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

import warnings
warnings.filterwarnings('ignore')

data = pd.read_csv("supply_chain_data.csv")

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]
```

```
data.tail()
```

```
   Product type    SKU      Price  Availability  Number of products
sold  \
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
\
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  ...  Location Lead time  Production volumes  \
95                26  ...    Mumbai        18                 450
96                32  ...    Mumbai        28                 648
97                 4  ...    Mumbai        10                 535
98                27  ...   Chennai        28                 581
99                59  ...   Chennai        29                 921

   Manufacturing lead time Manufacturing costs  Inspection results  \
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
95      1.210882                   Air  Route A  778.864241
96      3.872048                  Road  Route A  188.742141
97      3.376238                  Road  Route A  540.132423
98      2.908122                  Rail  Route A  882.198864
99      0.346027                  Rail  Route B  210.743009

[5 rows x 24 columns]
```

```
data.shape
```

```
(100, 24)
```

# Data Preparation and cleaning

1.Load the file using pandas

2.Look at some infromation about the data & the columns

3.Fix any missing or incorrect values

```
data.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')
```

```
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

data.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
```

# Checking Missing and Duplicate values

```
data.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
```

```
#Checking Duplicate Values
len(data[data.duplicated()])
```

```
0
```

```
#unique values for each column
data.nunique()
```

```
Product type                  3
SKU                         100
Price                       100
Availability                 63
Number of products sold      96
Revenue generated           100
Customer demographics         4
Stock levels                 65
Lead times                   29
Order quantities             61
Shipping times               10
Shipping carriers             3
Shipping costs              100
Supplier name                 5
Location                      5
Lead time                    29
Production volumes           96
Manufacturing lead time      30
Manufacturing costs         100
Inspection results            3
Defect rates                100
Transportation modes          4
Routes                        3
Costs                       100
dtype: int64
```

# Data Visualisation

## Sales Analysis

1.Analyze number of products sold and revenue generated to understand sales performance over time.

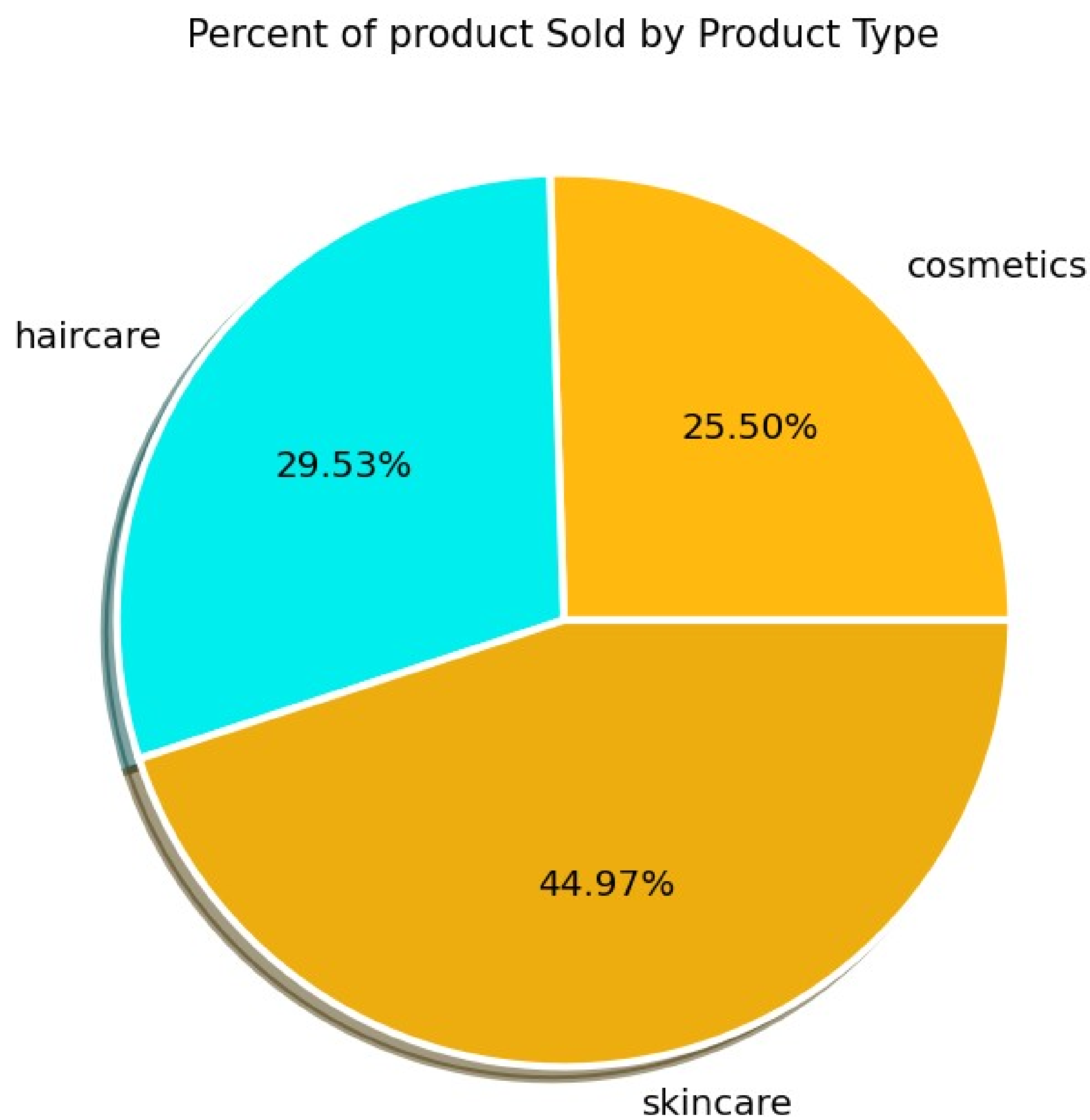
2.Identify customer demographics to determine which groups are purchasing the most products.

3.Track availability and stock levels to ensure the right products are in stock when customers are ready to buy.

```
# Aggregate number of products sold and revenue by product type
product_sold = data.groupby('Product type')[['Number of products sold', 'Revenue generated']].sum().reset_index()

# Round revenue to 2 decimal places
product_sold['Revenue generated'] = product_sold['Revenue generated'].round(2)

# Display the result
print(product_sold)
```

```
  Product type  Number of products sold  Revenue generated
0    cosmetics                    11757          161521.27
1     haircare                    13611          174455.39
2     skincare                    20731          241628.16
```

```
plt.figure(figsize = (12,8))
colors = ['#FFB90F', '#00EEEE', '#EEAD0E']
pie_chart = plt.pie(product_sold['Number of products sold'], labels = product_sold['Product type'], autopct = '%.2f%%',wedgeprops={'linewidth': 3.0, 'edgecolor': 'white'},
       textprops={'size': 'x-large'}, shadow =True, colors = colors)
plt.title('Percent of product Sold by Product Type', fontsize= 15)
plt.show()
```




So, the highest number of products sold of the three product categories is skincare, which means 45% of business comes from skincare, 29% from haircare, and 25% from cosmetics.

And most of the revenue comes from skincare products, followed by haircare, and then cosmetics products.

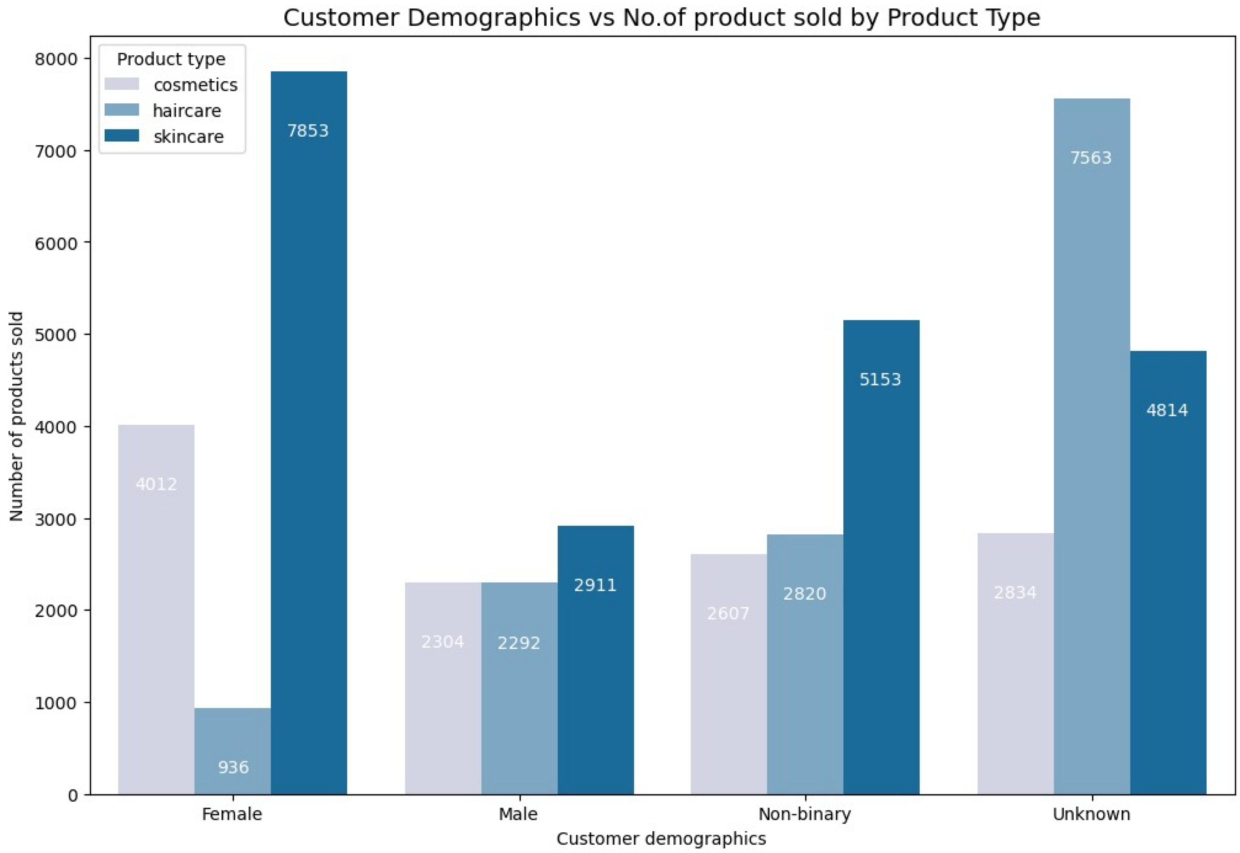
```
data['Customer demographics'].unique()
```

```
array(['Non-binary', 'Female', 'Unknown', 'Male'], dtype=object)
```

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

demographics
```

| | Customer demographics | Product type | Number of products sold |
|---|---|---|---|
| 0 | Female | cosmetics | 4012 |
| 1 | Female | haircare | 936 |
| 2 | Female | skincare | 7853 |
| 3 | Male | cosmetics | 2304 |
| 4 | Male | haircare | 2292 |
| 5 | Male | skincare | 2911 |
| 6 | Non-binary | cosmetics | 2607 |
| 7 | Non-binary | haircare | 2820 |
| 8 | Non-binary | skincare | 5153 |
| 9 | Unknown | cosmetics | 2834 |
| 10 | Unknown | haircare | 7563 |
| 11 | Unknown | skincare | 4814 |

```
plt.figure(figsize = (12,8))
p = sns.barplot(x = demographics['Customer demographics'], y =
demographics['Number of products sold'], hue = demographics['Product
type'], palette = 'PuBu')
for container in p.containers:
    p.bar_label(container,padding=-40, color='white', fontsize=10)
plt.title("Customer Demographics vs No.of product sold by Product
Type", fontsize = (14))
plt.show()
```



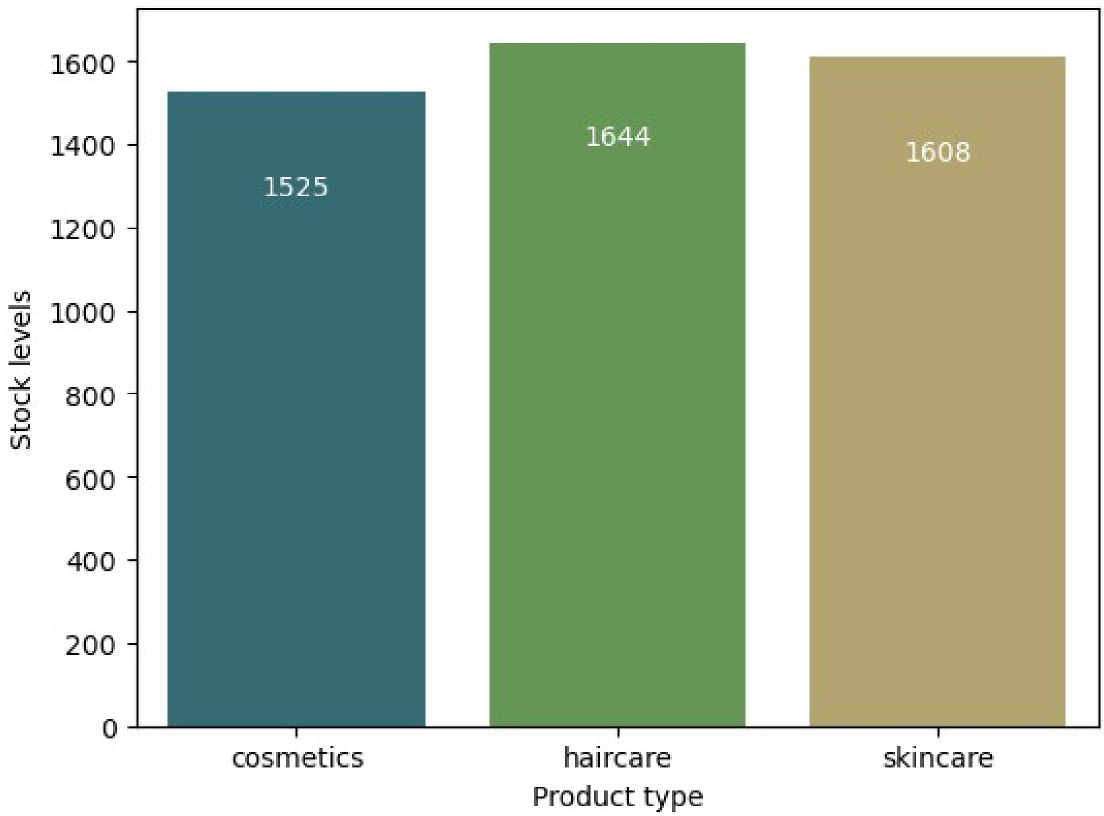

According to the graph, the female group purchases higher-quality skincare and cosmetic products, whereas the male group purchases products of about equal quality in terms of haircare and cosmetics. And an unknown group category purchases a higher quantity of all three products.

Skin care products are the most popular among all four product categories. Skincare products have a higher demand.

```
# Aggregate stock levels and availability by product type
stock = data.groupby('Product type')[['Stock levels',
'Availability']].sum().reset_index()

# Display the result
print(stock)
```

```
  Product type  Stock levels  Availability
0    cosmetics          1525          1332
1     haircare          1644          1471
2     skincare          1608          2037
```

```
p = sns.barplot(x ='Product type', y =('Stock levels') , data = stock,
palette = 'gist_earth')
for container in p.containers:
    p.bar_label(container,padding=-40, color='white', fontsize=10)
```




In the graph, green represents the availability and brown represents the stock levels.

So according to the graph, the company holds an equal quantity of inventory of haircare and skincare products and a bit less stock of cosmetic product.

So, skincare products had a higher availability and lower stock level, which means we can quickly manufacture and ship products as needed. On the other hand, cosmetics and haircare have a higher stock level and lower availability, which means the company cannot quickly ship product to the customer because,It took time to manufacture the product.

```
data.head(5)
```

```
  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]
```

# Operations Analysis

1.Analyze lead times, order quantities, and production volumes to optimize inventory management and reduce stockouts.

2.Track manufacturing lead time and costs to identify areas for improvement and cost savings.

3.Monitor inspection results and defect rates to identify quality issues and improve manufacturing processes.

```
data.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')
```

```
# Aggregate mean of Lead time, Order quantities, and Production
volumes by Product type
product = data.groupby('Product type')[['Lead time', 'Order
quantities', 'Production volumes']].mean().reset_index()

# Round the values to 2 decimal places
product['Order quantities'] = product['Order quantities'].round(2)
product['Lead time'] = product['Lead time'].round(2)
product['Production volumes'] = product['Production volumes'].round(2)

# Display the result
print(product)
```

```
  Product type  Lead time  Order quantities  Production volumes
0    cosmetics      13.54             51.65              479.27
1     haircare      18.71             43.53              586.97
2     skincare      18.00             52.48              609.15
```

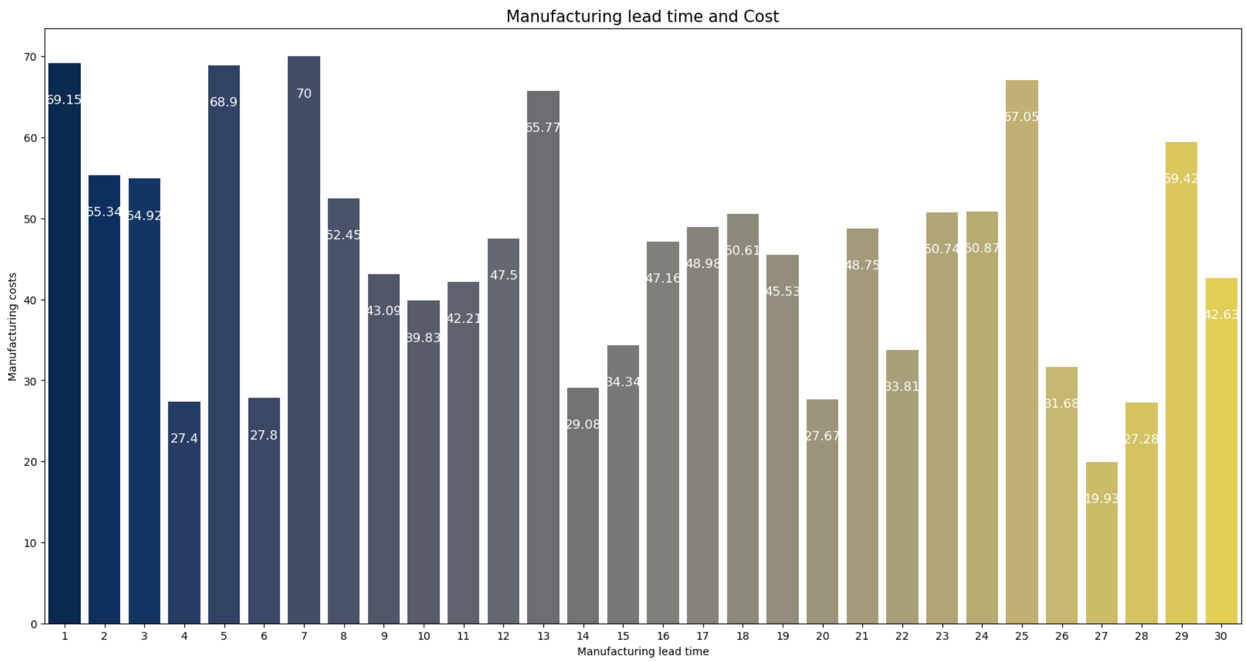
Skincare products have higher order quantities and a longer lead time. Furthermore, it has a higher production volume (production volume means the amount of products that are produced by the company), which means higher production volumes may require longer lead times to ensure that there is enough time to manufacture the products and meet customer demand.

Haircare products have a longer lead time and higher production volumes. This may be because haircare products require more specialised ingredients or manufacturing processes.

```
avg_costs = data.groupby(['Manufacturing lead time'])['Manufacturing costs'].mean().reset_index().sort_values(by = 'Manufacturing costs')
avg_costs['Manufacturing costs'] = avg_costs['Manufacturing costs'].round(2)

avg_costs
```

| | Manufacturing lead time | Manufacturing costs |
|---|---|---|
| 26 | 27 | 19.93 |
| 27 | 28 | 27.28 |
| 3 | 4 | 27.40 |
| 19 | 20 | 27.67 |
| 5 | 6 | 27.80 |
| 13 | 14 | 29.08 |
| 25 | 26 | 31.68 |
| 21 | 22 | 33.81 |
| 14 | 15 | 34.34 |
| 9 | 10 | 39.83 |
| 10 | 11 | 42.21 |
| 29 | 30 | 42.63 |
| 8 | 9 | 43.09 |
| 18 | 19 | 45.53 |
| 15 | 16 | 47.16 |
| 11 | 12 | 47.50 |
| 20 | 21 | 48.75 |
| 16 | 17 | 48.98 |
| 17 | 18 | 50.61 |
| 22 | 23 | 50.74 |
| 23 | 24 | 50.87 |
| 7 | 8 | 52.45 |
| 2 | 3 | 54.92 |
| 1 | 2 | 55.34 |
| 28 | 29 | 59.42 |
| 12 | 13 | 65.77 |
| 24 | 25 | 67.05 |
| 4 | 5 | 68.90 |
| 0 | 1 | 69.15 |
| 6 | 7 | 70.00 |

```
plt.figure(figsize = (20,10))
p = sns.barplot(x= avg_costs['Manufacturing lead time'], y =
avg_costs['Manufacturing costs'], palette = 'cividis')
for container in p.containers:
    p.bar_label(container,padding=-40, color='white', fontsize=12)

plt.title('Manufacturing lead time and Cost', fontsize = (15))
plt.show()
```




```
rate = data.groupby(['Product type', 'Inspection results'])['Defect
rates'].mean().reset_index()
rate['Defect rates'] = rate['Defect rates'].round(2)

rate
```

| | Product type | Inspection results | Defect rates |
|---|---|---|---|
| 0 | cosmetics | Fail | 2.19 |
| 1 | cosmetics | Pass | 1.82 |
| 2 | cosmetics | Pending | 1.71 |
| 3 | haircare | Fail | 2.53 |
| 4 | haircare | Pass | 2.92 |
| 5 | haircare | Pending | 2.27 |
| 6 | skincare | Fail | 2.90 |
| 7 | skincare | Pass | 1.68 |
| 8 | skincare | Pending | 2.33 |

```
data['Defect rates'].mean()

2.27715799273961
```

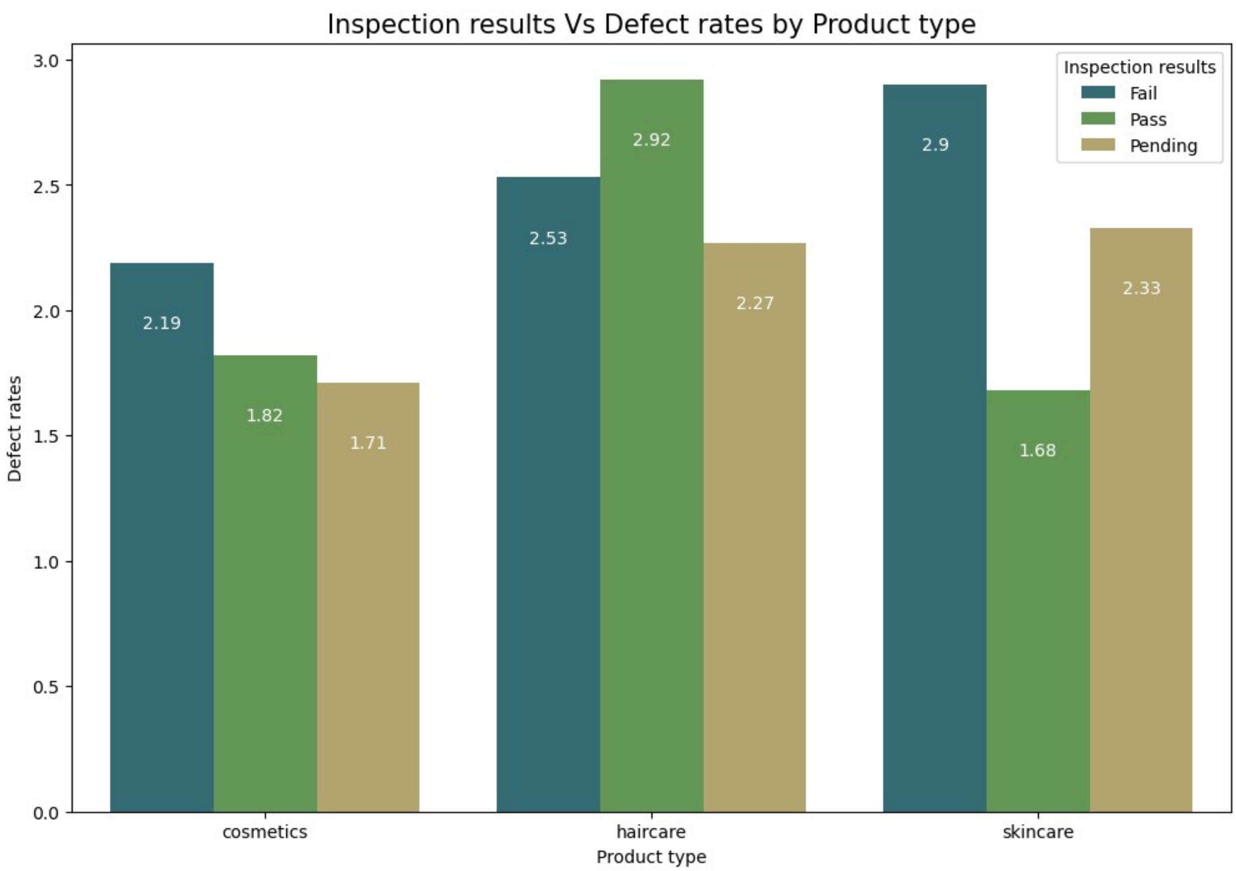
```
data['Defect rates'].max()
```

```
4.939255288620948
```

```
data['Defect rates'].min()
```

```
0.0186075676310149
```

```
plt.figure(figsize = (12,8))
p = sns.barplot(x = rate['Product type'], y = rate['Defect rates'],
hue = rate['Inspection results'], palette = 'gist_earth')
for container in p.containers:
    p.bar_label(container,padding=-40, color='white', fontsize=10)

plt.title("Inspection results Vs Defect rates by Product type",
fontsize = (15))
plt.show()
```



# Shipping Analysis

1.Analyze costs, transportation modes, and routes to optimize logistics and reduce shipping costs.

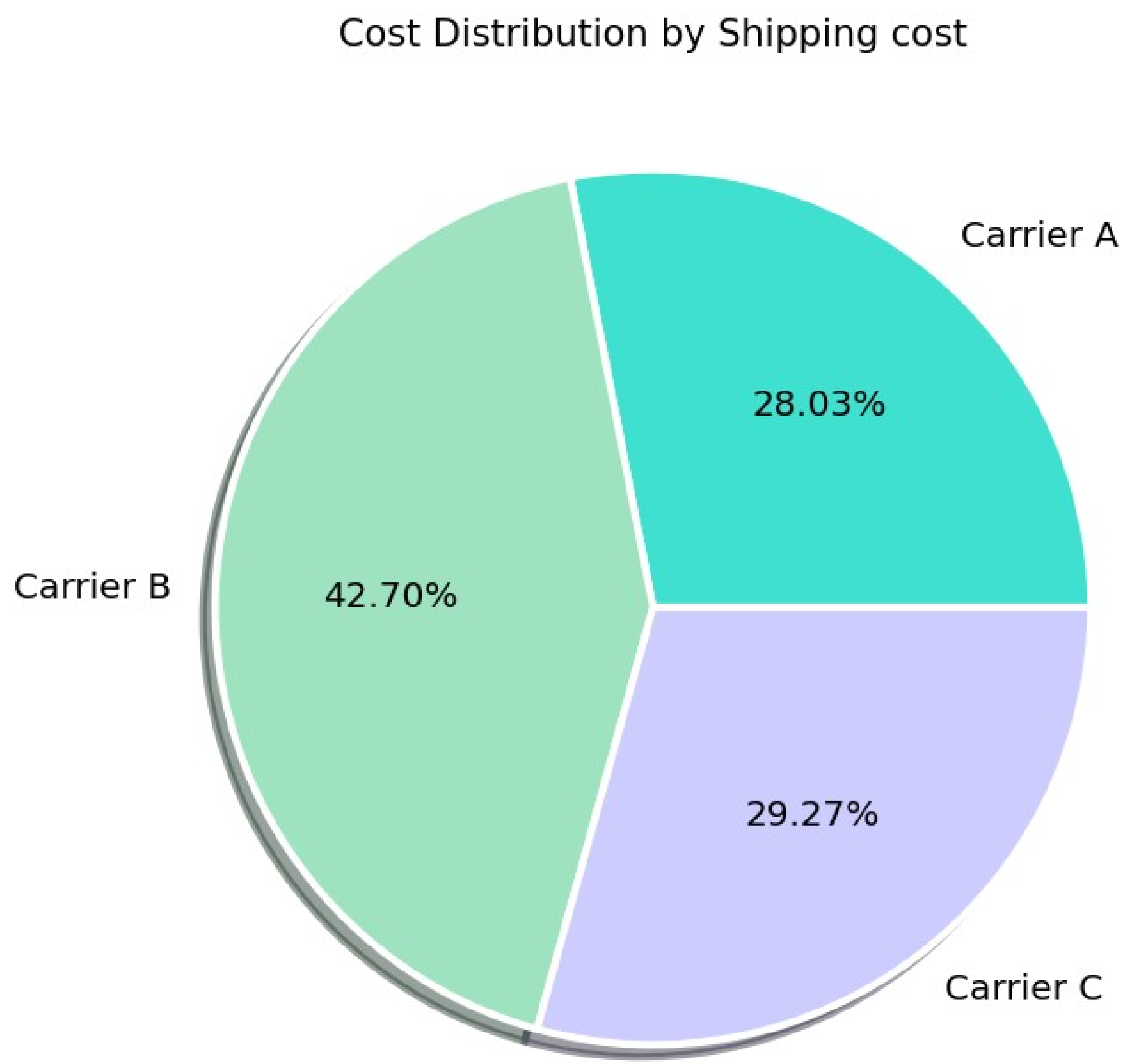
2.Monitor shipping times, shipping carriers, modes of transportation to ensure timely delivery to customers.

3.Track shipping costs associated with shipping carriers and revenue generated to identify areas for cost savings

```
shipping = data.groupby(['Shipping carriers'])['Shipping
costs'].sum().reset_index()

shipping
```

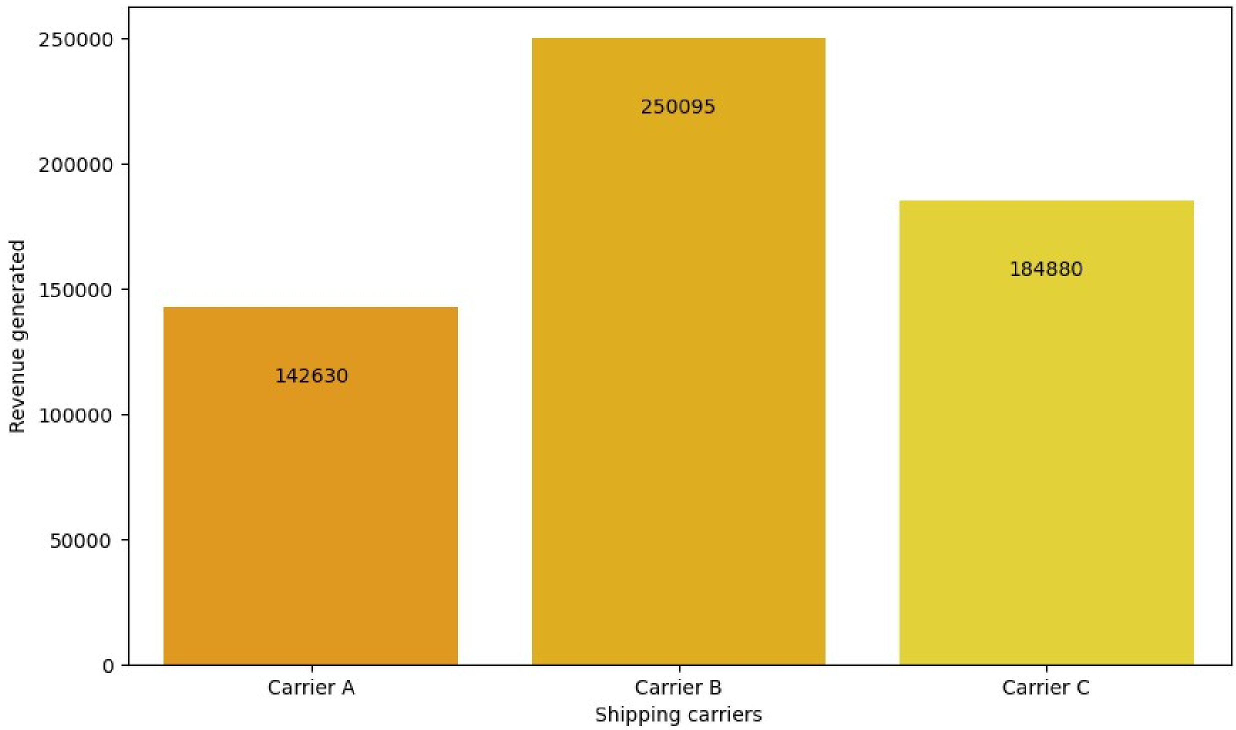
| | Shipping carriers | Shipping costs |
|---|---|---|
| 0 | Carrier A | 155.537831 |
| 1 | Carrier B | 236.897620 |
| 2 | Carrier C | 162.379457 |

```
plt.figure(figsize = (12,8))
colors = ['#40E0D0', '#9FE2BF','#CCCCFF']
plt.pie( shipping['Shipping costs'], labels = shipping['Shipping
carriers'],autopct = '%.2f%%', wedgeprops={'linewidth': 3.0,
'edgecolor': 'white'},
       textprops={'size': 'x-large'}, shadow =True, colors = colors)
plt.title('Cost Distribution by Shipping cost', fontsize = (15))
plt.show()
```




```
carrier_revenue = data.groupby(['Shipping carriers'])['Revenue
generated'].sum().reset_index()
carrier_revenue['Revenue generated'] = carrier_revenue['Revenue
generated'].round(2)

carrier_revenue

  Shipping carriers  Revenue generated
0         Carrier A          142629.99
1         Carrier B          250094.65
2         Carrier C          184880.18

plt.figure(figsize = (10,6))
p = sns.barplot(x = carrier_revenue['Shipping carriers'], y =
```

```
carrier_revenue['Revenue generated'], palette = 'Wistia_r')
for container in p.containers:
    p.bar_label(container,padding=-40, color='black', fontsize=10)

plt.show()
```

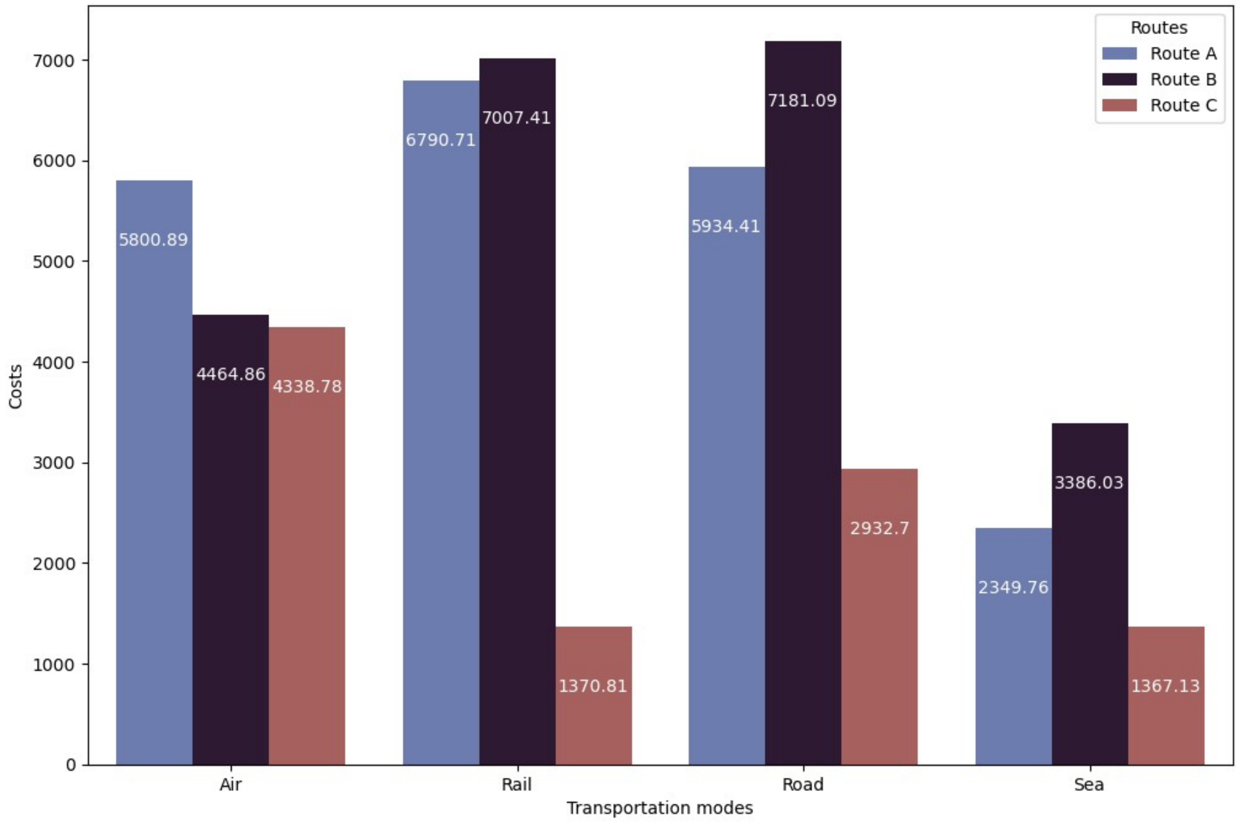



Both the graphs clearly show shipping carrier B is costly as well as generating higher revenue.

```
transport = data.groupby(['Transportation modes', 'Routes'])
['Costs'].sum().reset_index()

transport
```

| | Transportation modes | Routes | Costs |
|---|---|---|---|
| 0 | Air | Route A | 5800.887460 |
| 1 | Air | Route B | 4464.858025 |
| 2 | Air | Route C | 4338.782012 |
| 3 | Rail | Route A | 6790.710511 |
| 4 | Rail | Route B | 7007.410741 |
| 5 | Rail | Route C | 1370.810306 |
| 6 | Road | Route A | 5934.412107 |
| 7 | Road | Route B | 7181.085147 |
| 8 | Road | Route C | 2932.696386 |
| 9 | Sea | Route A | 2349.764416 |
| 10 | Sea | Route B | 3386.030113 |
| 11 | Sea | Route C | 1367.130992 |

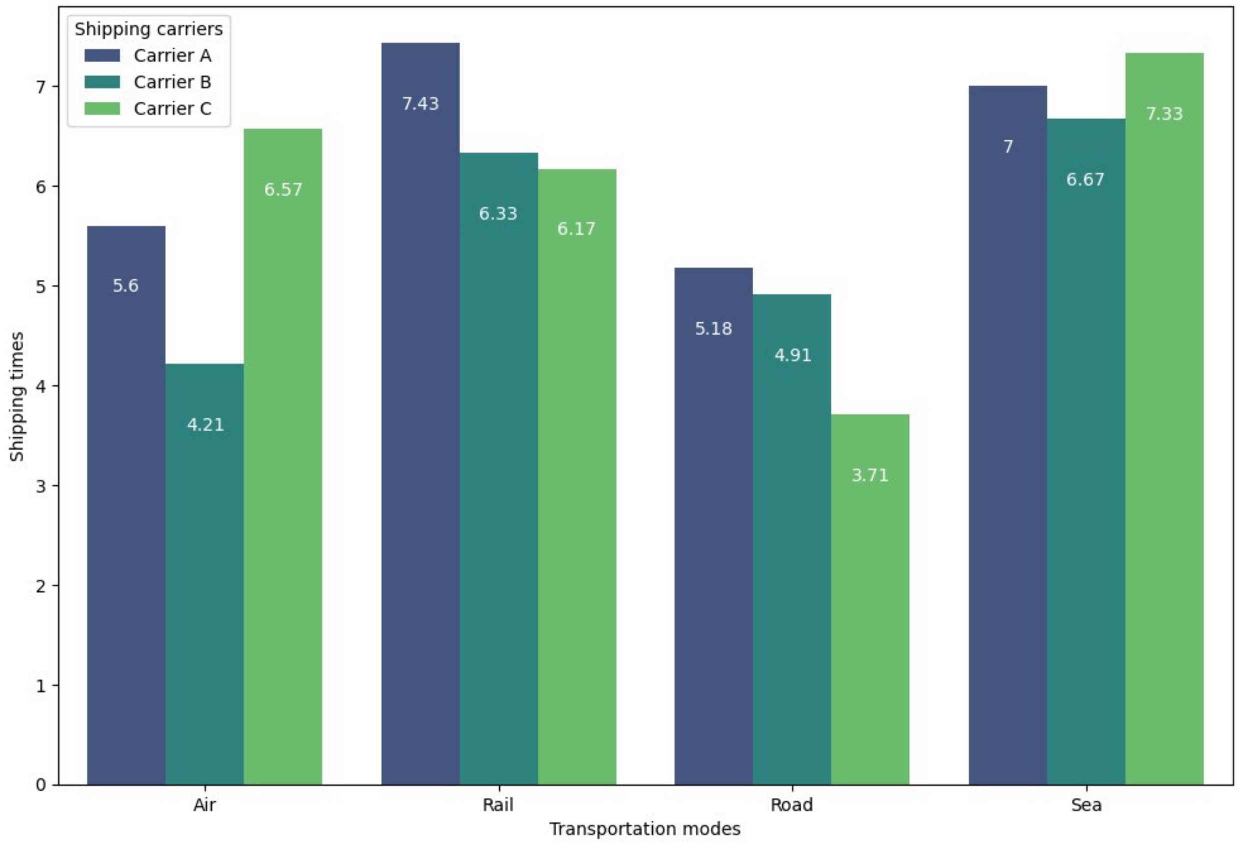
```python
plt.figure(figsize = (12,8))
p = sns.barplot(x = transport['Transportation modes'], y =
transport['Costs'], hue = transport['Routes'], palette = 'twilight')
for container in p.containers:
    p.bar_label(container,padding=-40, color='white', fontsize=10)
plt.show()
```




```python
shipping = data.groupby(['Shipping carriers', 'Transportation modes'])
['Shipping times'].mean().reset_index()
shipping['Shipping times'] = shipping['Shipping times'].round(2)
shipping
```

| | Shipping carriers | Transportation modes | Shipping times |
|---|---|---|---|
| 0 | Carrier A | Air | 5.60 |
| 1 | Carrier A | Rail | 7.43 |
| 2 | Carrier A | Road | 5.18 |
| 3 | Carrier A | Sea | 7.00 |
| 4 | Carrier B | Air | 4.21 |
| 5 | Carrier B | Rail | 6.33 |
| 6 | Carrier B | Road | 4.91 |
| 7 | Carrier B | Sea | 6.67 |
| 8 | Carrier C | Air | 6.57 |
| 9 | Carrier C | Rail | 6.17 |

```
10          Carrier C                          Road              3.71
11          Carrier C                           Sea              7.33

plt.figure(figsize = (12,8))
p = sns.barplot(x = shipping['Transportation modes'], y =
shipping['Shipping times'], hue = shipping['Shipping carriers'],
palette = 'viridis')
for container in p.containers:
    p.bar_label(container,padding=-40, color='white', fontsize=10)
plt.show()
```




According to the graph, the fastest and most efficient shipping option is Carrier B in all four transportation modes.