Supply Chain Optimization Project

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https://www.kaggle.com/code/gelarerouzbahani/data-analysis-supply-chain-optimization (https://www.kaggle.com/code/gelarerouzbahani/data-analysis-supply-chain-optimization)

Pre-Processing Data

Importing all required libraries

In [2]:
```
pip install scipy
```

```
Requirement already satisfied: scipy in e:\anaconda\lib\site-packages (1.11.1)
Requirement already satisfied: numpy<1.28.0,>=1.21.6 in e:\anaconda\lib\site-packages (from scipy) (1.24.3)
Note: you may need to restart the kernel to use updated packages.
```

In [3]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.api as sm
import datetime as dt
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis,QuadraticDiscriminantAnalysis
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn import preprocessing
from sklearn import model_selection
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import roc_auc_score,r2_score,mean_absolute_error,mean_squared_error,accuracy_score,classification_report,
from sklearn.model_selection import train_test_split,cross_val_score, cross_val_predict
from sklearn import svm,metrics,tree,preprocessing,linear_model
from sklearn.preprocessing import MinMaxScaler,StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LinearRegression,LogisticRegression
from sklearn.ensemble import RandomForestRegressor,RandomForestClassifier, GradientBoostingRegressor
from sklearn.metrics import accuracy_score,mean_squared_error,recall_score,confusion_matrix,f1_score,roc_curve, auc
from plotly.offline import iplot, init_notebook_mode
import pickle
import warnings
warnings.filterwarnings("ignore")
import datetime as dt
from datetime import datetime
import plotly.express as px
import ortools.constraint_solver
from ortools.constraint_solver import routing_enums_pb2
from ortools.constraint_solver import pywrapcp
from scipy.optimize import linprog
from pylab import rcParams
import scipy
from scipy.stats.stats import pearsonr
import seaborn as sb
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import preprocessing
from sklearn import utils
from sklearn.metrics import top_k_accuracy_score
from sklearn.metrics import classification_report
```

In [4]:
```
MPSCData=pd.read_csv("supply_chain_data.csv")
```

Descriptive Part

In [5]:
```
MPSCData.shape  #Checking the Lengths of the array dimensions
```

Out[5]: (100, 24)

In [6]:
```
1 MPSCData.dtypes  #Checking the number of variables and their type
```

Out[6]:
```
Product type               object
SKU                        object
Price                     float64
Availability                int64
Number of products sold     int64
Revenue generated         float64
Customer demographics      object
Stock levels                int64
Lead times                  int64
Order quantities            int64
Shipping times              int64
Shipping carriers          object
Shipping costs            float64
Supplier name              object
Location                   object
Lead time                   int64
Production volumes          int64
Manufacturing lead time     int64
Manufacturing costs       float64
Inspection results         object
Defect rates              float64
Transportation modes       object
Routes                     object
Costs                     float64
dtype: object
```

Column Descriptions

1. **Product type**: The category or classification of the product, which helps in segmenting and analyzing different product lines.
2. **SKU (Stock Keeping Unit)**: A unique identifier for each product, crucial for inventory management, tracking, and forecasting.
3. **Price**: The selling price of the product, which can be used in pricing strategies and revenue analysis.
4. **Availability**:the percentage of stock available, with values from 1 to 100. For example, a value of 100 means the product is fully stocked, while a value of 50 means only half of the stock is available. This helps in quickly assessing the stock status in relative terms.
5. **Number of products sold**: The total units sold, useful for sales trend analysis and demand forecasting.
6. **Revenue generated**: The total income from sales, calculated as the product of the number of units sold and the price, important for financial performance analysis.
7. **Customer demographics**: Data about the customers, such as age, gender, location, and purchasing behavior, which can be used for targeted marketing and customer segmentation.
8. **Stock levels**: The current inventory count, critical for inventory management and avoiding stockouts or overstock situations.
9. **Lead times**: The time taken from placing an order to receiving it, important for supply chain efficiency and planning.
10. **Order quantities**: The number of units ordered, which helps in understanding purchasing patterns and optimizing order sizes.
11. **Shipping times**: The duration it takes for products to reach customers, impacting customer satisfaction and logistics planning.
12. **Shipping carriers**: The logistics companies responsible for transportation, which can affect shipping costs and delivery reliability.
13. **Shipping costs**: The expenses associated with shipping, important for cost management and pricing strategies.
14. **Supplier name**: The name of the supplier, useful for supplier relationship management and performance evaluation.
15. **Location**: The geographical location of suppliers or warehouses, which can impact lead times and shipping costs.
16. **Lead time**: The time required to procure or manufacture the product, crucial for production planning and inventory management.
17. **Production volumes**: The quantity of products produced, which helps in capacity planning and efficiency analysis.
18. **Manufacturing lead time**: The time taken to produce the product, important for production scheduling and meeting demand.
19. **Manufacturing costs**: The expenses involved in production, including materials, labor, and overhead, essential for cost control and pricing.
20. **Inspection results**: The outcomes of quality checks, which help in maintaining product quality and reducing defect rates.
21. **Defect rates**: The percentage of products that fail quality standards, important for quality control and process improvement.
22. **Transportation modes**: The methods used for transporting products, such as air, sea, or road, which can affect costs and delivery times.
23. **Routes**: The paths taken by transportation carriers, which can impact delivery efficiency and costs.
24. **Costs**: The overall expenses associated with producing, shipping, and delivering products, crucial for profitability analysis and cost optimization.

In [7]:
```
1 MPSCData.head(10)  #Checking the top 10 rows in the dataset
```

Out[7]:

	Product type	SKU	Price	Availability	Number of products sold	Revenue generated	Customer demographics	Stock levels	Lead times	Order quantities	...	Location	Lead time	Production volumes	Manufacturing lead time	Manuf
0	haircare	SKU0	69.808006	55	802	8661.996792	Non-binary	58	7	96	...	Mumbai	29	215	29	4
1	skincare	SKU1	14.843523	95	736	7460.900065	Female	53	30	37	...	Mumbai	23	517	30	3
2	haircare	SKU2	11.319683	34	8	9577.749626	Unknown	1	10	88	...	Mumbai	12	971	27	3
3	skincare	SKU3	61.163343	68	83	7766.836426	Non-binary	23	13	59	...	Kolkata	24	937	18	3
4	skincare	SKU4	4.805496	26	871	2686.505152	Non-binary	5	3	56	...	Delhi	5	414	3	9
5	haircare	SKU5	1.699976	87	147	2828.348746	Non-binary	90	27	66	...	Bangalore	10	104	17	5
6	skincare	SKU6	4.078333	48	65	7823.476560	Male	11	15	58	...	Kolkata	14	314	24	
7	cosmetics	SKU7	42.958384	59	426	8496.103813	Female	93	17	11	...	Bangalore	22	564	1	9
8	cosmetics	SKU8	68.717597	78	150	7517.363211	Female	5	10	15	...	Mumbai	13	769	8	1
9	skincare	SKU9	64.015733	35	980	4971.145988	Unknown	14	27	83	...	Chennai	29	963	23	4

10 rows × 24 columns

In [8]:
```
1 MPSCData.info()  #Checking the type of column structure
```

```
<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
```

In [9]:
```
1 MPSCData.describe()  # Returning statistical description of the data in the Dataset
```

Out[9]:

	Price	Availability	Number of products sold	Revenue generated	Stock levels	Lead times	Order quantities	Shipping times	Shipping costs	Lead time	Production volumes	Manufacturing lead time	Manu
count	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.000000	100.00000	1
mean	49.462461	48.400000	460.990000	5776.048187	47.770000	15.960000	49.220000	5.750000	5.548149	17.080000	567.840000	14.77000	
std	31.168193	30.743317	303.780074	2732.841744	31.369372	8.785801	26.784429	2.724283	2.651376	8.846251	263.046861	8.91243	
min	1.699976	1.000000	8.000000	1061.618523	0.000000	1.000000	1.000000	1.000000	1.013487	1.000000	104.000000	1.00000	
25%	19.597823	22.750000	184.250000	2812.847151	16.750000	8.000000	26.000000	3.750000	3.540248	10.000000	352.000000	7.00000	
50%	51.239831	43.500000	392.500000	6006.352023	47.500000	17.000000	52.000000	6.000000	5.320534	18.000000	568.500000	14.00000	
75%	77.198228	75.000000	704.250000	8253.976921	73.000000	24.000000	71.250000	8.000000	7.601695	25.000000	797.000000	23.00000	
max	99.171329	100.000000	996.000000	9866.465458	100.000000	30.000000	96.000000	10.000000	9.929816	30.000000	985.000000	30.00000	

A brief explanation of the values in the table above:

Since the target variables are "Stock levels" and "Route Costs", their descriptive statistics indicators are significant. 1)The average of the "Stock level" is 47.77, with a minimum of 0, and a maximum of 100.0. This variable has a very wide Range, so its values are more dispersed. As the Second Quantile (Q2) is the Median, the median value is 47.50, which is almost the same as the mean, so the data are normally distributed (symmetric).

Also, the minimum stock level is an alarm for the company that is facing shortage of inventory for that SKU.

2)The average of the "Route Costs" is 529.25, with a minimum of 103.92, and a maximum of 997.41. This variable has a very wide Range. As the Second Quantile (Q2) is the Median, the median value is 520.43, almost equal to the mean, so the data are normally distributed (symmetric).

Data Cleaning

Missing Values

In [10]:
```
1 np.sum(MPSCData.isna()) #Checking the number of missing values for each variable
```

Out[10]:
```
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
```

As can be seen, there are no missing values in this dataset.

Duplicate Values

In [11]:
```
1 MPSCData.duplicated().sum()
```

Out[11]:
```
0
```

This dataset also has no duplicate values.

Cleaning

In [12]:
```
1 MPSCData.columns = [col.lower().replace(' ', '_') for col in MPSCData.columns]
2 MPSCData.rename(columns=lambda x: x.replace("(", "").replace(")", ""), inplace=True)
```

In [13]:
```
1 MPSCData.columns
```

Out[13]:
```
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')
```

Correlation Matrix

In the business world, knowing the relationship between two variables is very valuable for data-driven decision-making. In this case, the "correlation coefficient" can be used to calculate the relationship between two quantitative variables.

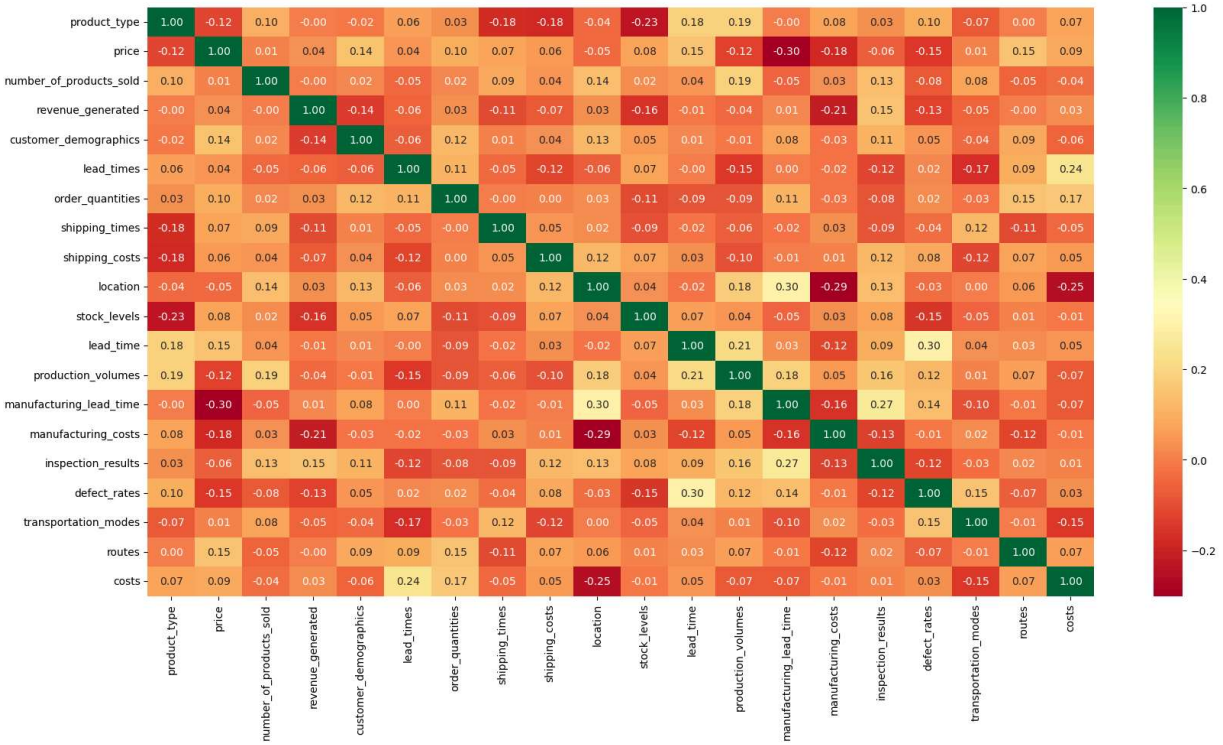
To examine the relationship between the product type, customer demographics, shipping carriers, location, transportation modes, inspection results, routes, and the two target variables of inventory level and transport cost, we must first convert these object characteristics into the "int" type using the following library and code:

In [14]:
```
1 MP_SC = MPSCData.copy()
```

In [15]:
```
le = preprocessing.LabelEncoder()# create the Labelencoder object
MP_SC['product_type']= le.fit_transform(MP_SC['product_type'])#convert the categorical columns into numeric
MP_SC['customer_demographics']= le.fit_transform(MP_SC['customer_demographics'])
MP_SC['shipping_carriers']= le.fit_transform(MP_SC['shipping_carriers'])
MP_SC['location']= le.fit_transform(MP_SC['location'])
MP_SC['sku']= le.fit_transform(MP_SC['sku'])
MP_SC['inspection_results']= le.fit_transform(MP_SC['inspection_results'])
MP_SC['transportation_modes']= le.fit_transform(MP_SC['transportation_modes'])
MP_SC['routes']= le.fit_transform(MP_SC['routes'])
MP_SC['supplier_name']= le.fit_transform(MP_SC['supplier_name'])
```

In [16]:
```
SC_features=MP_SC[['product_type','price',
       'number_of_products_sold', 'revenue_generated', 'customer_demographics', 'lead_times', 'order_quantities', 'shipping_tim
        'shipping_costs', 'location', 'stock_levels',
       'lead_time', 'production_volumes', 'manufacturing_lead_time',
       'manufacturing_costs', 'inspection_results', 'defect_rates',
       'transportation_modes', 'routes', 'costs']]
fig = plt.figure(figsize=(20,10))
sns.heatmap(SC_features.corr(), annot = True, fmt = '.2f', cmap = "RdYlGn")
```

Out[16]: <Axes: >

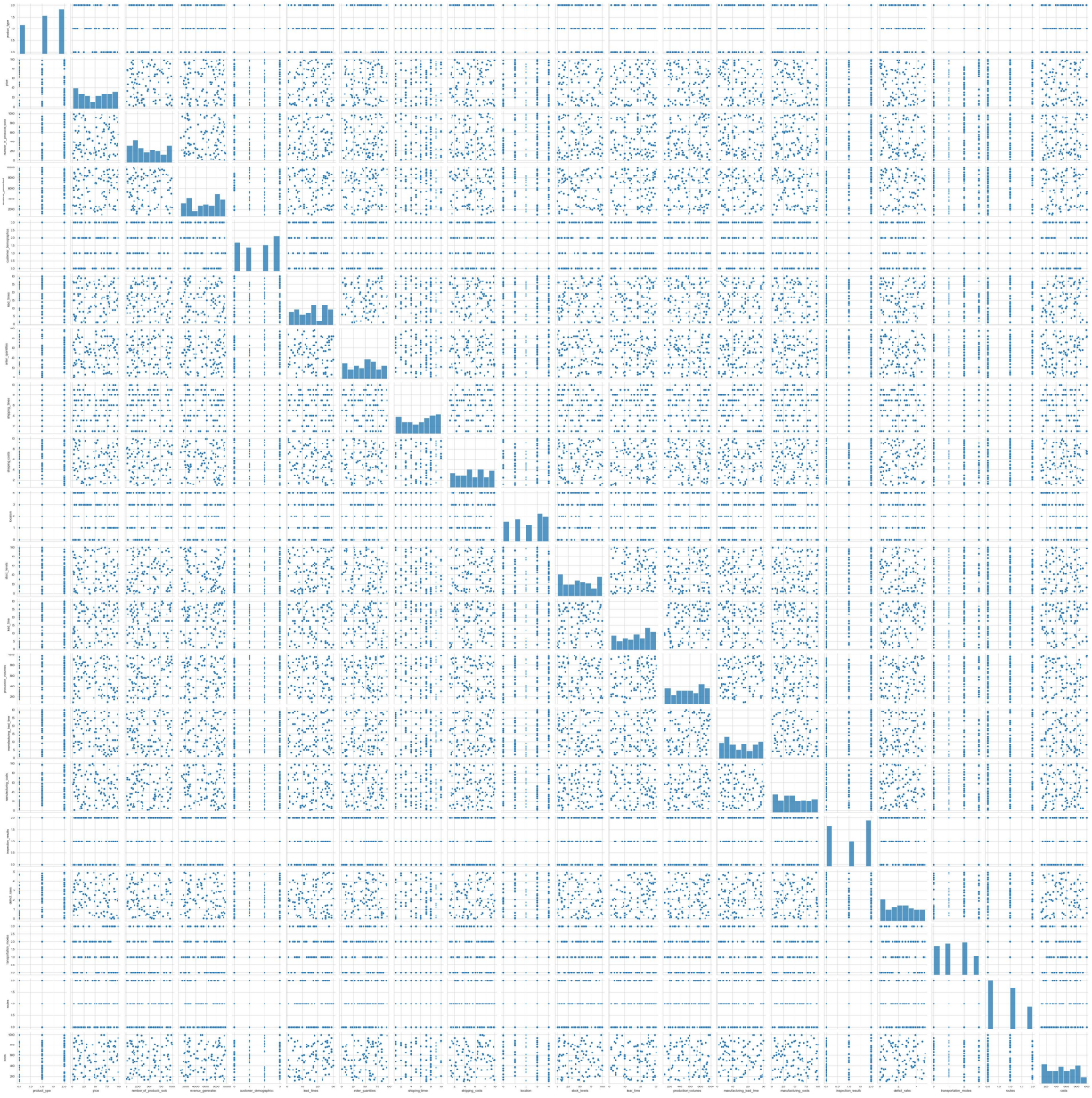


In [17]:
```
%matplotlib inline
rcParams['figure.figsize']=5,4
sb.set_style('whitegrid')
```

In [18]:
```
MP=MP_SC[['product_type','price',
       'number_of_products_sold', 'revenue_generated', 'customer_demographics', 'lead_times', 'order_quantities', 'shipping_tim
        'shipping_costs', 'location', 'stock_levels',
       'lead_time', 'production_volumes', 'manufacturing_lead_time',
       'manufacturing_costs', 'inspection_results', 'defect_rates',
       'transportation_modes', 'routes', 'costs']]
```

In [19]:
```
1 sb.pairplot(MP)
```

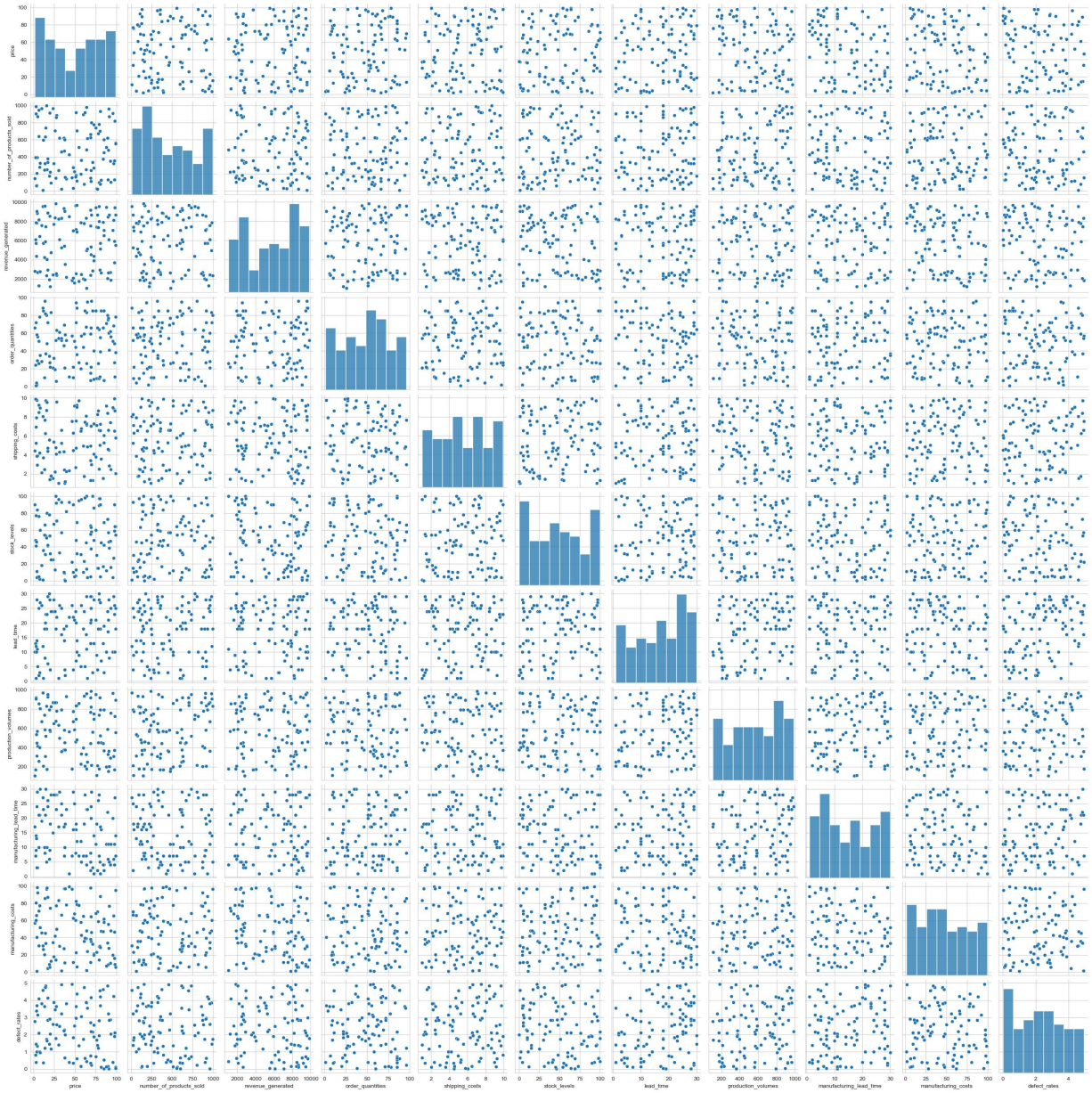
Out[19]: <seaborn.axisgrid.PairGrid at 0x26495b46d90>



In [20]:

```
STOCK=MP_SC[['price',
       'number_of_products_sold', 'revenue_generated', 'order_quantities',
        'shipping_costs', 'stock_levels',
       'lead_time', 'production_volumes', 'manufacturing_lead_time',
       'manufacturing_costs', 'defect_rates']]
sb.pairplot(STOCK)
```

Out[20]: <seaborn.axisgrid.PairGrid at 0x264aa5b2850>



In [21]:

```
STOCK=MP_SC[['product_type','price',
       'number_of_products_sold', 'revenue_generated', 'customer_demographics', 'lead_times', 'order_quantities', 'shipping_tim
        'shipping_costs', 'location', 'stock_levels',
       'lead_time', 'production_volumes', 'manufacturing_lead_time',
       'manufacturing_costs', 'inspection_results', 'defect_rates',
       'transportation_modes', 'routes', 'costs']]
```

In [22]:

```
corr=STOCK.corr()
corr
```

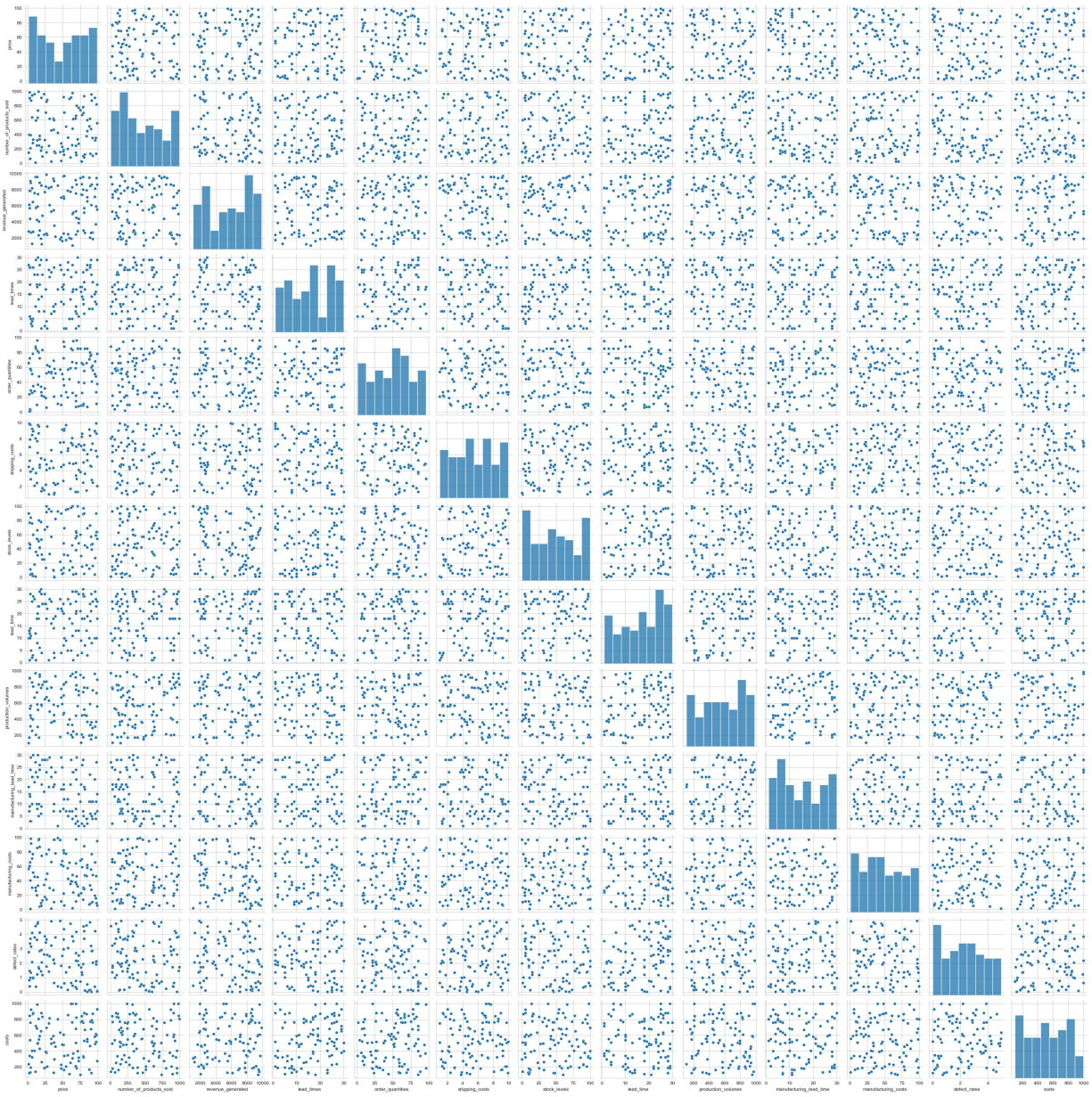
Out[22]:

	product_type	price	number_of_products_sold	revenue_generated	customer_demographics	lead_times	order_quantities	shipping_ti
product_type	1.000000	-0.118260	0.104189	-0.003482	-0.015001	0.063697	0.031378	-0.177
price	-0.118260	1.000000	0.005739	0.038424	0.141159	0.044855	0.095819	0.071
number_of_products_sold	0.104189	0.005739	1.000000	-0.001641	0.015365	-0.046419	0.015992	0.087
revenue_generated	-0.003482	0.038424	-0.001641	1.000000	-0.143585	-0.057296	0.029422	-0.109
customer_demographics	-0.015001	0.141159	0.015365	-0.143585	1.000000	-0.062386	0.121561	0.009
lead_times	0.063697	0.044855	-0.046419	-0.057296	-0.062386	1.000000	0.105459	-0.045
order_quantities	0.031378	0.095819	0.015992	0.029422	0.121561	0.105459	1.000000	-0.002
shipping_times	-0.177486	0.071942	0.087315	-0.109211	0.009490	-0.045156	-0.002561	1.000
shipping_costs	-0.184026	0.058543	0.044285	-0.072892	0.036614	-0.120746	0.004261	0.045
location	-0.042242	-0.045747	0.139708	0.033924	0.127493	-0.061358	0.028195	0.021
stock_levels	-0.234523	0.078261	0.022189	-0.158480	0.051869	0.072571	-0.111455	-0.094
lead_time	0.182971	0.152185	0.041230	-0.014178	0.014808	-0.002818	-0.086189	-0.022
production_volumes	0.188841	-0.124575	0.187945	-0.037441	-0.007385	-0.145324	-0.086567	-0.060
manufacturing_lead_time	-0.002508	-0.301313	-0.048939	0.014073	0.078132	0.003364	0.112347	-0.016
manufacturing_costs	0.077401	-0.184123	0.034284	-0.214025	-0.025202	-0.024441	-0.026784	0.029
inspection_results	0.032807	-0.060739	0.133273	0.152314	0.107667	-0.115951	-0.083564	-0.091
defect_rates	0.099739	-0.147247	-0.082726	-0.125335	0.048838	0.015681	0.018986	-0.036
transportation_modes	-0.073864	0.008989	0.075610	-0.052785	-0.042649	-0.169066	-0.025173	0.117
routes	0.003619	0.149359	-0.053316	-0.002071	0.088044	0.093482	0.148212	-0.105
costs	0.070671	0.088501	-0.036951	0.027252	-0.056375	0.243686	0.167306	-0.045

In [23]:

```
COSTS=MP_SC[['price',
       'number_of_products_sold', 'revenue_generated', 'lead_times', 'order_quantities',
        'shipping_costs', 'stock_levels',
       'lead_time', 'production_volumes', 'manufacturing_lead_time',
       'manufacturing_costs', 'defect_rates', 'costs']]
sb.pairplot(COSTS)
```

Out[23]: <seaborn.axisgrid.PairGrid at 0x264b7432850>



In [24]:

```
COSTS=MP_SC[['product_type','price',
       'number_of_products_sold', 'revenue_generated', 'customer_demographics', 'lead_times', 'order_quantities', 'shipping_tim
        'shipping_costs', 'location', 'stock_levels',
       'lead_time', 'production_volumes', 'manufacturing_lead_time',
       'manufacturing_costs', 'inspection_results', 'defect_rates',
       'transportation_modes', 'routes', 'costs']]
```

In [25]:
```
corr=COSTS.corr()
corr
```

Out[25]:

	product_type	price	number_of_products_sold	revenue_generated	customer_demographics	lead_times	order_quantities	shipping_ti
product_type	1.000000	-0.118260	0.104189	-0.003482	-0.015001	0.063697	0.031378	-0.17
price	-0.118260	1.000000	0.005739	0.038424	0.141159	0.044855	0.095819	0.07
number_of_products_sold	0.104189	0.005739	1.000000	-0.001641	0.015365	-0.046419	0.015992	0.08
revenue_generated	-0.003482	0.038424	-0.001641	1.000000	-0.143585	-0.057296	0.029422	-0.10
customer_demographics	-0.015001	0.141159	0.015365	-0.143585	1.000000	-0.062386	0.121561	0.00
lead_times	0.063697	0.044855	-0.046419	-0.057296	-0.062386	1.000000	0.105459	-0.04
order_quantities	0.031378	0.095819	0.015992	0.029422	0.121561	0.105459	1.000000	-0.00
shipping_times	-0.177486	0.071942	0.087315	-0.109211	0.009490	-0.045156	-0.002561	1.00
shipping_costs	-0.184026	0.058543	0.044285	-0.072892	0.036614	-0.120746	0.004261	0.04
location	-0.042242	-0.045747	0.139708	0.033924	0.127493	-0.061358	0.028195	0.02
stock_levels	-0.234523	0.078261	0.022189	-0.158480	0.051869	0.072571	-0.111455	-0.09
lead_time	0.182971	0.152185	0.041230	-0.014178	0.014808	-0.002818	-0.086189	-0.02
production_volumes	0.188841	-0.124575	0.187945	-0.037441	-0.007385	-0.145324	-0.086567	-0.06
manufacturing_lead_time	-0.002508	-0.301313	-0.048939	0.014073	0.078132	0.003364	0.112347	-0.01
manufacturing_costs	0.077401	-0.184123	0.034284	-0.214025	-0.025202	-0.024441	-0.026784	0.02
inspection_results	0.032807	-0.060739	0.133273	0.152314	0.107667	-0.115951	-0.083564	-0.09
defect_rates	0.099739	-0.147247	-0.082726	-0.125335	0.048838	0.015681	0.018986	-0.03
transportation_modes	-0.073864	0.008989	0.075610	-0.052785	-0.042649	-0.169066	-0.025173	0.11
routes	0.003619	0.149359	-0.053316	-0.002071	0.088044	0.093482	0.148212	-0.10
costs	0.070671	0.088501	-0.036951	0.027252	-0.056375	0.243686	0.167306	-0.04

Data Visualisation

GroupBy:

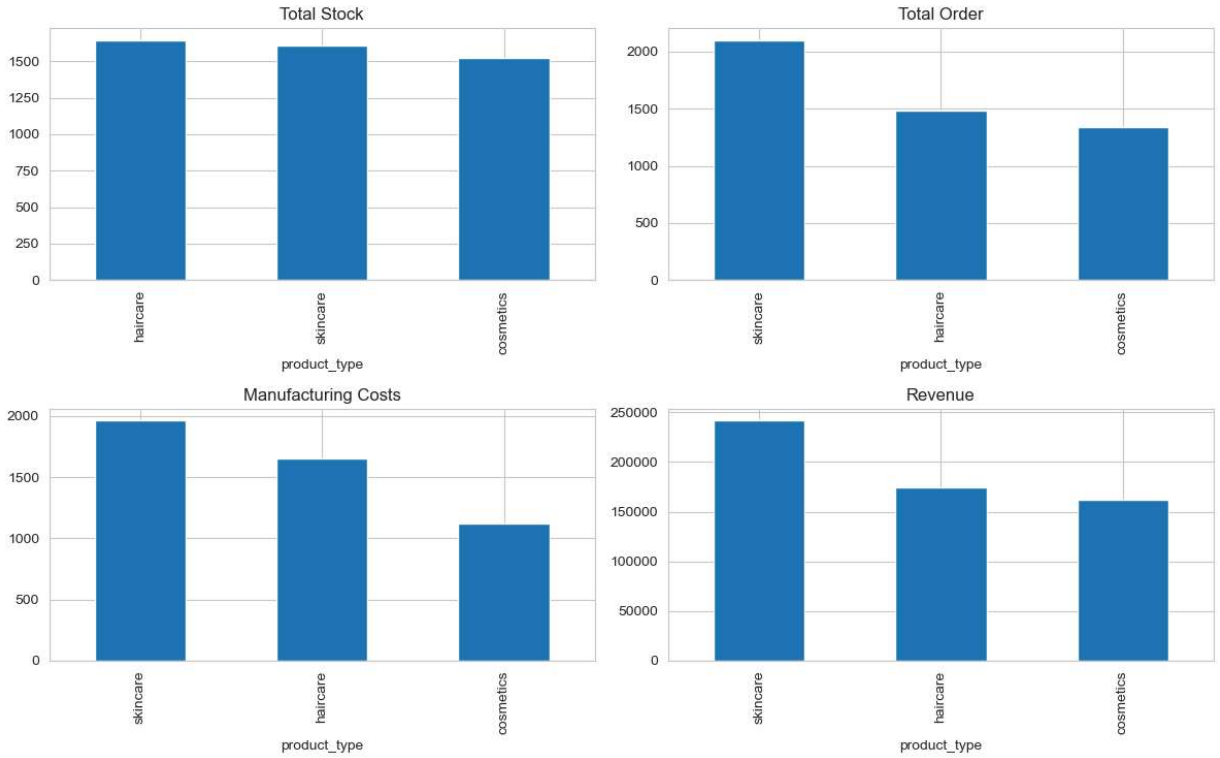
Product type, Routes, Customer demographics, Shipping carrier, Location, and Transportation modes are divided into distinct groups using the "group by" method, and in each category, the key elements like Revenue, Costs, Stock levels, and Order quantities are examined.

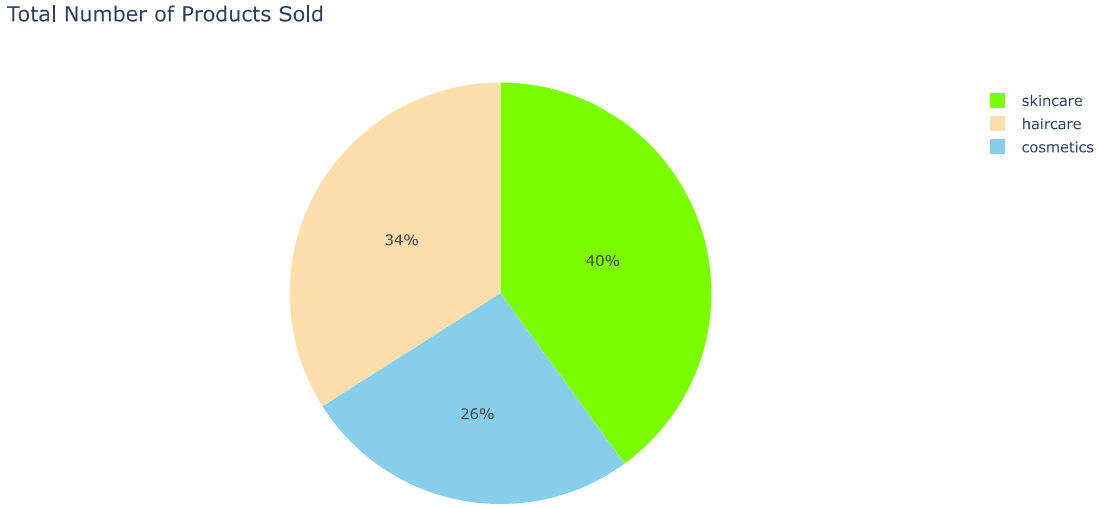
In [26]:
```
Product = MPSCData.groupby('product_type')
Route = MPSCData.groupby('routes')
Customer=MPSCData.groupby('customer_demographics')
Shipping=MPSCData.groupby('shipping_carriers')
Location=MPSCData.groupby('location')
Transportation=MPSCData.groupby('transportation_modes')
```

Products Analysis

In [27]:

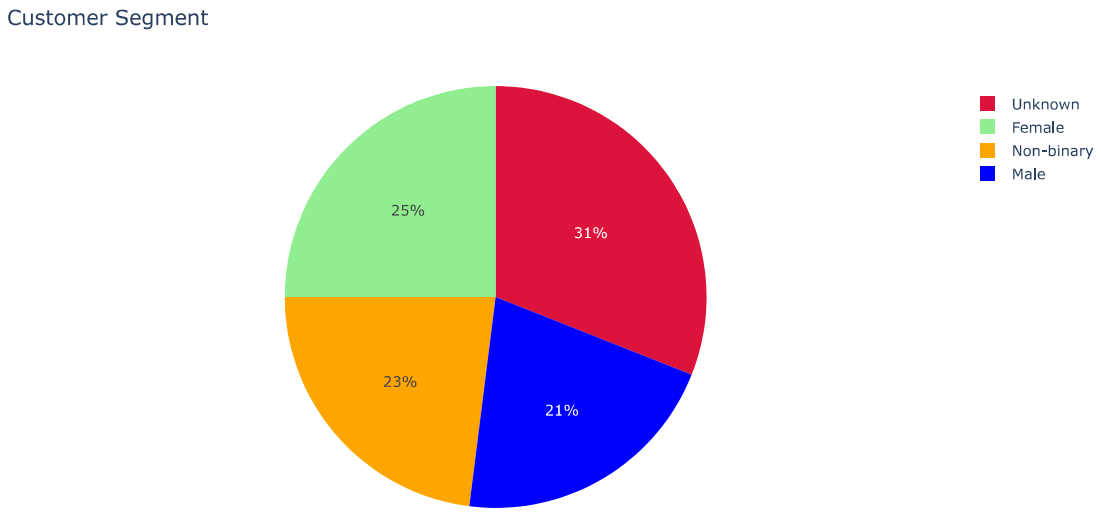
```
plt.figure(figsize=(8,8))
plt.subplot(4, 2, 1)
Product['stock_levels'].sum().sort_values(ascending=False).plot.bar(figsize=(12,14), title="Total Stock")

plt.subplot(4, 2, 2)
Product['order_quantities'].sum().sort_values(ascending=False).plot.bar(figsize=(12,14), title="Total Order")

plt.subplot(4, 2, 3)
Product['manufacturing_costs'].sum().sort_values(ascending=False).plot.bar(figsize=(12,14), title="Manufacturing Costs")

plt.subplot(4, 2, 4)
Product['revenue_generated'].sum().sort_values(ascending=False).plot.bar(figsize=(12,14), title="Revenue")

plt.tight_layout()
plt.show()

data_Products=MPSCData.groupby(['product_type'])['sku'].count().reset_index(name='number_of_products_sold').sort_values(by= 'nu
px.pie(data_Products, values='number_of_products_sold', names= 'product_type' , title= 'Total Number of Products Sold',
       color='product_type',
             color_discrete_map={'cosmetics':'skyblue',
                                 'haircare':'navajowhite',
                                'skincare':'lawngreen'})
```





Customers Analysis

In [28]:
```
data_Customers=MPSCData.groupby(['customer_demographics'])['sku'].count().reset_index(name='number_of_products_sold').sort_valu
px.pie(data_Customers, values='number_of_products_sold', names= 'customer_demographics' , title= 'Customer Segment',
       color='customer_demographics',
             color_discrete_map={'Female':'lightgreen',
                                 'Male':'blue',
                                 'Non-binary':'orange',
                               'Unknown':'crimson'})

```



Customer Segment by Products

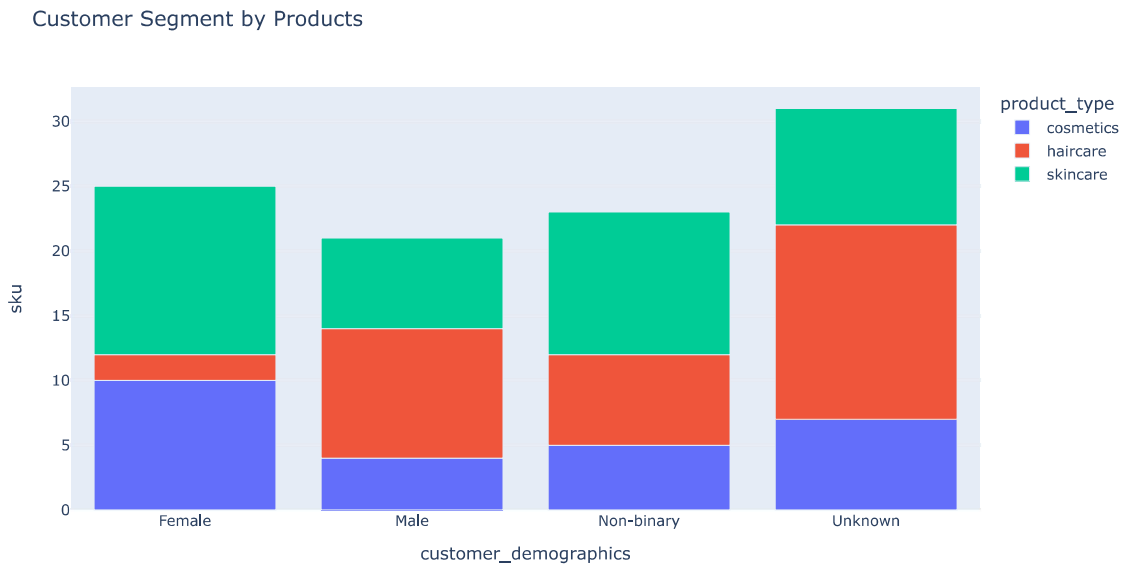
In [29]:
```
Customer_Segment_by_Products= MPSCData.groupby(["customer_demographics","product_type"])["sku"].count().reset_index()
Customer_Segment_by_Products
```

Out[29]:

	customer_demographics	product_type	sku
0	Female	cosmetics	10
1	Female	haircare	2
2	Female	skincare	13
3	Male	cosmetics	4
4	Male	haircare	10
5	Male	skincare	7
6	Non-binary	cosmetics	5
7	Non-binary	haircare	7
8	Non-binary	skincare	11
9	Unknown	cosmetics	7
10	Unknown	haircare	15
11	Unknown	skincare	9

In [30]:

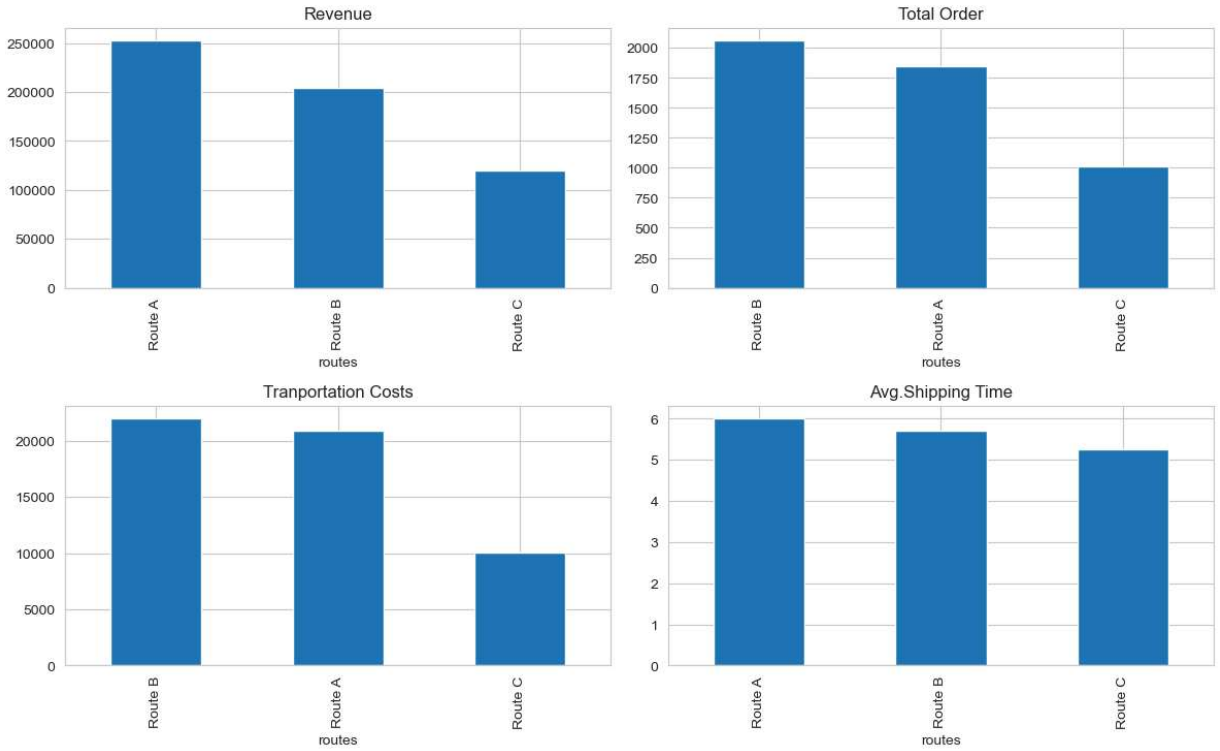
```
bar_Customer_Segment_by_Products = px.bar(Customer_Segment_by_Products, x='customer_demographics', y='sku', \
    title='Customer Segment by Products',color='product_type')
bar_Customer_Segment_by_Products.show()
```

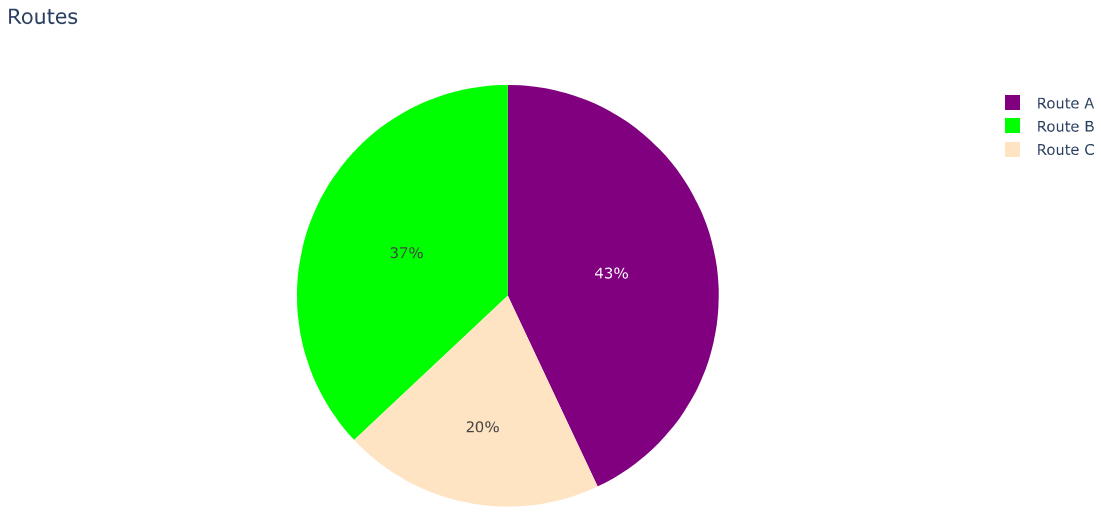


Routes Analysis

In [31]:

```
plt.figure(figsize=(8,8))
plt.subplot(4, 2, 1)
Route['revenue_generated'].sum().sort_values(ascending=False).plot.bar(figsize=(12,14), title="Revenue")

plt.subplot(4, 2, 2)
Route['order_quantities'].sum().sort_values(ascending=False).plot.bar(figsize=(12,14), title="Total Order")

plt.subplot(4, 2, 3)
Route['costs'].sum().sort_values(ascending=False).plot.bar(figsize=(12,14), title="Tranportation Costs")

plt.subplot(4, 2, 4)

Route['shipping_times'].mean().sort_values(ascending=False).plot.bar(figsize=(12,14), title="Avg.Shipping Time")

plt.tight_layout()
plt.show()


data_Routes=MPSCData.groupby(['routes'])['sku'].count().reset_index(name='number_of_products_sold').sort_values(by= 'number_of_
px.pie(data_Routes, values='number_of_products_sold', names= 'routes' , title= 'Routes',
       color='routes',
             color_discrete_map={'Route A':'purple',
                                 'Route B':'lime',
                                 'Route C':'bisque'})
```

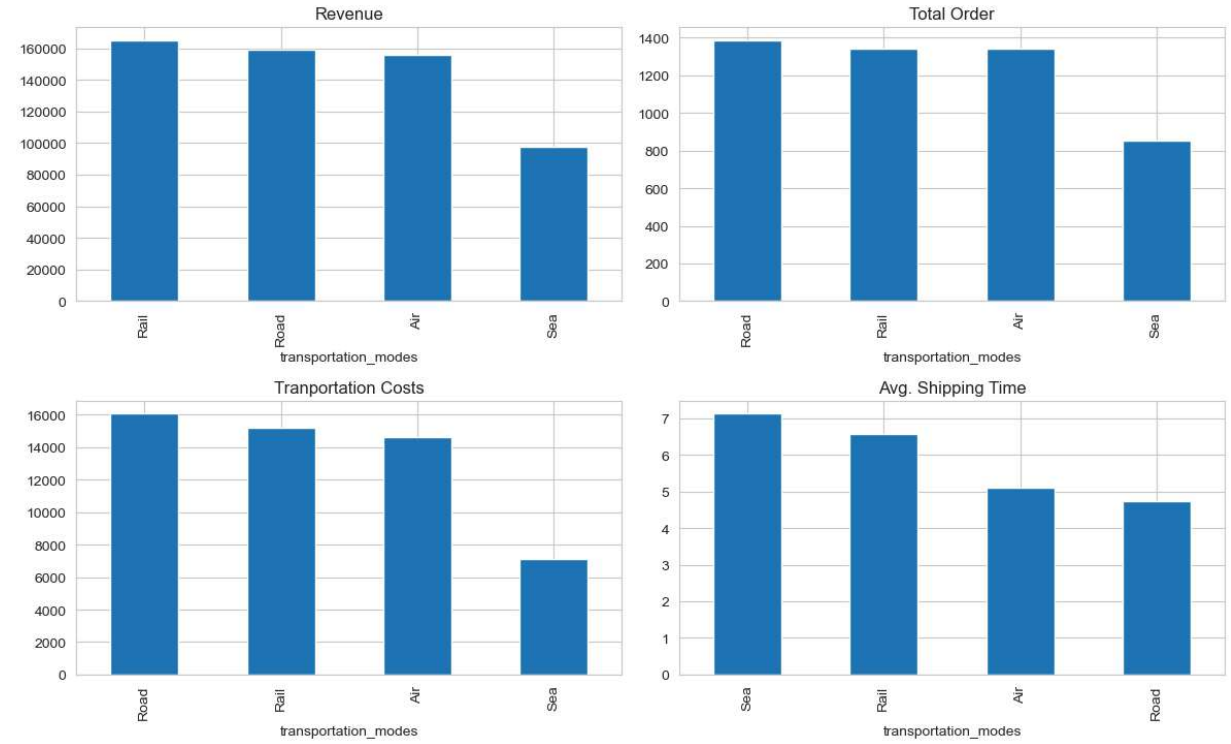


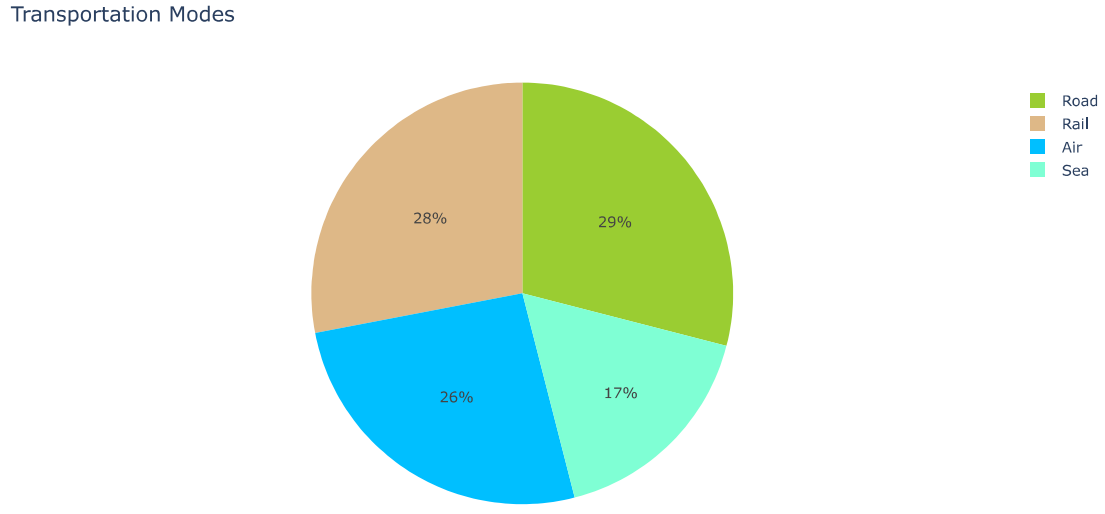


Transportation Modes

In [32]:

```
plt.figure(figsize=(8,8))
plt.subplot(4, 2, 1)
Transportation['revenue_generated'].sum().sort_values(ascending=False).plot.bar(figsize=(12,14), title="Revenue")

plt.subplot(4, 2, 2)
Transportation['order_quantities'].sum().sort_values(ascending=False).plot.bar(figsize=(12,14), title="Total Order")

plt.subplot(4, 2, 3)
Transportation['costs'].sum().sort_values(ascending=False).plot.bar(figsize=(12,14), title="Tranportation Costs")

plt.subplot(4, 2, 4)

Transportation['shipping_times'].mean().sort_values(ascending=False).plot.bar(figsize=(12,14), title="Avg. Shipping Time")

plt.tight_layout()
plt.show()



data_Transportation=MPSCData.groupby(['transportation_modes'])['sku'].count().reset_index(name='number_of_products_sold').sort_
px.pie(data_Transportation, values='number_of_products_sold', names= 'transportation_modes' , title= 'Transportation Modes',
       color='transportation_modes',
             color_discrete_map={'Air':'deepskyblue',
                                 'Rail':'burlywood',
                                 'Road':'yellowgreen',
                               'Sea':'aquamarine'})
```





Routes and Transportation modes

In [33]:
```
Routes_by_Transportation= MPSCData.groupby(["routes","transportation_modes"])["sku"].count().reset_index()
Routes_by_Transportation
```

Out[33]:

	routes	transportation_modes	sku
0	Route A	Air	11
1	Route A	Rail	14
2	Route A	Road	11
3	Route A	Sea	7
4	Route B	Air	7
5	Route B	Rail	11
6	Route B	Road	13
7	Route B	Sea	6
8	Route C	Air	8
9	Route C	Rail	3
10	Route C	Road	5
11	Route C	Sea	4

In [34]:
```
bar_Routes_by_Transportation = px.bar(Routes_by_Transportation, x='routes', y='sku', \
    title='Routes_by_Transportation Modes',color='transportation_modes')
bar_Routes_by_Transportation.show()
```

Data Modelling

Data modelling in supply chain management allows a company to respond quickly to market trends, adapt production, and optimise logistics to ensure optimal supply chain performance. Consequently, a company will be able to maximise production, optimise transportation, and save money. Furthermore, the company can make data-driven decisions and take proactive measures to meet customer expectations, streamline processes, and optimise resources (Siththardhan, 2023).

Regression Models

Regression models can identify patterns, recognize demand indications, and identify correlations between variables in large datasets. According to McKinsey ML-based supply chain solutions can cut prediction mistakes by up to 50%.

In [35]:
```
train_MPSC = MP_SC.copy()
```

Linear Regression for *Stock Level*

In [36]:
```
train_MPSC['lead_times']=train_MPSC['lead_times'].astype(int)
train_MPSC['shipping_times']= train_MPSC['shipping_times'].astype(int)
train_MPSC['lead_time']= train_MPSC['lead_time'].astype(int)
train_MPSC['manufacturing_lead_time']= train_MPSC['manufacturing_lead_time'].astype(int)
```

In [37]:
```
X=train_MPSC[[ 'sku', 'price',
        'revenue_generated',
        'lead_times', 'shipping_times', 'shipping_costs',
       'lead_time', 'production_volumes', 'manufacturing_lead_time',
       'manufacturing_costs', 'inspection_results', 'defect_rates', 'routes', 'costs']]

Y=train_MPSC[['stock_levels']]

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=42)
```

In [38]:
```
scaler = StandardScaler()# Scale the data
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [39]:
```
# Train a linear regression model
model = LinearRegression()
model.fit(X_train_scaled, Y_train)
```

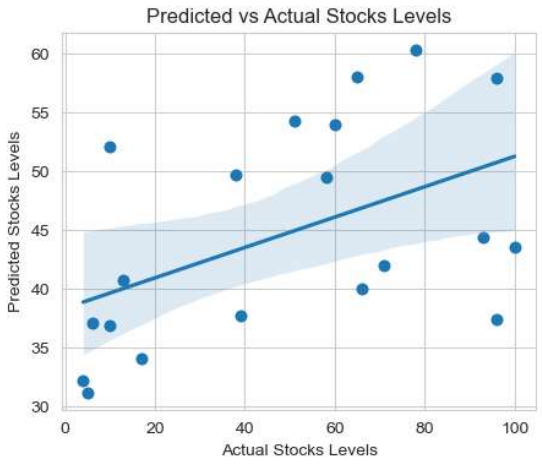
Out[39]:
```
LinearRegression (https://scikit-learn.org/1.5/modules/generated/sklearn.linear_model.LinearRegression.html)
LinearRegression()
```

In [40]:
```
# Evaluate the model on the testing set
Y_pred = model.predict(X_test_scaled)
r2 = r2_score(Y_test, Y_pred)
print(f"R-squared: {r2}")

```

```
R-squared: 0.17137875821294113
```

Cohen (1988) suggested R2 values for endogenous latent variables are assessed as follows: 0.26 (substantial), 0.13 (moderate), 0.02 (weak).

In [41]:
```
# Create a scatter plot with the actual Stocks Levels on the x-axis and the predicted Stocks Levels values on the y-axis
plt.scatter(Y_test, Y_pred)

# Plot a regression line to see how well the model has fit the data
sns.regplot(x=Y_test, y=Y_pred)

plt.xlabel('Actual Stocks Levels')
plt.ylabel('Predicted Stocks Levels')
plt.title('Predicted vs Actual Stocks Levels')
plt.show()
```



Linear Regression for *Transportation Costs*

In [42]:
```
train_MPSC['Intercept'] = 1
X=train_MPSC[['Intercept', 'sku', 'lead_times', 'order_quantities', 'location']]

Y=train_MPSC[['costs']]

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=42)
```

In [43]:
```
scaler = StandardScaler()# Scale the data
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [44]:
```
# Train a linear regression model
model = LinearRegression()
model.fit(X_train_scaled, Y_train)
```

Out[44]:
```
LinearRegression (https://scikit-learn.org/1.5/modules/generated/sklearn.linear_model.LinearRegression.html)
LinearRegression()
```

In [45]:

```
# Evaluate the model on the testing set
Y_pred = model.predict(X_test_scaled)
r2 = r2_score(Y_test, Y_pred)
print(r2)
ols_model = sm.OLS(MP_SC['costs'], X)
results = ols_model.fit()
results.summary()
```

Out[45]:

OLS Regression Results

Dep. Variable:	costs	**R-squared:**	0.168
Model:	OLS	**Adj. R-squared:**	0.133
Method:	Least Squares	**F-statistic:**	4.796
Date:	Thu, 05 Sep 2024	**Prob (F-statistic):**	0.00144
Time:	14:42:05	**Log-Likelihood:**	-687.61
No. Observations:	100	**AIC:**	1385.
Df Residuals:	95	**BIC:**	1398.
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	354.4269	91.656	3.867	0.000	172.466	536.388
sku	1.5393	0.853	1.804	0.074	-0.155	3.233
lead_times	6.3040	2.773	2.274	0.025	0.799	11.809
order_quantities	1.8121	0.928	1.952	0.054	-0.031	3.655
location	-42.8092	16.928	-2.529	0.013	-76.415	-9.203

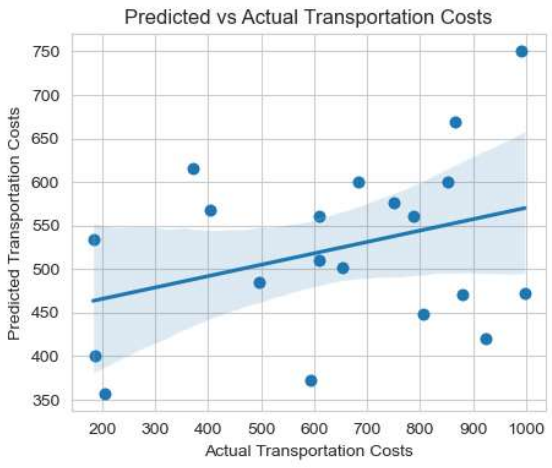
Omnibus:	6.692	**Durbin-Watson:**	2.085
Prob(Omnibus):	0.035	**Jarque-Bera (JB):**	2.874
Skew:	-0.003	**Prob(JB):**	0.238
Kurtosis:	2.169	**Cond. No.**	289.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

1. I examined the p-value for predictor variables. To decide on the retention of a predictor variable in the model, its p-value must be less than 0.05 which means that the test hypothesis is false or should be rejected.
2. If the p-value is less than 0.05, it can be said that there is a statistically significant relationship between these predictor variables and the response variable.
3. If the p-value is greater than 0.05 for the predictor variables, it means that no effect was observed. So this variable does not affect the response variable.
4. I performed the OLS regression model again by removing the predictor variables that had a p-value above 0.05.

In [46]:

```
# Create a scatter plot with the actual Transportation Costs on the x-axis and the predicted Transportation Costs values on the
plt.scatter(Y_test, Y_pred)

# Plot a regression line to see how well the model has fit the data
sns.regplot(x=Y_test, y=Y_pred)

plt.xlabel('Actual Transportation Costs')
plt.ylabel('Predicted Transportation Costs')
plt.title('Predicted vs Actual Transportation Costs')
plt.show()
```



Classification Models

In machine learning, classification is the process of predicting a categorical label for a given input point. A trained algorithm uses input features to map inputs to class

labels (datacamp, 2023)

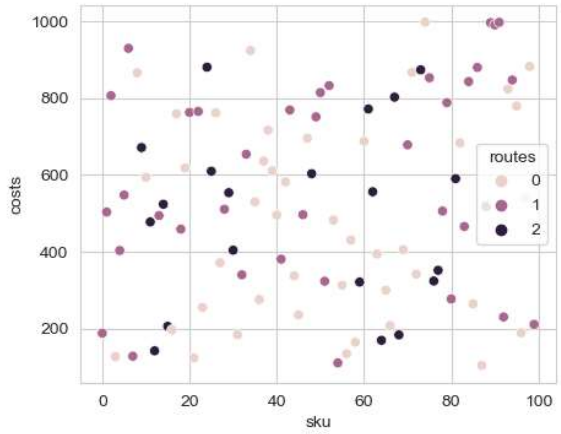
KNN Classifier for Routes

KNN is the most basic classification algorithm in Machine Learning. It belongs to the supervised learning domain and is used extensively for pattern recognition, data mining, and intrusion detection." The KNN algorithm is non-parametric, meaning it does not assume anything about the distribution of the data and the model structure is determined entirely by the data. To predict the classification of a new sample point based on the K (integer number) closest points in a database, it uses a database in which the data points are separated into several classes. We use the k-nearest neighbour algorithm to fit historical data and predict the future.

In [47]:
```
train_MP=MP_SC.copy()
```

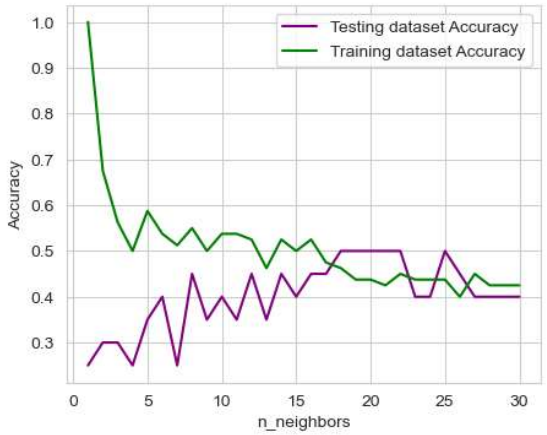
In [48]:
```
sns.scatterplot(x=train_MP['sku'],y=train_MP['costs'], hue=train_MP['routes'])
```

Out[48]: <Axes: xlabel='sku', ylabel='costs'>



I use cross-validation to find the accuracy scores, which means the data needs to scale, then loop over the values and add the scores to the list. I pass an instance of the kNN model as well as the data and several splits to be performed. I use five splits, which means that the model divides the data into five equal-sized groups, four of which are used to train and one to test the outcome. It will loop through each group and give an accuracy score, which it will average to find the best model.

In [49]:
```
# Create feature and target arrays
X = train_MP[['product_type', 'sku', 'price', 'availability', 'number_of_products_sold', 'revenue_generated', 'customer_demogra
y = train_MP[['routes']]


# Split into training and test set
X_train, X_test, y_train, y_test = train_test_split(
             X, y, test_size = 0.2, random_state=42)


neighbors = np.arange(1, 31)
train_accuracy = np.empty(len(neighbors))
test_accuracy = np.empty(len(neighbors))

# Loop over K values
for i, k in enumerate(neighbors):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)

    # Compute training and test data accuracy
    train_accuracy[i] = knn.score(X_train, y_train)
    test_accuracy[i] = knn.score(X_test, y_test)

# Generate plot
plt.plot(neighbors, test_accuracy, label = 'Testing dataset Accuracy', color="purple")
plt.plot(neighbors, train_accuracy, label = 'Training dataset Accuracy', color="green")

plt.legend()
plt.xlabel('n_neighbors')
plt.ylabel('Accuracy')
plt.show()
```



In [50]:
```
#Setup a knn classifier with k neighbors
knn = KNeighborsClassifier(n_neighbors=30)

#Fit the model
knn.fit(X_train,y_train)
#Get accuracy.
#Note: In case of classification algorithms score method
#represents accuracy.
knn.score(X_test,y_test)

```

Out[50]: 0.4

In [51]:
```
X = train_MP[['product_type', 'sku', 'price', 'availability', 'number_of_products_sold', 'revenue_generated', 'customer_demogra
y = train_MP[['routes']]


# Split into training and test set
X_train, X_test, y_train, y_test = train_test_split(
            X, y, test_size = 0.2, random_state=42)

knn = KNeighborsClassifier(n_neighbors=10)
knn.fit(X_train, y_train)

  # Calculate the accuracy of the model
y_pred = knn.predict(X_test)
print(confusion_matrix(y_test, y_pred))
```

```
[[3 4 1]
 [3 5 0]
 [2 2 0]]
```

In [52]:
```
k_values = [i for i in range (1,31)]
scores = []

scaler = StandardScaler()
X = scaler.fit_transform(X)

for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)
    score = cross_val_score(knn, X, y, cv=5)
    scores.append(np.mean(score))

```

In [53]:
```
sns.lineplot(x = k_values, y = scores, marker = 'o')
plt.xlabel("K Values")
plt.ylabel("Accuracy Score")
```

Out[53]: Text(0, 0.5, 'Accuracy Score')