

Graduation Project for DEPi

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# Project Overview

### **OBJECTIE**

Analyze a supply chain dataset to uncover insights and visualize key findings

## **PROCESS OVERVIEW**

Data Cleaning and Preprocessing using Python

Analyzing data to answer key business questions

Visualizing insights with Tableau

## **TOOLS USED**

Python (Pandas, Matplotlib), Tableau

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt # for visualization
import plotly.express as px
import seaborn as sns
from scipy.stats import chi2_contingency
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor, GradientBoo
from statsmodels.tsa.arima.model import ARIMA
from sklearn.neural_network import MLPRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_e
from sklearn.preprocessing import OneHotEncoder
pd.set_option('display.max_columns', None)
```

```
# Read CSV file into DataFrame
df = pd.read_csv("./supply_chain_data.csv")
```

df.head()

	Product type	SKU	Price	Availability	Number of products sold	Revenue generated	Customer demographics
0	haircare	SKU0	69.808006	55	802	8661.996792	Non-binary
1	skincare	SKU1	14.843523	95	736	7460.900065	Female
2	haircare	SKU2	11.319683	34	8	9577.749626	Unknown
3	skincare	SKU3	61.163343	68	83	7766.836426	Non-binary
4	skincare	SKU4	4.805496	26	871	2686.505152	Non-binary

<class 'pandas.core.frame.dataframe'=""></class>									
RangeIndex: 100 entries, 0 to 99									
Data	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							
1.0	(2) (54/5) (1.54/5)	1.1 (0)							

RangeIndex: 100 entries, 0 to 99								
Data columns (total 24 columns):								
#	Column	Non-Null Count	Dtype					
0	Product type	100 non-null	category					
1	SKU	100 non-null	category					
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	category					
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	category					
12	Shipping costs	100 non-null	float64					
13	Supplier name	100 non-null	category					
14	Location	100 non-null	category					
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	category					
20	Defect rates	100 non-null	float64					
21	Transportation modes	100 non-null	category					
22	Routes	100 non-null	category					
23	Costs	100 non-null	float64					
dtypes: category(9), float64(6), int64(9)								

## - Check for duplicates

### Check for duplicate data

```
if df.duplicated().any():
    print(f"There are as many as {df.duplicated().sum()} duplicate data.")
else:
    print("There are no duplicate data.")
There are no duplicate data.
```

## - Check for negative values

### Check for negative values

df.describe()

# from min row no negative

	Price	Availability	Number of products sold	Revenue generated	Stock levels	Lead times	Order quantities	Shipping times	
count	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	1
mean	49.462461	48.400000	460.990000	5776.048187	47.770000	15.960000	49.220000	5.750000	
std	31.168193	30.743317	303.780074	2732.841744	31.369372	8.785801	26.784429	2.724283	
min	1.699976	1.000000	8.000000	1061.618523	0.000000	1.000000	1.000000	1.000000	
25%	19.597823	22.750000	184.250000	2812.847151	16.750000	8.000000	26.000000	3.750000	
50%	51.239831	43.500000	392.500000	6006.352023	47.500000	17.000000	52.000000	6.000000	
75%	77.198228	75.000000	704.250000	8253.976921	73.000000	24.000000	71.250000	8.000000	
max	99.171329	100.000000	996.000000	9866.465458	100.000000	30.000000	96.000000	10.000000	

## - Detect Outlier

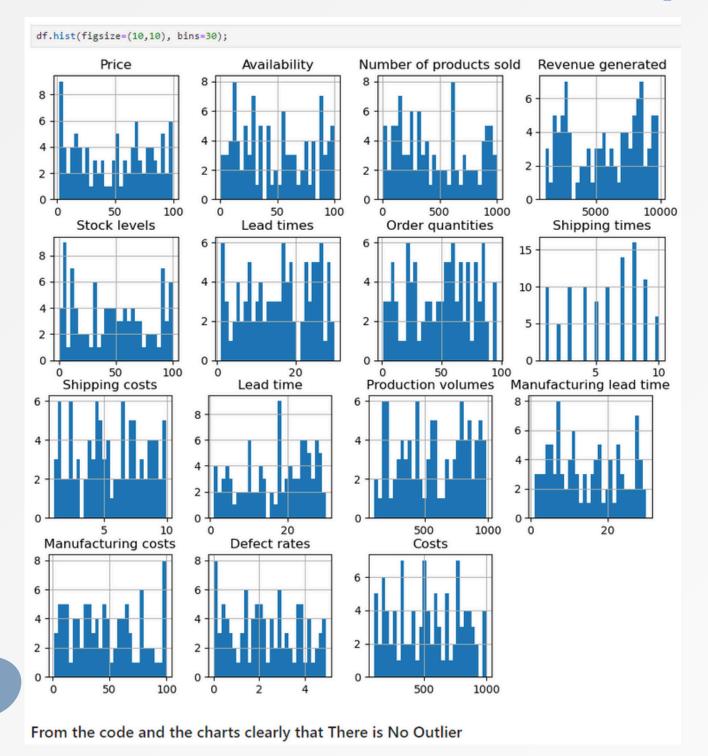
```
#Outlier detection
flag=0
for column in df.columns:
    if df[column].dtype=="int64" or df[column].dtype =="float64":
        max_value = df[column].max()
        Q1 = df[column].quantile(0.25)
        Q3 = df[column].quantile(0.75)
        IQR = Q3 - Q1
        outlier_threshold = Q3 + 1.5 * IQR
        if max_value > outlier_threshold :
            print(f"{column} has an outlier: {max_value}")
            flag=1

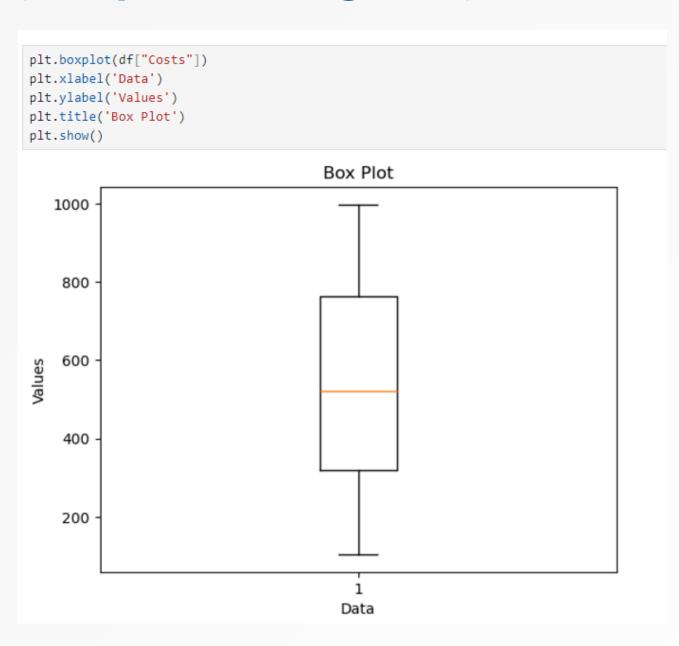
if flag==0:
        print("There is No Outlier")
```

There is No Outlier

```
plt.boxplot(df["Costs"])
plt.xlabel('Data')
plt.ylabel('Values')
plt.title('Box Plot')
plt.show()
                                       Box Plot
   1000
    800
    200
                                         Data
```

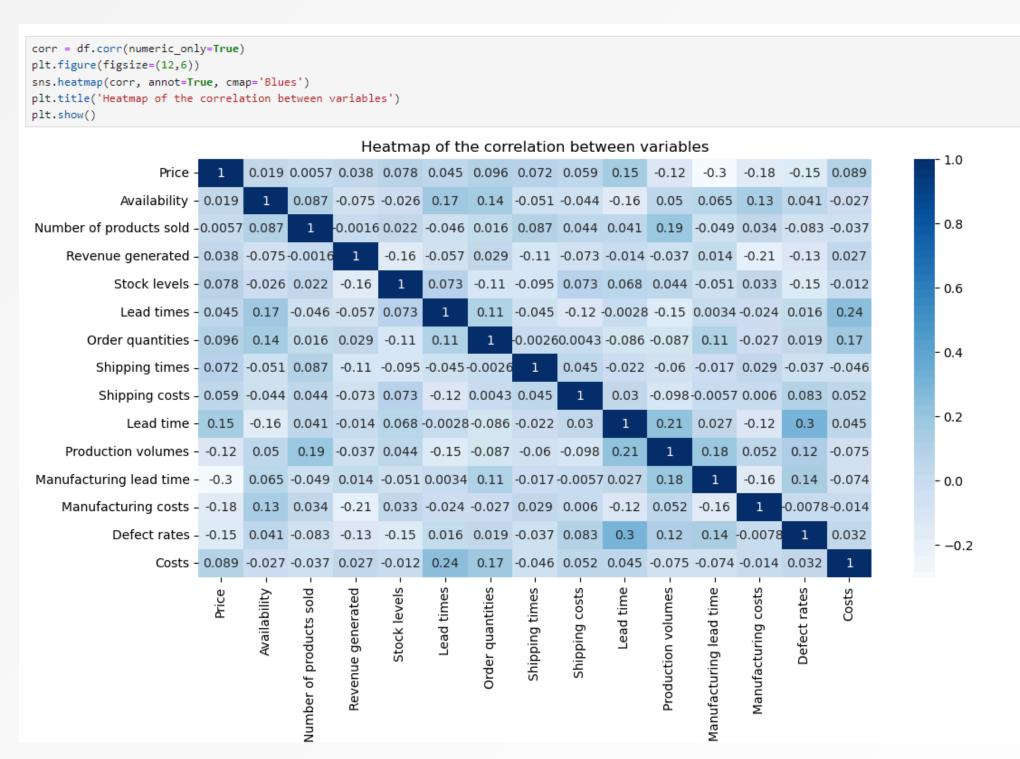
- Conduct Univariate Analysis (box plot & histograms)





## - Check Correlation

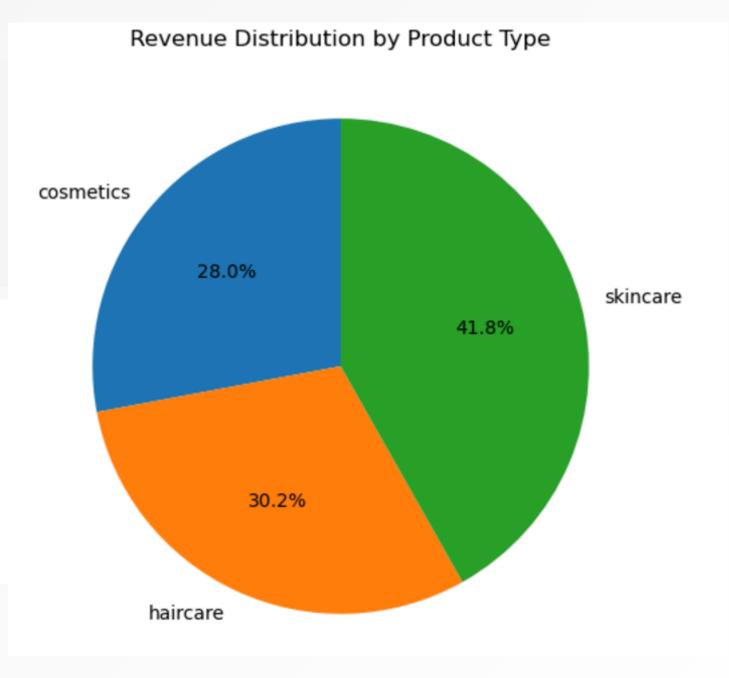
There is no Correlation except
 - a week one between Defect
 rates and Lead time
 - a week negative one between
 Price and Manufacturing costs



## 1- What is the impact of Product Category on Revenue?

```
data = df.groupby('Product type', observed=True) ['Revenue generated'].sum()
#create the pie chart
plt.figure(figsize = (6, 6))
plt.pie(data, labels=data.index,autopct='%1.1f%%', startangle=90)
plt.title('Revenue Distribution by Product Type')
plt.show()
```

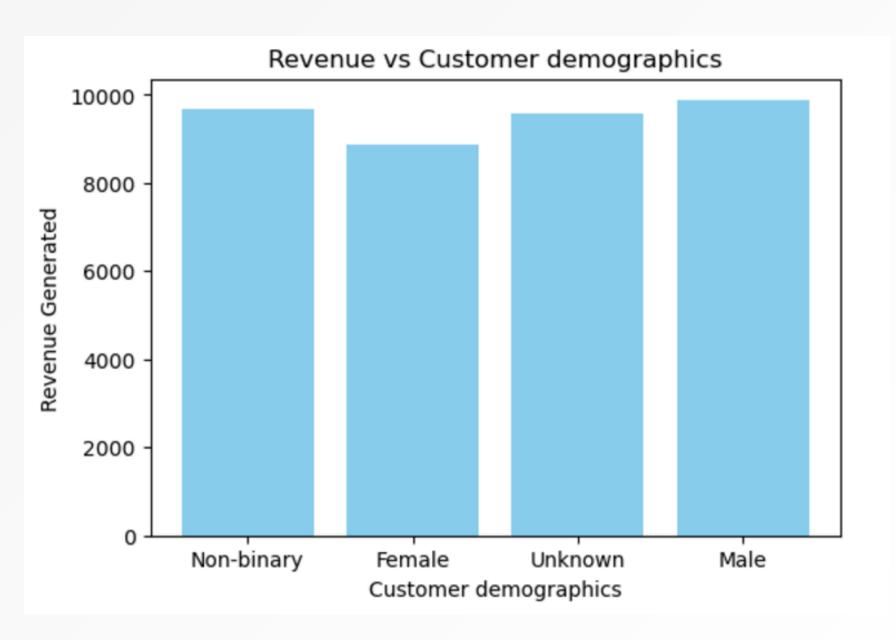




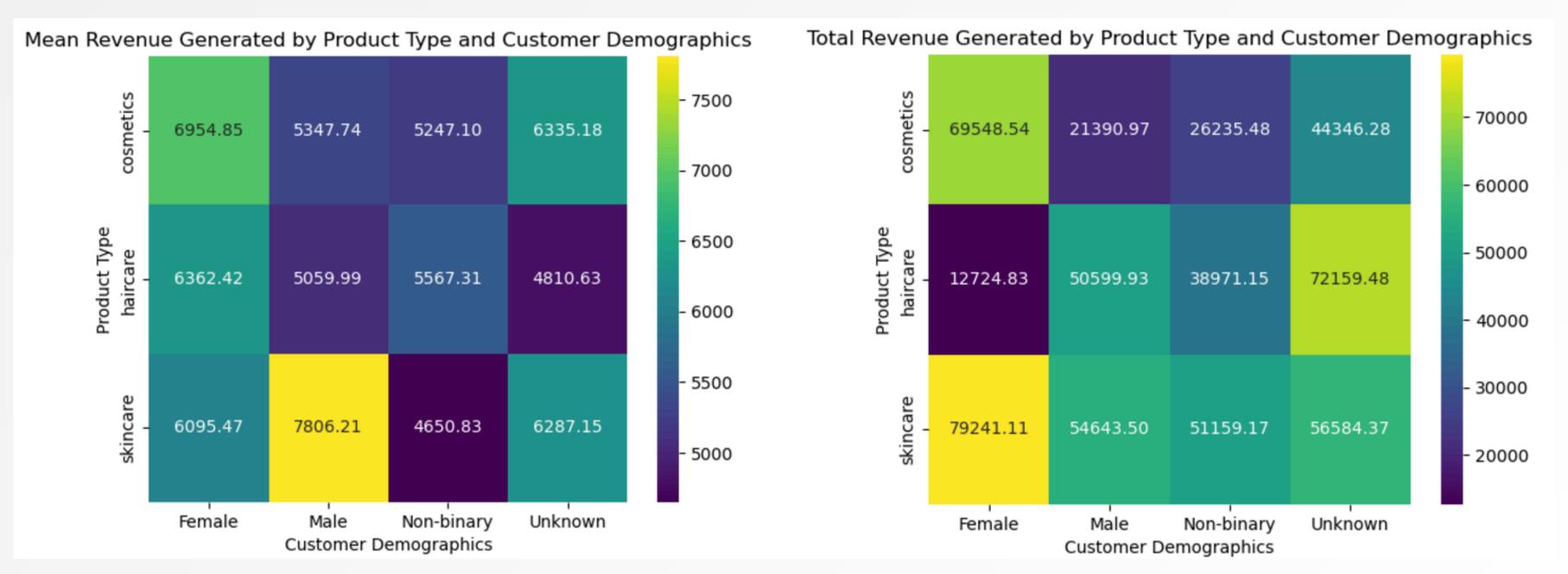


## 2- How do customers demographics influence purchasing behaviour?

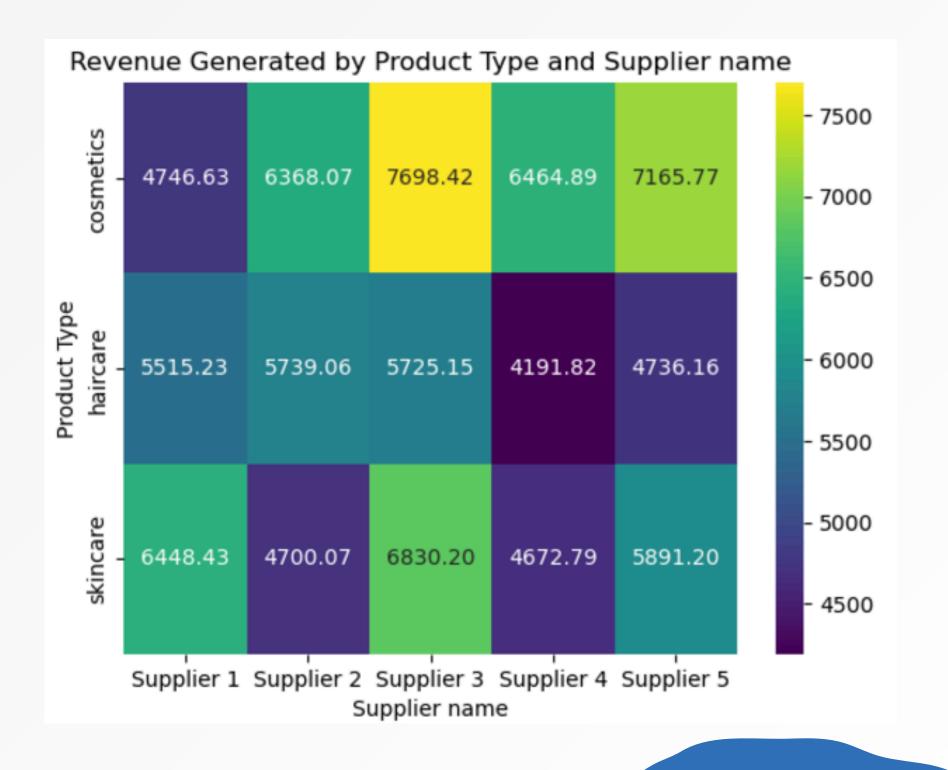
```
plt.figure(figsize=(6, 4)) # Set the size of the chart
plt.bar(df['Customer demographics'], df['Revenue generated'], color='skyblue')
# Add LabeLs and title
plt.xlabel('Customer demographics') # X-axis LabeL
plt.ylabel('Revenue Generated') # Y-axis LabeL
plt.title('Revenue vs Customer demographics') # Title
# Display the chart
plt.show()
```



3- How do customers demographics influence purchasing behavior of different Product types?



4- How do Supplier influence purchasing behavior of different Product types?



## 5- What is the Impact of Transportation modes on Manufacturing lead time?

```
revenue_by_product = df.groupby('Transportation modes', observed=True)['Manufacturing lead time'].sum().reset_index()

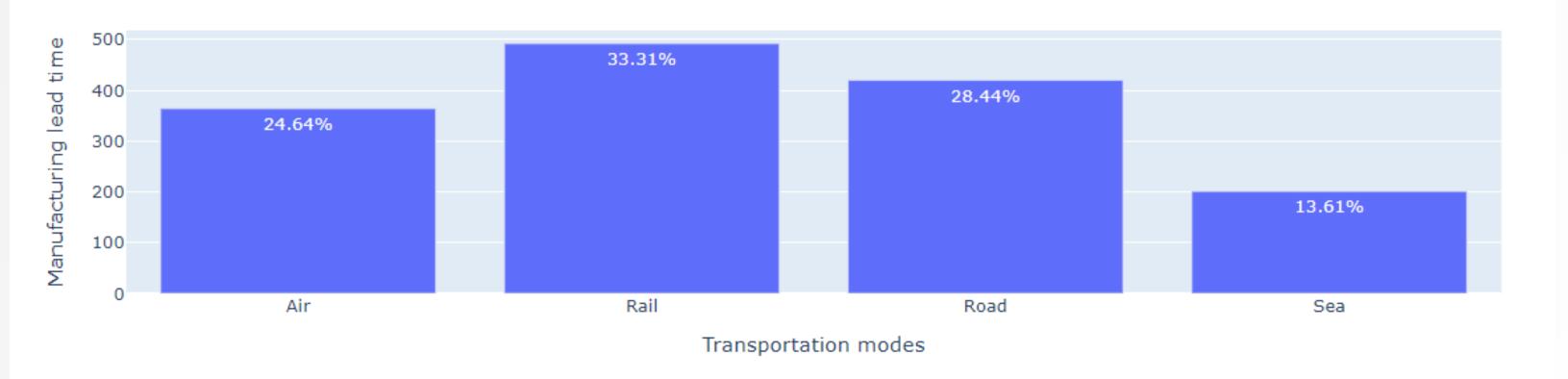
# Calculate the total revenue

total_revenue = revenue_by_product['Manufacturing lead time'].sum()

# Calculate the percentage of total revenue for each product type

revenue_by_product['Percent of Total'] = ((revenue_by_product['Manufacturing lead time'] / total_revenue) * 100).round(2).astype(str) + '%'

fig = px.bar(revenue_by_product, x='Transportation modes', y='Manufacturing lead time', title='Impact of Transportation modes on Manufacturing lead time'
fig.update_xaxes(title_text='Transportation modes') # Update x-axis label
fig.update_yaxes(title_text='Manufacturing lead time') # Update y-axis label
fig.show()
```



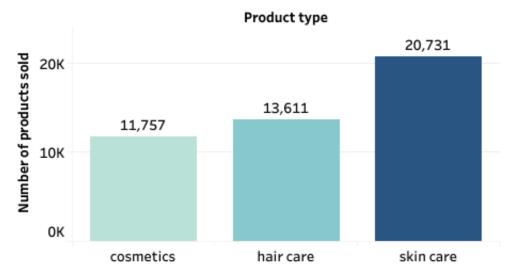


## Tableau Dashboard

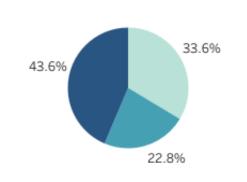
#### Important Numbers

Revenue generated	Number of products sold	Availability	Shipping costs
577,605	46,099	4,840	555

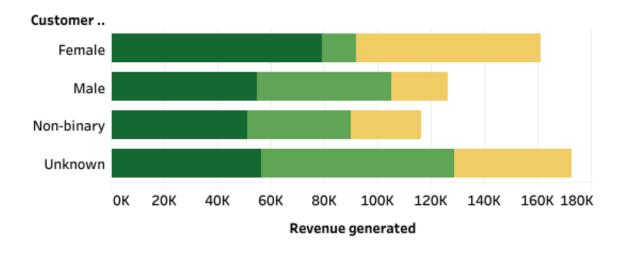
#### Number of products sold by category



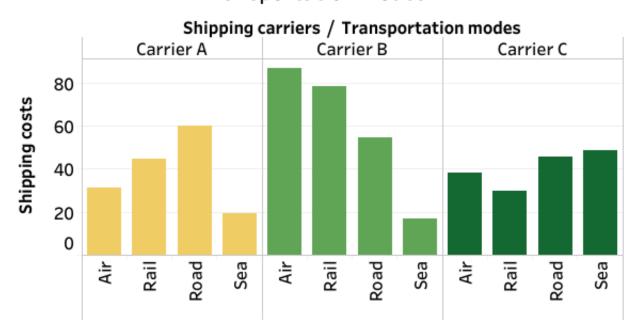
### Shipping cost by Inspection result



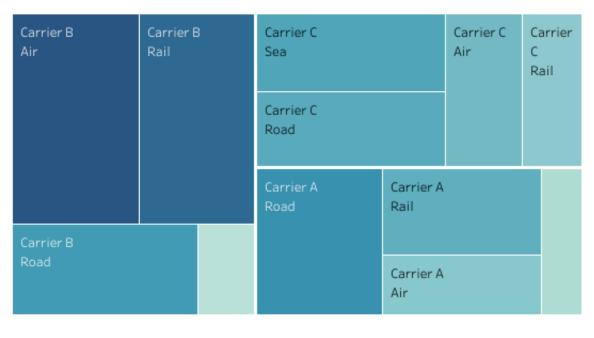
### Revenue generated by customer demography



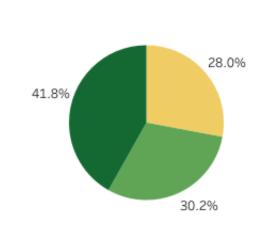
### Transportation modes







#### Revenue generated by category



#### Product type cosmetics hair care

skin care

Revenue generated 577,605

#### Shipping costs



Shipping costs 554.8

#### Product type

- ✓ cosmetics
- ✓ hair care
- ✓ skin care

#### Customer demographics

- ✓ Female
- ✓ Male
- ✓ Non-binary ✓ Unknown



