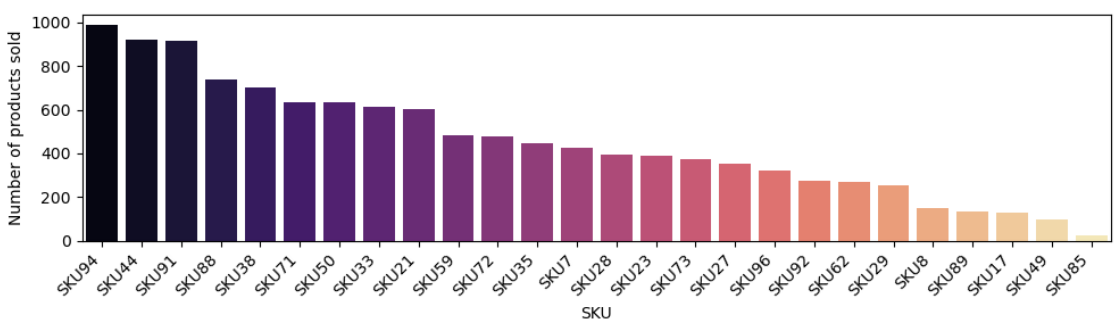
5.1 Number of sold Skincare products by SKU

[92]:
```
df_skincare = df[df['Product type'] == 'skincare'].sort_values(by=['Number of␣
↪products sold'], ascending=False)
fig, ax = plt.subplots(figsize=(10, 3))
colors = sns.color_palette("magma", n_colors=len(df_skincare))
sns.barplot(data=df_skincare, x='SKU', y='Number of products sold', ax=ax,␣
↪hue='SKU', palette=colors, dodge=False)
ax.set_xticks(range(len(df_skincare['SKU'])))
ax.set_xticklabels(df_skincare['SKU'], rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



5.2 Number of sold cosmetics by SKU

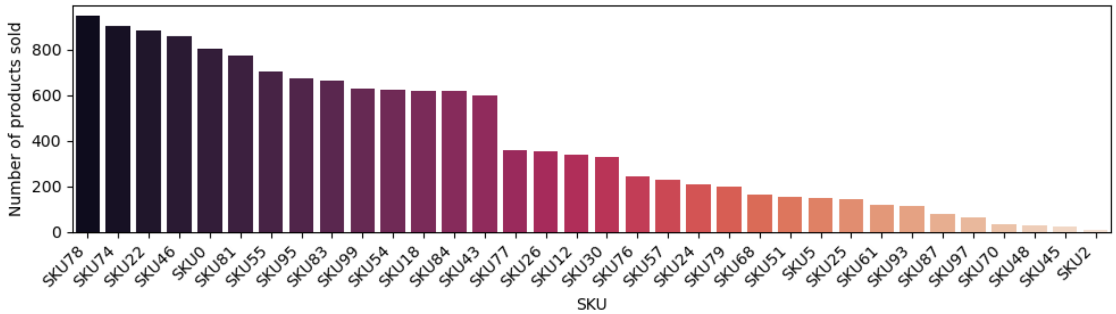
[95]:
```
df_cosmetics = df[df['Product type'] == 'cosmetics'].sort_values(by=['Number of␣
↪products sold'], ascending=False)
fig, ax = plt.subplots(figsize=(10, 3))
colors = sns.color_palette("magma", n_colors=len(df_cosmetics))
sns.barplot(data=df_cosmetics, x='SKU', y='Number of products sold', ax=ax,␣
↪hue='SKU', palette=colors, dodge=False)
ax.set_xticks(range(len(df_cosmetics['SKU'])))
ax.set_xticklabels(df_cosmetics['SKU'], rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



5.3 Number of sold Haircare products by SKU

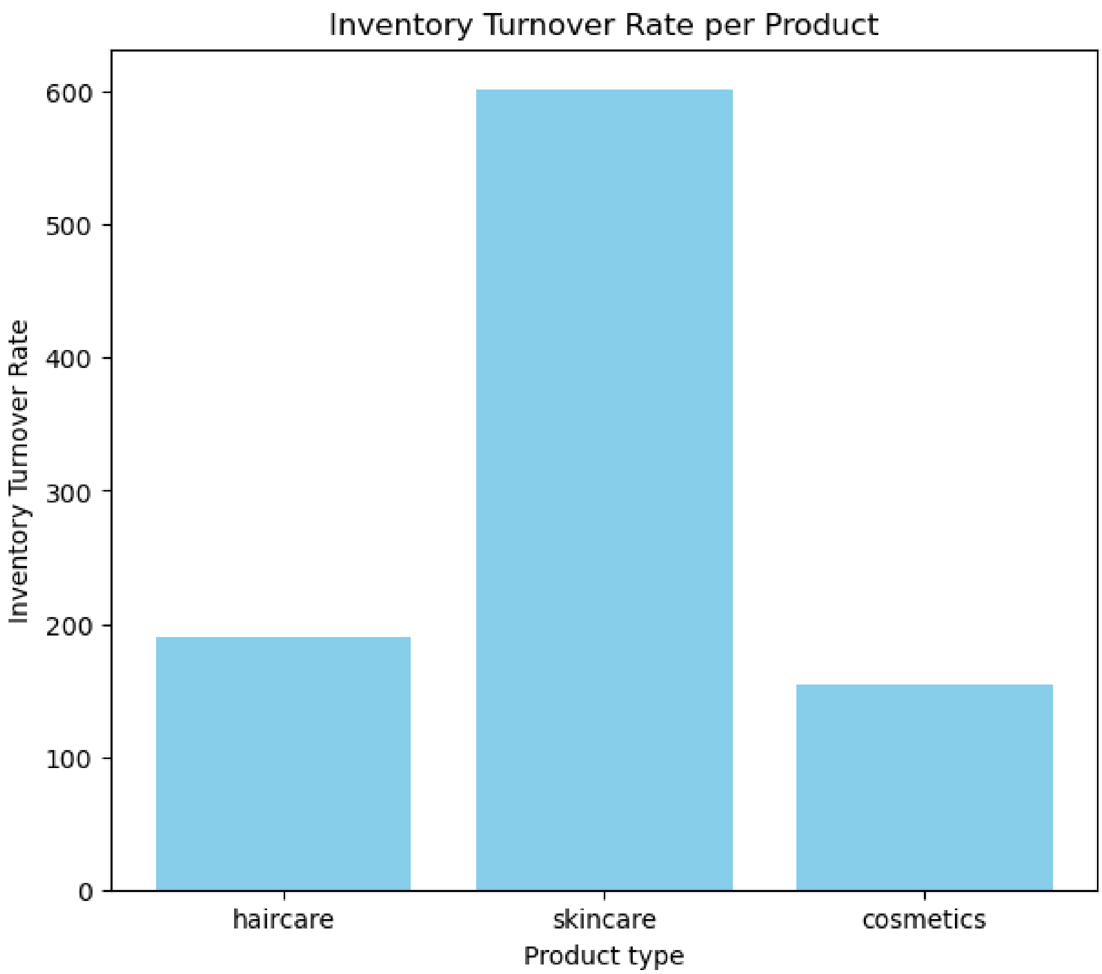
[97]:
```
df_haircare = df[df['Product type'] == 'haircare'].sort_values(by=['Number of␣
↪products sold'], ascending=False)
fig, ax = plt.subplots(figsize=(10, 3))
colors = sns.color_palette("rocket", n_colors=len(df_haircare))
sns.barplot(data=df_haircare, x='SKU', y='Number of products sold', ax=ax,␣
↪hue='SKU', palette=colors, dodge=False)
ax.set_xticks(range(len(df_haircare['SKU'])))
```

```
ax.set_xticklabels(df_haircare['SKU'], rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



5.4 Inventory Turnover Rate Per Product

[99]:
```
plt.figure(figsize=(7, 6))
plt.bar(df['Product type'], df['Inventory Turnover'], color='skyblue')
plt.title('Inventory Turnover Rate per Product')
plt.xlabel('Product type')
plt.ylabel('Inventory Turnover Rate')
plt.show()
```

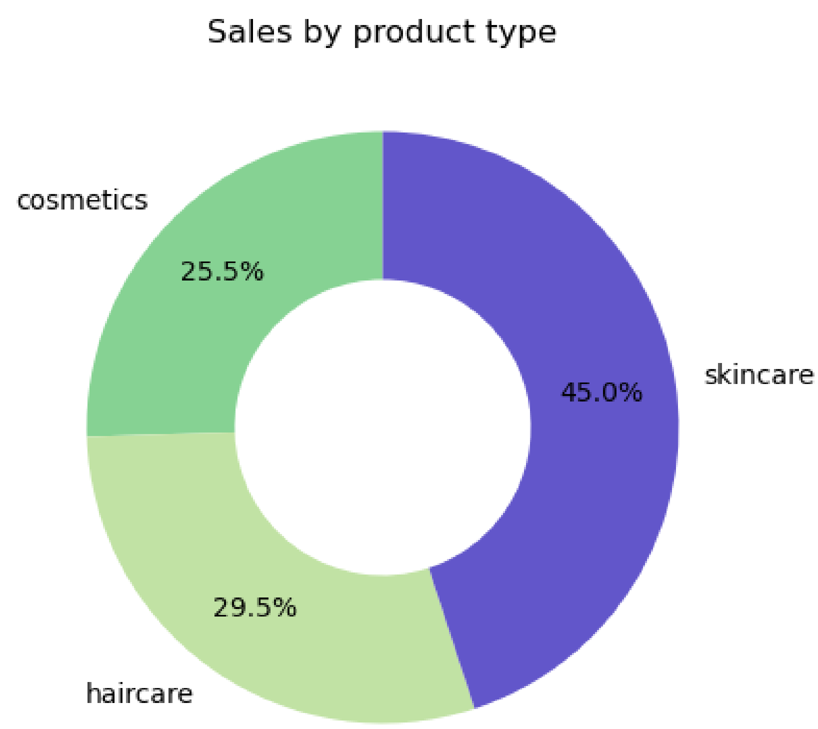


5.4.1 The analysis indicates that skincare products have the highest inventory levels, reflecting strong demand and consumer interest in skincare solutions.

5.5 Sales by product type

[102]:
```
colors=['#86D293','#C1E2A4','#6256CA']
product_sales=df.groupby('Product type')['Number of products sold'].sum().
 ↪reset_index()
plt.figure(figsize=(8, 5))
plt.pie(product_sales['Number of products sold'],
         labels=product_sales['Product type'],
         autopct='%1.1f%%',startangle=90, colors=colors␣
 ↪,wedgeprops=dict(width=0.5),pctdistance=0.75 )
plt.title('Sales by product type')
plt.show
```

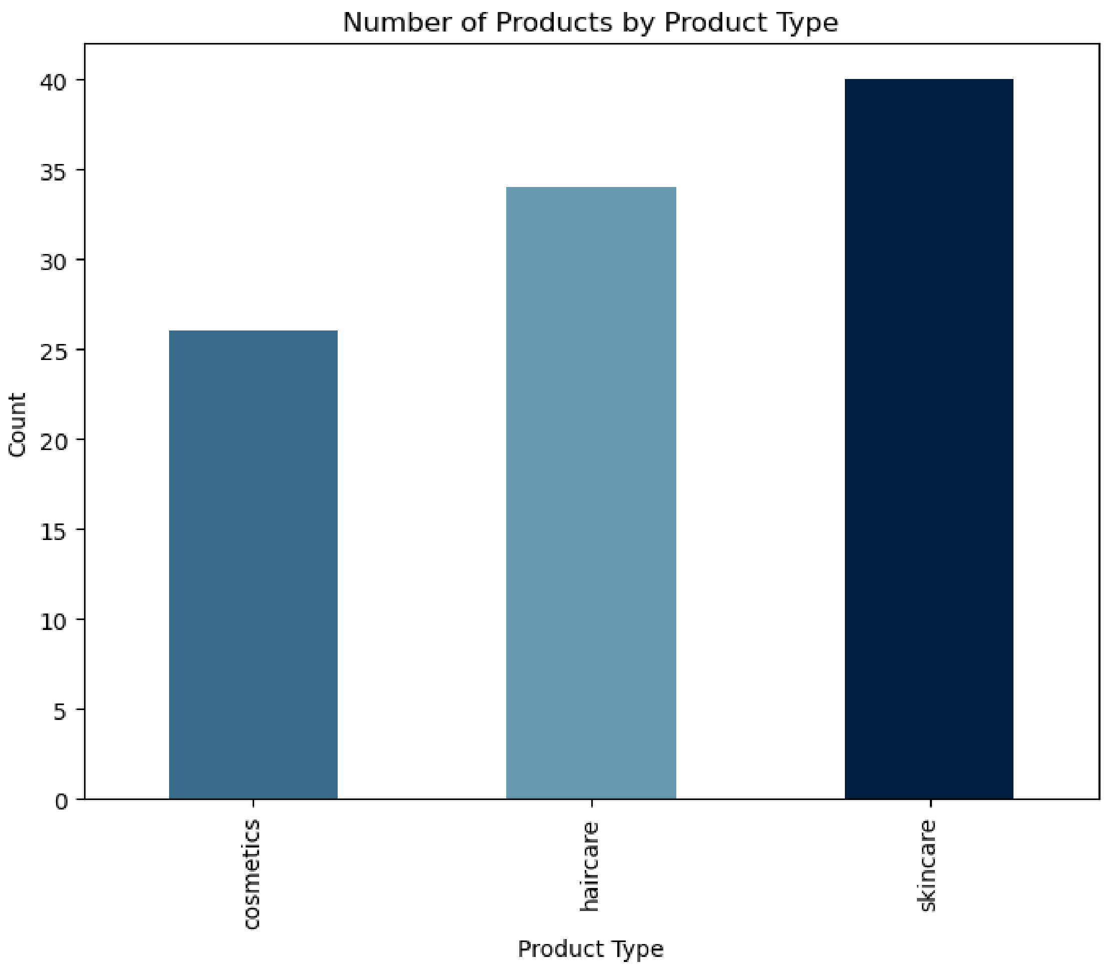
[102]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



5.5.1 Skincare products are the most preferred products as they are the highest in sales.

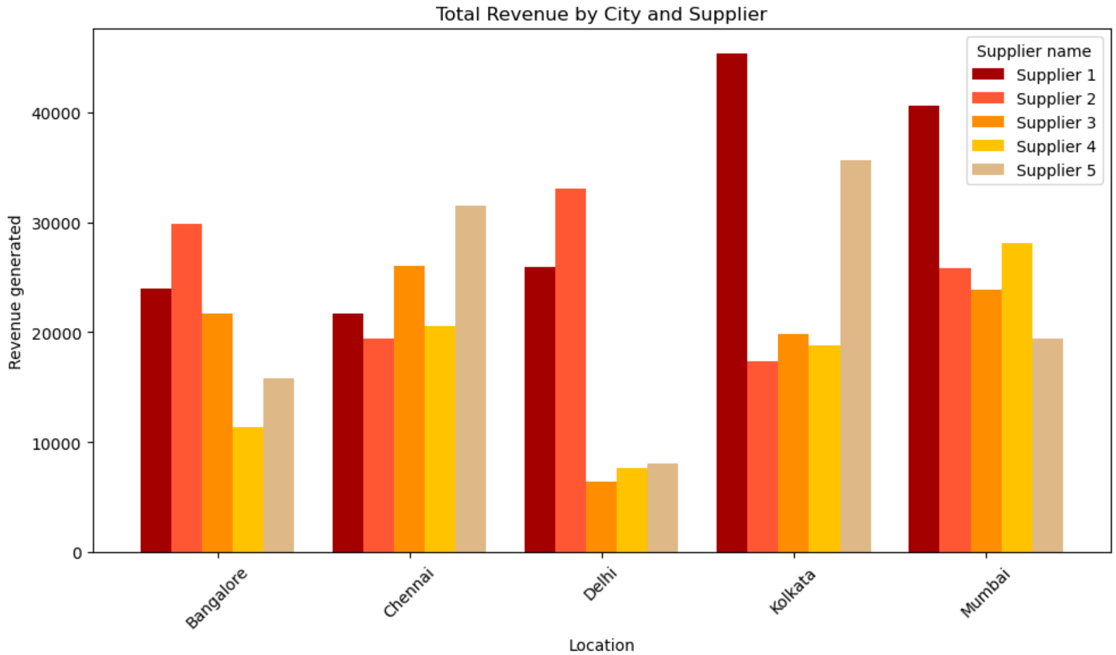
5.6 Total Number of Products per Category

[106]:
```
colors=['#3A6D8C','#6A9AB0','#001F3F']
product_type_counts = df .groupby(['Product type'])['Product type'].count()
product_type_counts.plot(kind='bar', figsize=(8, 6), color=colors)
plt.title('Number of Products by Product Type')
plt.xlabel('Product Type')
plt.ylabel('Count')
plt.show()
```



5.7 Total Revenue by City and Supplier

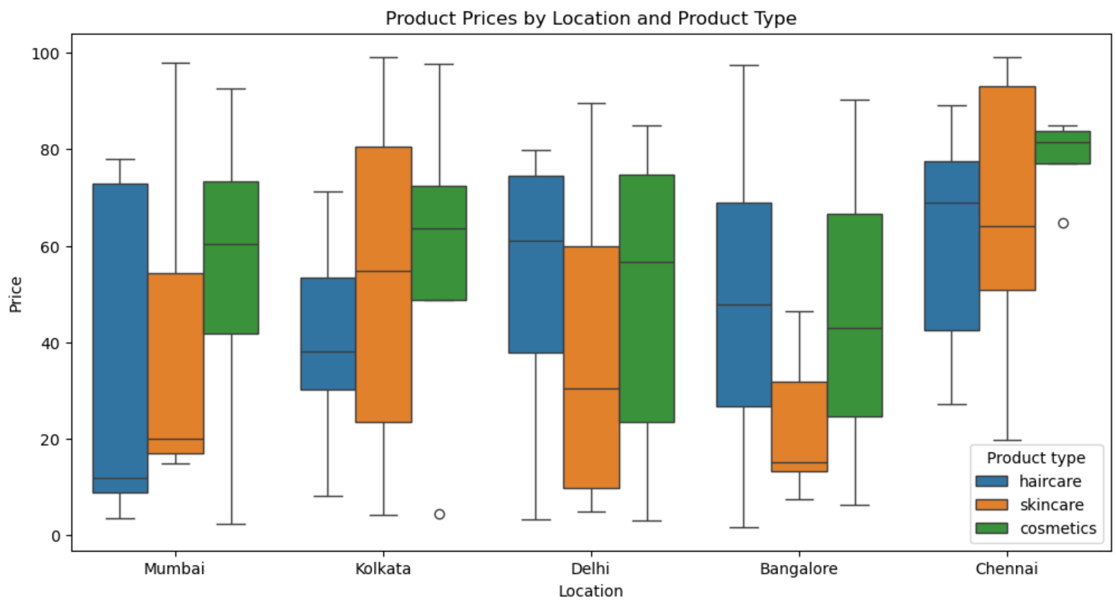
[109]:
```
city_supplier_sales = df.groupby(['Location', 'Supplier name'])['Revenue␣
 ↪generated'].sum().unstack().fillna(0)
colors = ['#A50000', '#FF5733', '#FF8D00', '#FFC300', '#DEB887']
city_supplier_sales.plot(kind='bar', color=colors, figsize=(10,6), width=0.8)
plt.xlabel('Location')
plt.ylabel('Revenue generated')
plt.title('Total Revenue by City and Supplier')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



5.7.1 Supplier 1 generates the highest revenue in the city of Kolkata.

5.8 Distribution of Product Prices by Location and Type

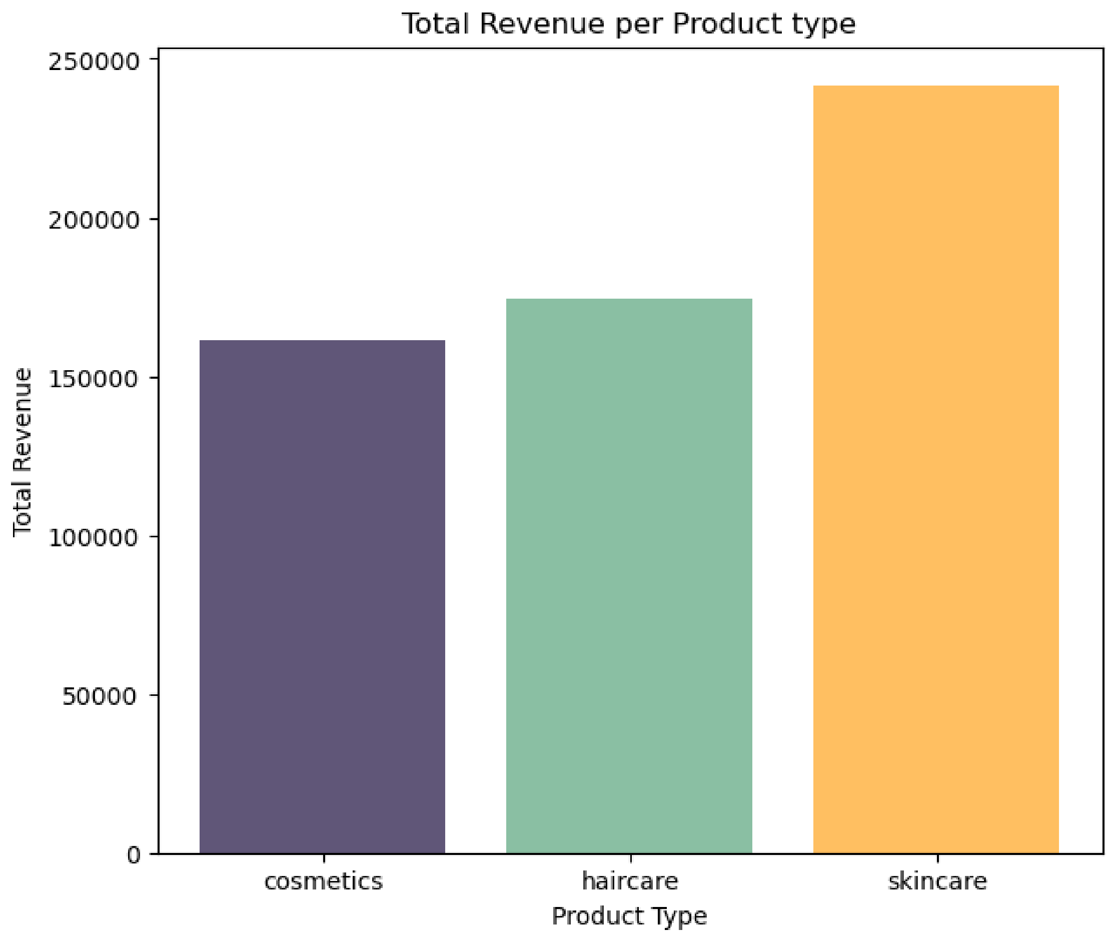
[113]:
```
plt.figure(figsize=(12, 6))
sns.boxplot(data=df, x='Location', y='Price', hue='Product type')
plt.title('Product Prices by Location and Product Type')
plt.xlabel('Location')
plt.ylabel('Price')
plt.show()
```



5.8.1 When it comes to prices, Chennai leads in all the categories.

5.9 Total Revenue by product type

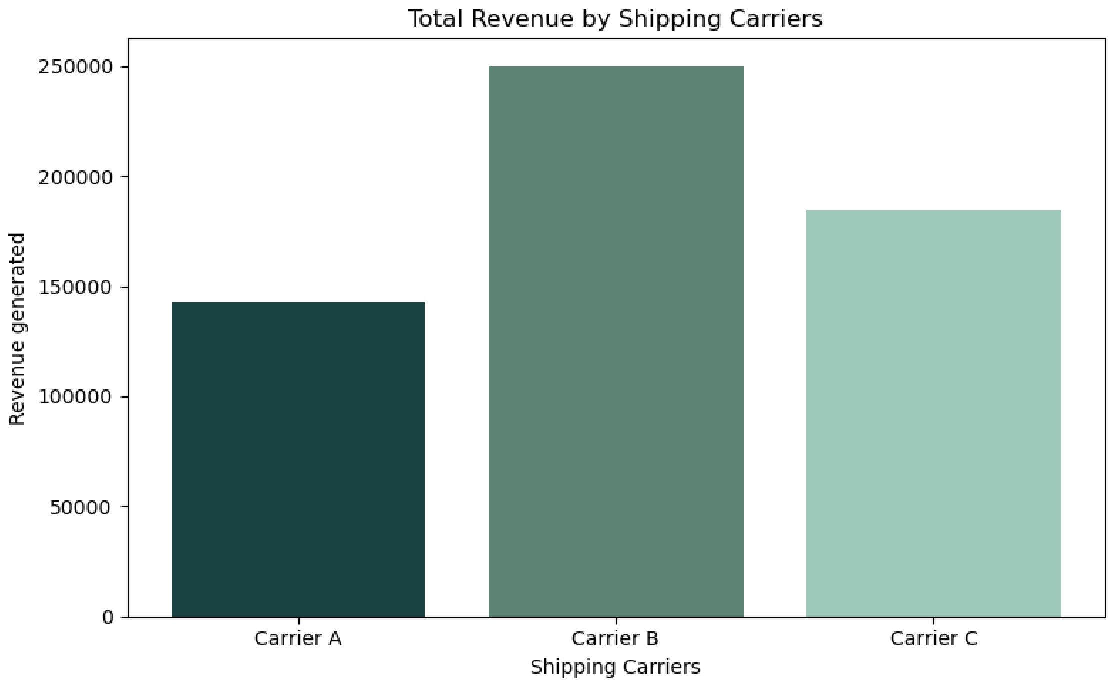
[119]:
```
colors=['#605678','#8ABFA3','#FFBF61']
revenue_per_product = df.groupby('Product type')['Revenue generated'].sum().
    ↪reset_index()
plt.figure(figsize=(7, 6))
plt.bar(revenue_per_product['Product type'], revenue_per_product['Revenue␣
    ↪generated'], color=colors)
plt.title('Total Revenue per Product type')
plt.xlabel('Product Type')
plt.ylabel('Total Revenue')
plt.show()
```



5.9.1 Skincare products generate the highest revenue.

5.10 Total Revenue by shipping carrier

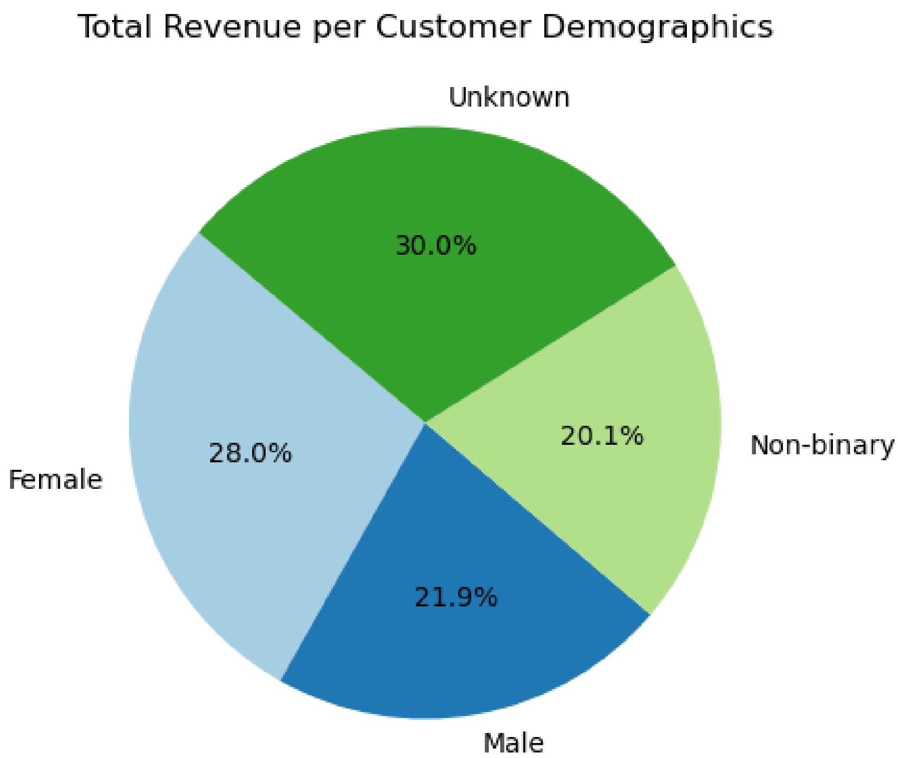
[122]:
```
colors=['#1B4242','#5C8374','#9EC8B9']
carrier_revenue=df.groupby('Shipping carriers')['Revenue generated'].sum().
 ↪reset_index()
plt.figure(figsize=(8,5))
plt.bar(carrier_revenue['Shipping carriers'],carrier_revenue['Revenue␣
 ↪generated'], color=colors)
plt.xlabel('Shipping Carriers')
plt.ylabel('Revenue generated')
plt.title('Total Revenue by Shipping Carriers')
plt.tight_layout()
plt.show()
```



5.10.1 The company use 3 Carriers for transportation and carrier B helps the company in generating more revenue.

5.11 Revenue distribution by customers demographics

[126]:
```
revenue_per_demographics = df.groupby('Customer demographics')['Revenue␣
↪generated'].sum().reset_index()
plt.figure(figsize=(5, 5))
plt.pie(revenue_per_demographics['Revenue generated'],␣
↪labels=revenue_per_demographics['Customer demographics'], autopct='%1.1f%%',␣
↪startangle=140, colors=plt.cm.Paired.colors)
plt.title('Total Revenue per Customer Demographics')
plt.show()
```



5.11.1 so 28% of total revenue comes from Femals & 21% comes from Males.

5.12 Analyzing Lead Time and Manufacturing cost

5.12.1 Average lead time and Average Manufacturing Cost for all the products

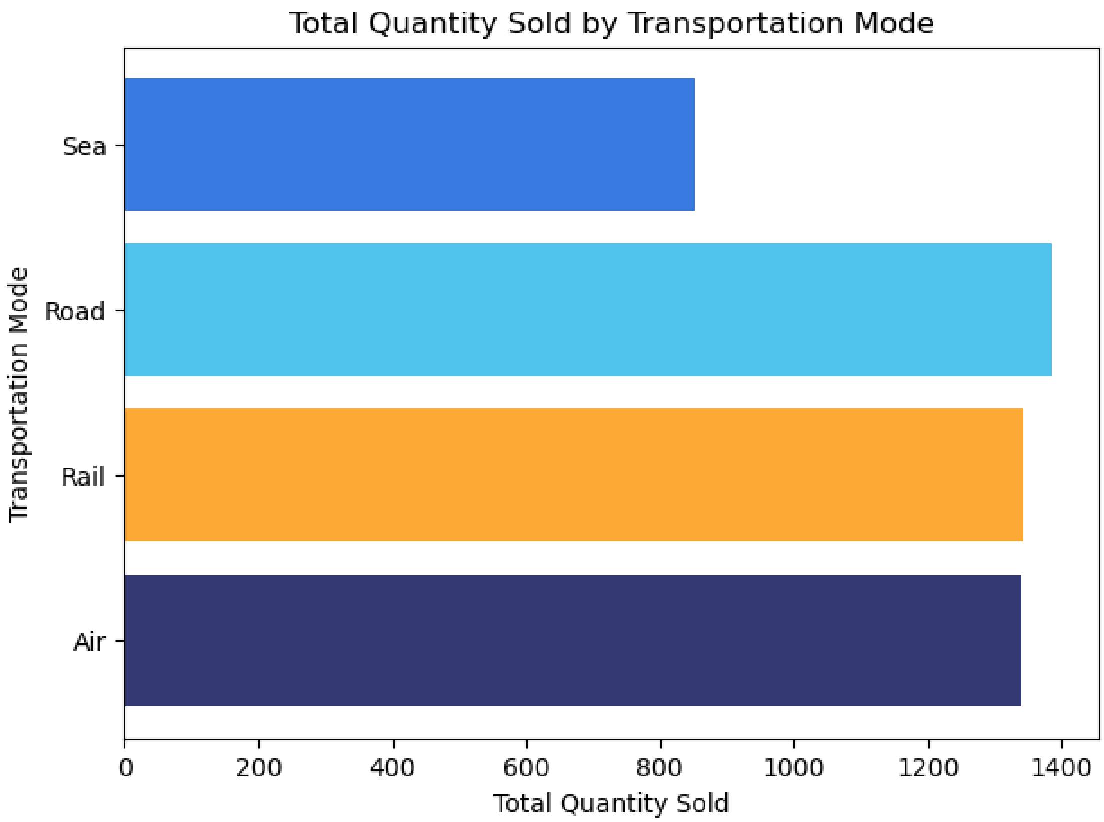
[129]:
```
av_time=df.groupby('Product type')['Lead time'].mean().reset_index()
av_manufacturecost=df.groupby('Product type')['Manufacturing costs'].mean().
 ↪reset_index()
comb=pd.merge(av_time,av_manufacturecost ,on='Product type')
comb.rename(columns={'Lead time': 'Average Lead Time', 'Manufacturing costs':␣
 ↪'Average Manufacturing Costs'}, inplace=True)
comb
```

[129]:

	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

5.13 Total Quantity Sold by Transportation Mode

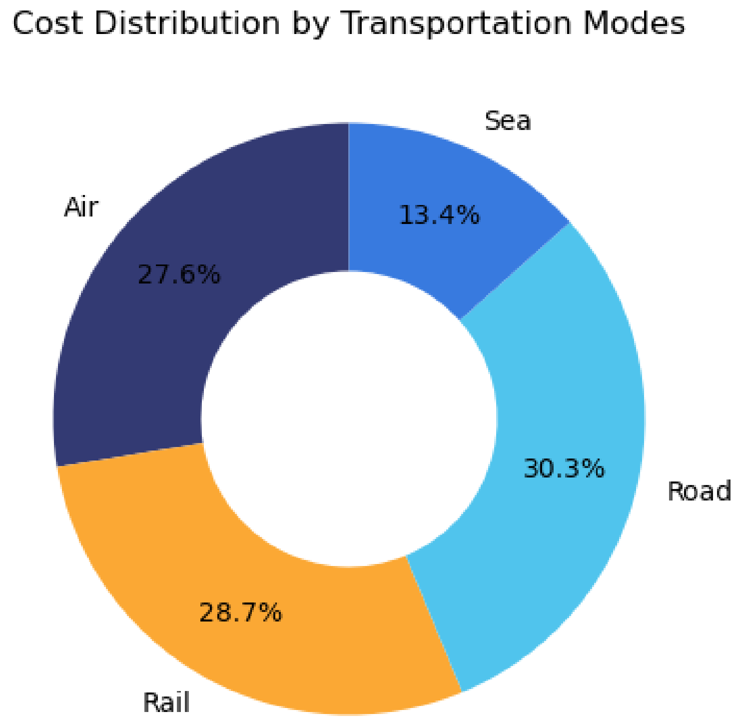
[132]:
```
colors=['#333A73','#FBA834','#50C4ED','#387ADF']
usage_per_transportation = df.groupby('Transportation modes')['Order␣
↪quantities'].sum().reset_index()
plt.figure(figsize=(7, 5))
plt.barh(usage_per_transportation['Transportation modes'],␣
↪usage_per_transportation['Order quantities'],color=colors )
plt.title('Total Quantity Sold by Transportation Mode')
plt.xlabel('Total Quantity Sold')
plt.ylabel('Transportation Mode')
plt.show()
```



5.14 Cost Distribution by Transportation Modes

[135]:
```
colors=['#333A73','#FBA834','#50C4ED','#387ADF']
Tcosts=df.groupby('Transportation modes')['Costs'].sum().reset_index()
plt.figure(figsize=(8, 5))
plt.pie(Tcosts['Costs'],labels=Tcosts['Transportation modes'],
        autopct='%1.1f%%',startangle=90 ,colors=colors ,wedgeprops=dict(width=0.
↪5),pctdistance=0.75 )
```

```
plt.title('Cost Distribution by Transportation Modes')
plt.show()
```

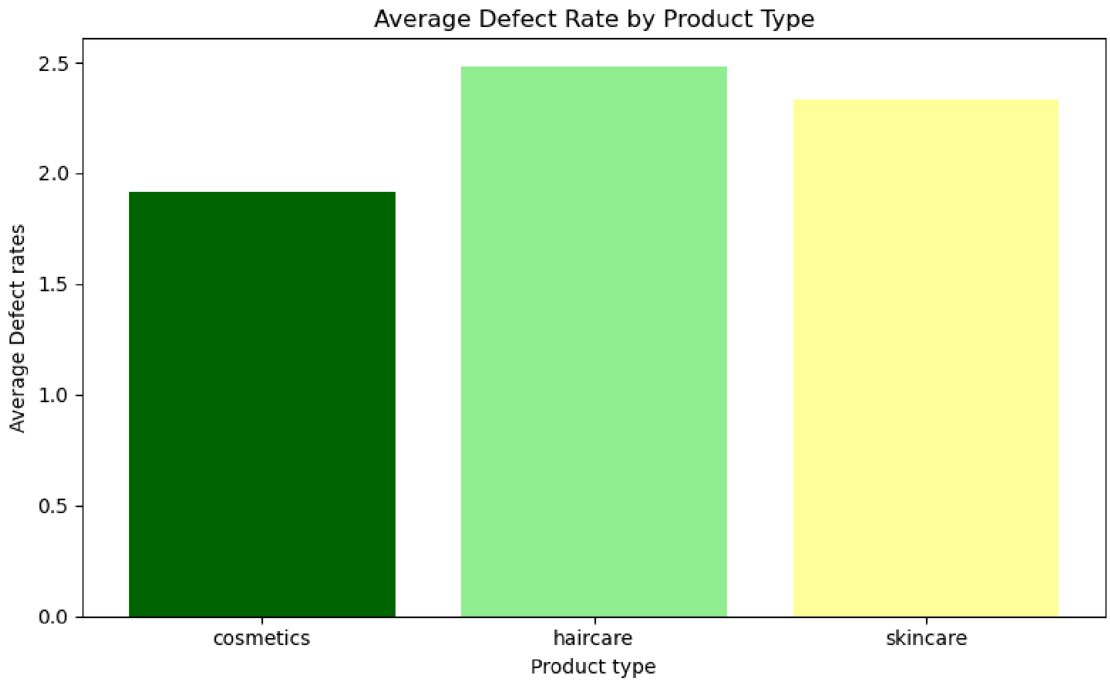


5.14.1 Road and Rail transportation methods are more expensive for the company compared to other forms of transport.

5.15 Analyzing Defect Rate

5.15.1 Average Defect Rate by Product Type

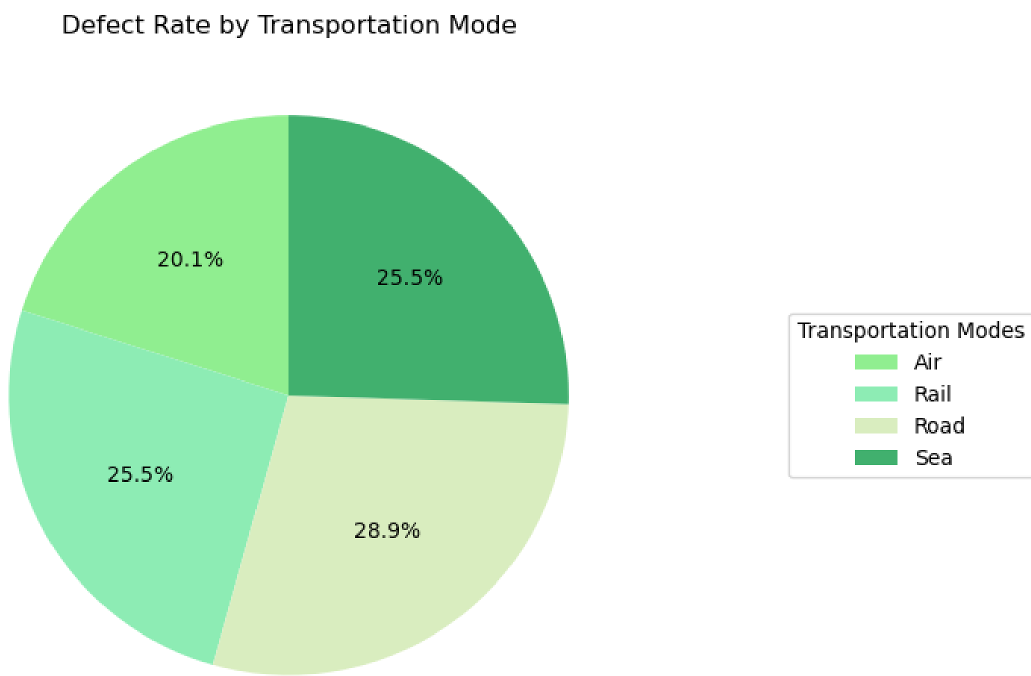
[142]:
```
colors=['#006400','#90EE90','#FFFF99']
avg_defect=df.groupby('Product type')['Defect rates'].mean().reset_index()
plt.figure(figsize=(8,5))
plt.bar(avg_defect['Product type'],avg_defect['Defect rates'], color=colors)
plt.xlabel('Product type')
plt.ylabel('Average Defect rates')
plt.title('Average Defect Rate by Product Type')
plt.tight_layout()
plt.show()
```



5.15.2 The defect rate for haircare products is the highest one.

5.15.3 Defect Rate by Transportation Mode

[147]:
```
colors=['#90EE90','#8DECB4','#D9EDBF','#41B06E']
T_defect=df.groupby('Transportation modes')['Defect rates'].mean().reset_index()
plt.figure(figsize=(8, 6))
plt.pie(T_defect['Defect rates'],
        labels=None,
        autopct='%1.1f%%',startangle=90, colors=colors,labeldistance=1.1)
plt.title('Defect Rate by Transportation Mode')
plt.legend(T_defect['Transportation modes'], title="Transportation Modes",␣
 ↪loc="center left",bbox_to_anchor=(1.2, 0.5))
plt.show()
```



5.15.4 Products delivered by road have the highest chance of being defective, while products delivered by air have the lowest rate of defects.

5.15.5 "Revenue vs. Manufacturing Scatter Plot"

[169]:
```
regr = linear_model.LinearRegression()
train_x = np.asanyarray(df[['Revenue generated']])
train_y = np.asanyarray(df[['Manufacturing costs']])
regr.fit(train_x, train_y)

print ('Coefficients: ', regr.coef_)
print ('Intercept: ',regr.intercept_)

y_pred = regr.predict(train_x)
r2 = r2_score(train_y, y_pred)

print("R-squared:", r2)

plt.scatter(df[['Revenue generated']], df[['Manufacturing costs']], ␣
↪color='blue')
plt.plot(train_x, regr.coef_[0][0]*train_x + regr.intercept_[0], '-r')
plt.xlabel('Revenue generated')
plt.ylabel("Manufacturing costs")
```

```
plt.title('Revenue vs Manufacturing Costs with Regression Line')
```

```
Coefficients:  [[-0.00226982]]
Intercept:  [60.37727428]
R-squared: 0.0458067325432433
```

[169]: Text(0.5, 1.0, 'Revenue vs Manufacturing Costs with Regression Line')

5.15.6 Based on the linear regression analysis shown in the image, the R-squared value of 0.0458 indicates that the relationship between Manufacturing and Revenue is very weak. It also showed that all the tested data gave the same result..