Group: JJ

Bhavana Raju (4000149) Sevim Bozkurt (4001158) Shree Shangaavi Nagaraj (4000243) Vignesh Mallya (4001498)

Prediction for E-Commerce Product Delivery

This project's goal is to forecast whether or not an online retailer's merchandise will arrive on schedule. This research also examines consumer behavior and assesses a number of variables that impact product delivery.

Data Dictionary

The dataset used for model building contains 10999 observations of 12 variables. The data contains the following information:

Variable	Description
ID	ID Number of Customers
Warehouse_block	The Company have big Warehouse which is divided into block such as A,B,C,D,E
Mode_of_Shipment	The Company Ships the products in multiple way such as Ship, Flight and Road
Customer_care_calls	The number of calls made from enquiry for enquiry of the shipment
Customer_rating	The company has rated from every customer. 1 is the lowest (Worst), 5 is the highest (Best)
Cost_of_the_Product	Cost of the Product in US Dollars
Prior_purchases	The Number of Prior Purchase
Product_importance	The company has categorized the product in the various parameter such as low, medium, high
Gender	Male and Female
Discount_offered	Discount offered on that specific product
Weight_in_gms	It is the weight in grams
Reached.on.Time_Y.N	It is the target variable, where 1 Indicates that the product has NOT reached on time and 0 indicates it has reached on time

In [1]:
```
#Importing the libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
#Loading the dataset
df = pd.read_csv('E_Commerce.csv')
df.head()
```

Out[2]:

	ID	Warehouse_block	Mode_of_Shipment	Customer_care_calls	Customer_rating	Cost_of_the_Product	Prior_purchases	Product_importance	Gender	Discount_offered	Weight_in_gms	Reached.on.Time_Y.N
0	1	D	Flight	4	2	177	3	low	F	44	1233	1
1	2	F	Flight	4	5	216	2	low	M	59	3088	1
2	3	A	Flight	2	2	183	4	low	M	48	3374	1
3	4	B	Flight	3	3	176	4	medium	M	10	1177	1
4	5	C	Flight	2	2	184	3	medium	F	46	2484	1

Data Preprocessing 1

In [3]:
```
#Checking the shape of the dataset
print(df.shape)

#Checking data types of the columns
print(df.dtypes)
```

```
(10999, 12)
ID                      int64
Warehouse_block        object
Mode_of_Shipment       object
Customer_care_calls     int64
Customer_rating         int64
Cost_of_the_Product     int64
Prior_purchases         int64
Product_importance     object
Gender                 object
Discount_offered        int64
Weight_in_gms           int64
Reached.on.Time_Y.N     int64
dtype: object
```

In [4]:
```
#Dropping column ID because it is an index column
df.drop(['ID'], axis=1, inplace=True)
```

In [5]:
```
#Checking for null/missing values
df.isnull().sum()
```

Out[5]:
```
Warehouse_block        0
Mode_of_Shipment       0
Customer_care_calls    0
Customer_rating        0
Cost_of_the_Product    0
Prior_purchases        0
Product_importance     0
Gender                 0
Discount_offered       0
Weight_in_gms          0
Reached.on.Time_Y.N    0
dtype: int64
```

In [6]:
```
#Checking for duplicate values
df.duplicated().sum()
```

Out[6]: 0

Descriptive Statistics

In [7]:
```
df.describe()
```

Out[7]:

	Customer_care_calls	Customer_rating	Cost_of_the_Product	Prior_purchases	Discount_offered	Weight_in_gms	Reached.on.Time_Y.N
count	10999.000000	10999.000000	10999.000000	10999.000000	10999.000000	10999.000000	10999.000000
mean	4.054459	2.990545	210.196836	3.567597	13.373216	3634.016729	0.596691
std	1.141490	1.413603	48.063272	1.522860	16.205527	1635.377251	0.490584
min	2.000000	1.000000	96.000000	2.000000	1.000000	1001.000000	0.000000
25%	3.000000	2.000000	169.000000	3.000000	4.000000	1839.500000	0.000000
50%	4.000000	3.000000	214.000000	3.000000	7.000000	4149.000000	1.000000
75%	5.000000	4.000000	251.000000	4.000000	10.000000	5050.000000	1.000000
max	7.000000	5.000000	310.000000	10.000000	65.000000	7846.000000	1.000000

In [8]:
```
df.head()
```

Out[8]:

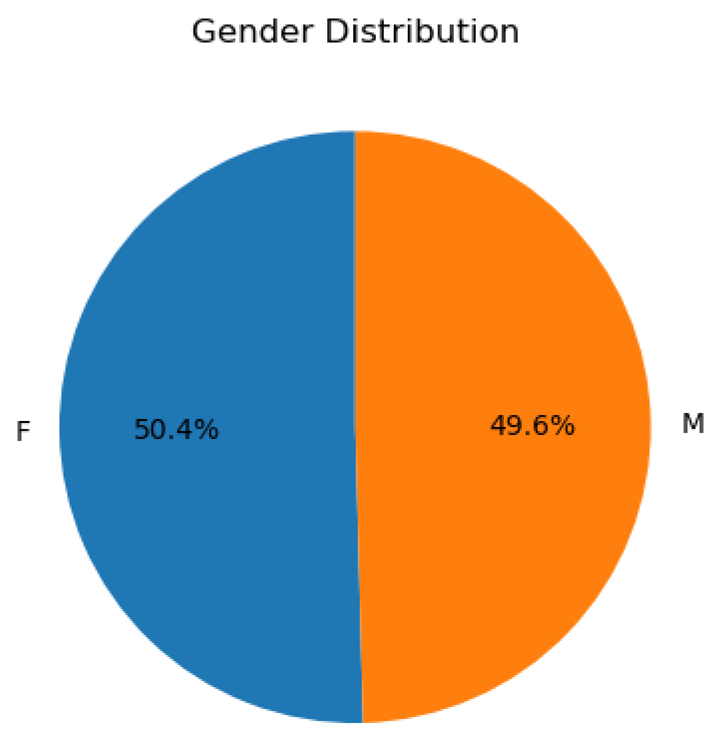
	Warehouse_block	Mode_of_Shipment	Customer_care_calls	Customer_rating	Cost_of_the_Product	Prior_purchases	Product_importance	Gender	Discount_offered	Weight_in_gms	Reached.on.Time_Y.N
0	D	Flight	4	2	177	3	low	F	44	1233	1
1	F	Flight	4	5	216	2	low	M	59	3088	1
2	A	Flight	2	2	183	4	low	M	48	3374	1
3	B	Flight	3	3	176	4	medium	M	10	1177	1
4	C	Flight	2	2	184	3	medium	F	46	2484	1

Exploratory Data Analysis

During the exploratory data analysis, We will examine the correlation between the target variable and other variables. Additionally, we will assess the distribution of variables throughout the dataset to gain a deeper understanding of the data.

Customer Gender Distribution

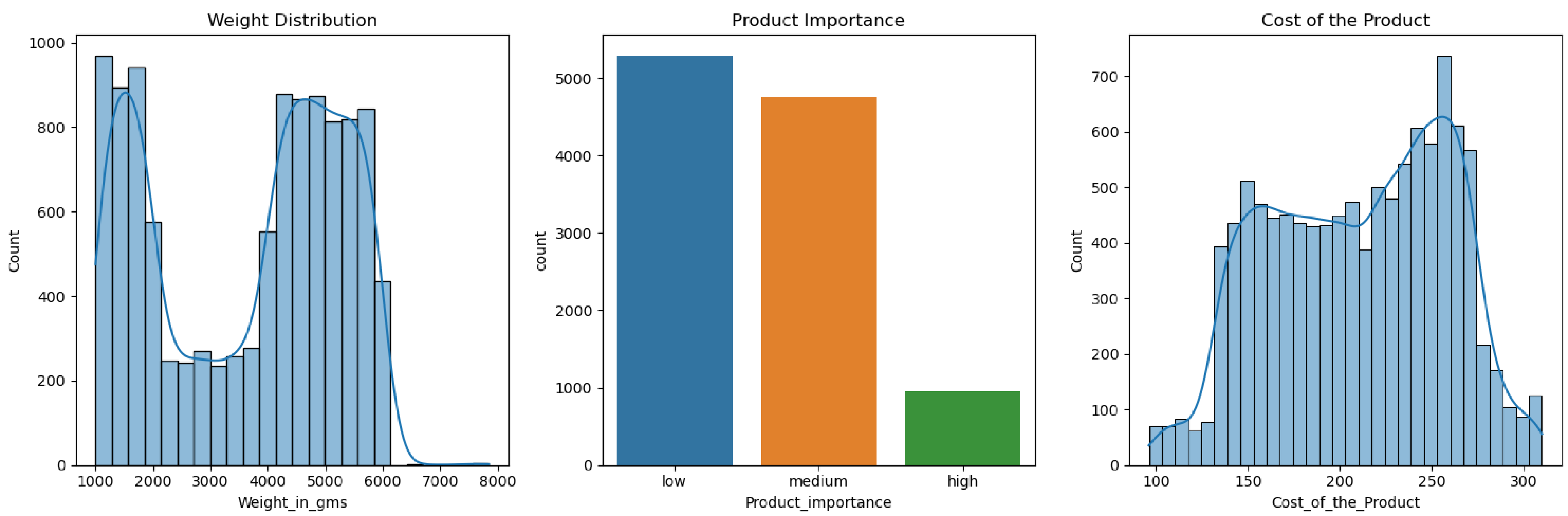
In [9]:
```
gender_counts = df['Gender'].value_counts()
plt.pie(gender_counts, labels=gender_counts.index, autopct='%1.1f%%', startangle=90)
plt.title('Gender Distribution')
plt.show()
```



The dataset has an equal number of male and female customers, with percentages of 49.6% and 50.4%, respectively.

Product Properties

In [10]:
```
fig, axes = plt.subplots(1, 3, figsize=(15, 5))
sns.histplot(df['Weight_in_gms'], kde=True, ax=axes[0]).set_title('Weight Distribution')
sns.countplot(x='Product_importance', data=df, ax=axes[1]).set_title('Product Importance')
sns.histplot(df['Cost_of_the_Product'], kde=True, ax=axes[2]).set_title('Cost of the Product')
plt.tight_layout()
plt.show()
```

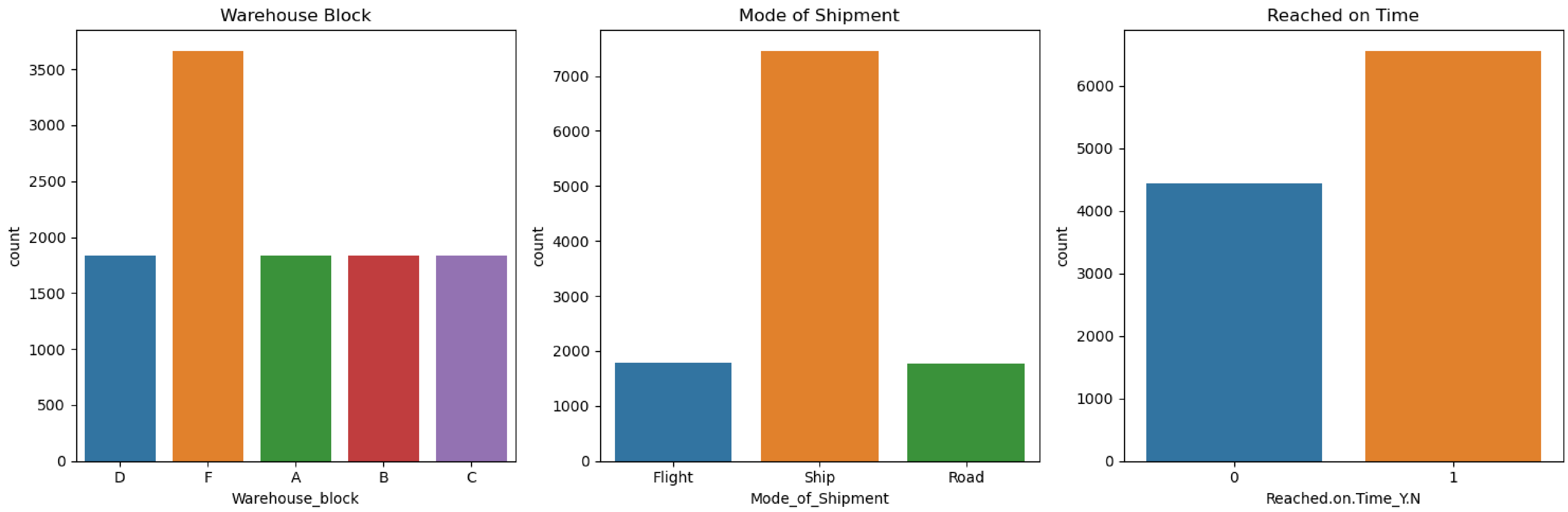


These three charts depict the distribution of product attributes—Weight, Cost, and Importance—within the dataset. Initially, examining the weight distribution reveals a prevalence of products weighing between 1000-2000 grams and 4000-6000 grams, indicating higher sales in these weight categories. Moving to the second chart, it illustrates the distribution of product importance, showcasing that most products hold low to medium importance. Lastly, the third chart delves into the cost distribution, revealing increased prevalence between 150-200 and 225-275 dollars.

Based on these findings, it can be inferred that the majority of products weigh less than 6000 grams, possess low or medium importance, and are priced between 150-275 dollars.

Logistics

In [11]:
```
fig, ax = plt.subplots(1, 3, figsize=(15, 5))
sns.countplot(x='Warehouse_block', data=df, ax=ax[0]).set_title('Warehouse Block')
sns.countplot(x='Mode_of_Shipment', data=df, ax=ax[1]).set_title('Mode of Shipment')
sns.countplot(x='Reached.on.Time_Y.N', data=df, ax=ax[2]).set_title('Reached on Time')
plt.tight_layout()  # Adjust layout for better visualization
plt.show()  # Show the plot
```



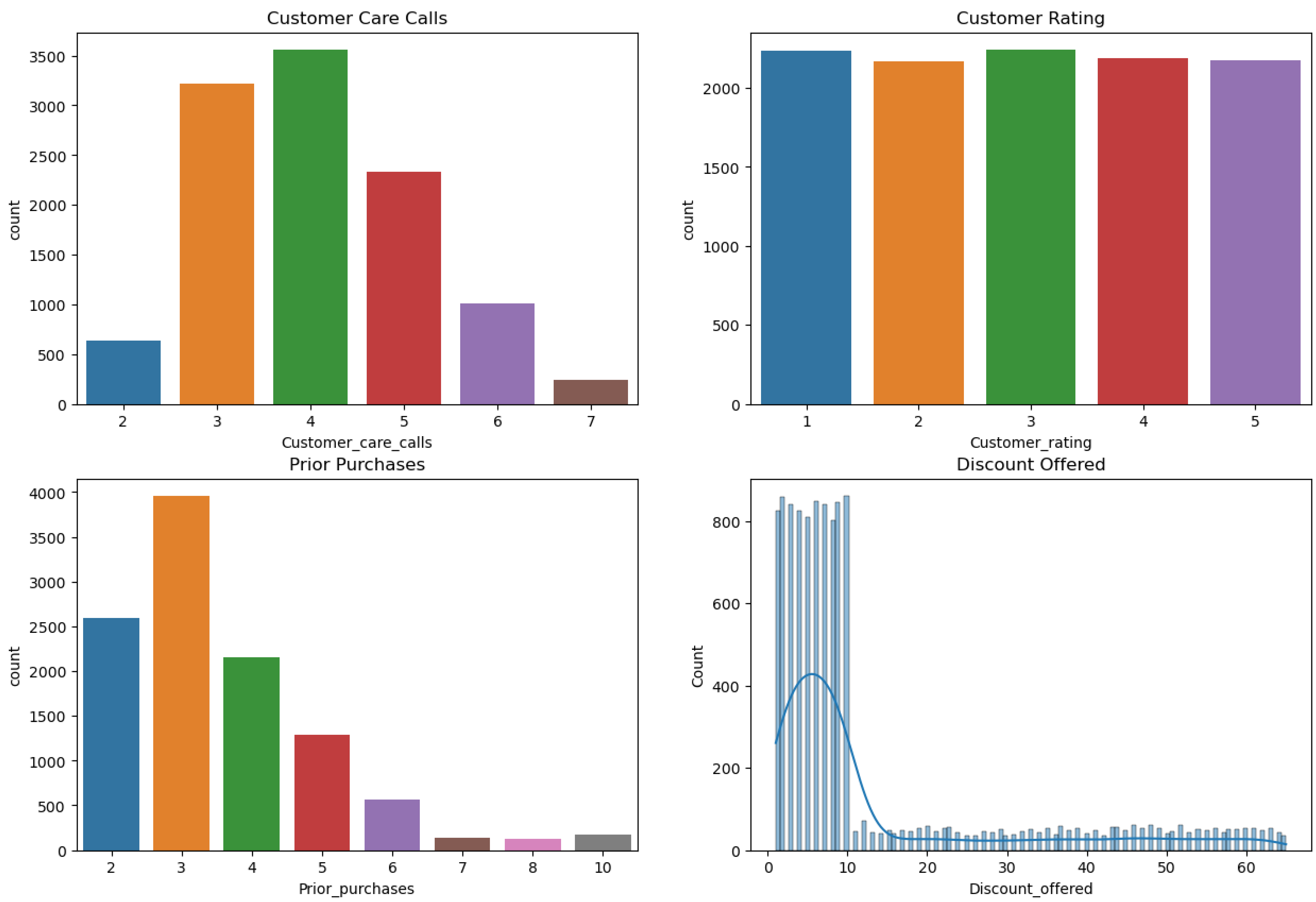
The graphs above depict the logistics and distribution of the product. In the initial graph, Warehouse F stands out with a product count of 3500, whereas the other warehouses show a relatively uniform distribution. The second graph illustrates shipping methods, with the majority utilizing ships, while approximately 2000 products are shipped via air and road. The third graph focuses on timely deliveries, indicating that more products are delivered punctually compared to those that are not.

According to the analysis of the graphs, it can be inferred that Warehouse F likely has proximity to a seaport, given its significant product volume and the prevalence of shipping via ships.

Customer Experience

In [12]:
```
fig, ax = plt.subplots(2,2,figsize=(15,10))
sns.countplot(x = 'Customer_care_calls', data = df, ax=ax[0,0]).set_title('Customer Care Calls')
sns.countplot(x = 'Customer_rating', data = df, ax=ax[0,1]).set_title('Customer Rating')
sns.countplot(x = 'Prior_purchases', data = df, ax=ax[1,0]).set_title('Prior Purchases')
sns.histplot(x = 'Discount_offered', data = df, ax=ax[1,1], kde = True).set_title('Discount Offered')
```

Out[12]: Text(0.5, 1.0, 'Discount Offered')



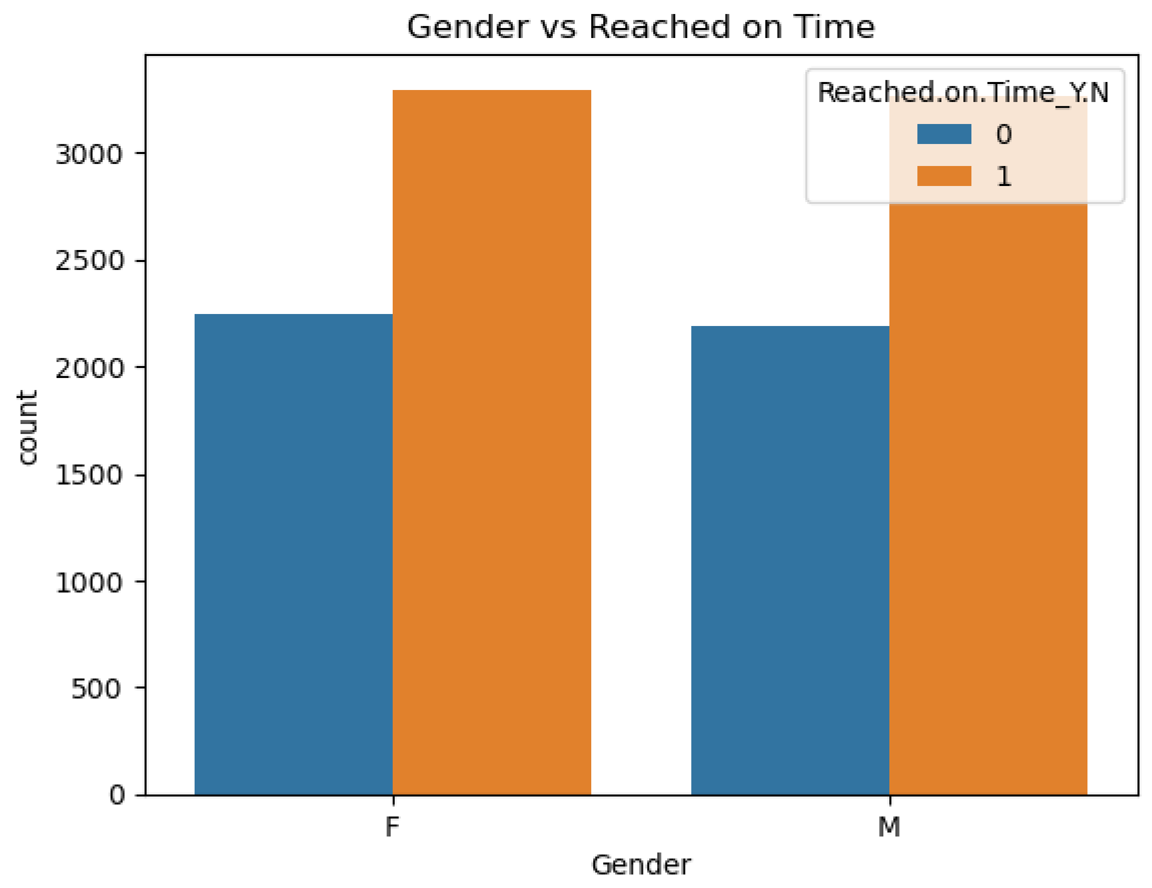
The preceding visualizations depict the customer experience gleaned from their interactions with customer care, ratings, prior purchases, and offered discounts. The initial graph illustrates the frequency of customer care calls, revealing that a significant portion of customers have made 3-4 calls, suggesting potential issues with product delivery. Subsequently, the second graph indicates an even distribution of customer ratings, albeit with a slight increase in the count of rating 1, indicating dissatisfaction with the service.

The third visualization focuses on customers' prior purchases, highlighting that the majority have made 2-3 purchases, suggesting satisfaction and continued patronage. Finally, the fourth graph showcases the distribution of discounts offered on products, with the majority falling within the 0-10% range, indicating conservative discounting practices by the company.

Customer Gender and Product Delivery

In [13]:
```
sns.countplot(x = 'Gender', data = df, hue = 'Reached.on.Time_Y.N').set_title('Gender vs Reached on Time')
```

Out[13]: Text(0.5, 1.0, 'Gender vs Reached on Time')

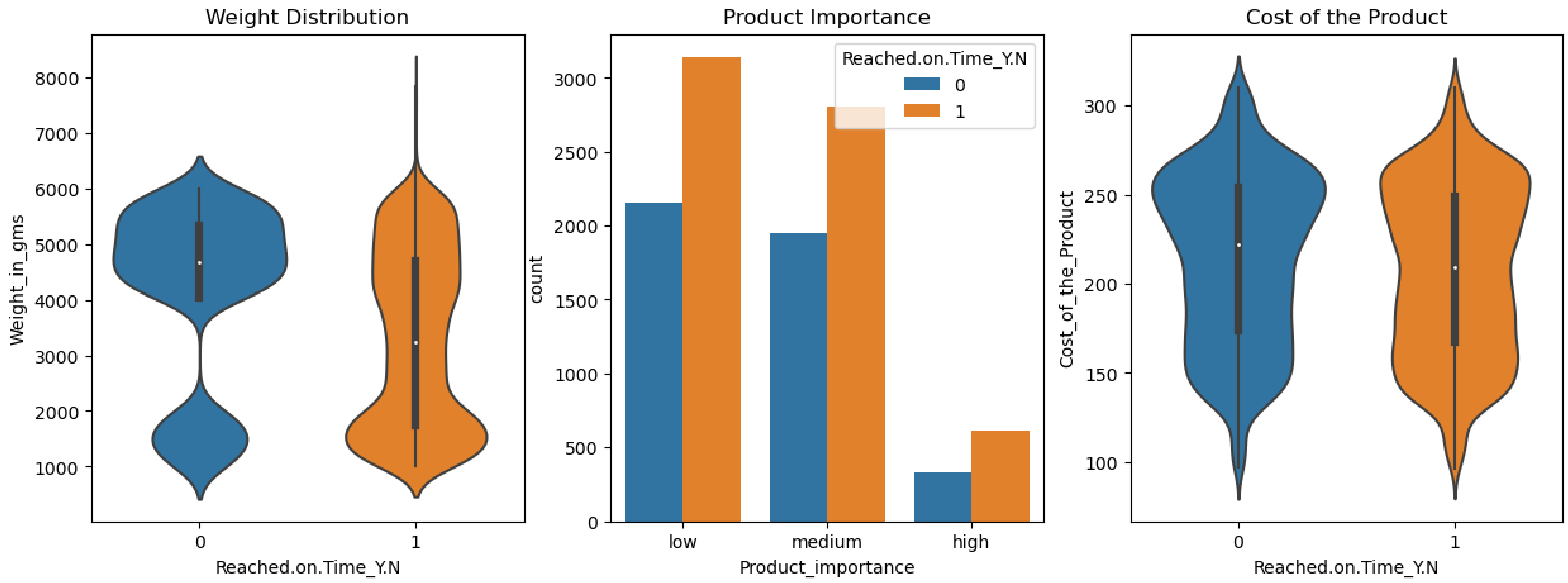


The number of products timely delivered for both the genders is same, which means there is no relation of customer gender and product delivery.

Product Properties and Product Delivery

In [16]:
```
fig, ax = plt.subplots(1,3,figsize=(15,5))
sns.violinplot(y = df['Weight_in_gms'], ax=ax[0], kde=True, x = df['Reached.on.Time_Y.N']).set_title('Weight Distribution')
sns.countplot(x = 'Product_importance', data = df, ax=ax[1], hue = 'Reached.on.Time_Y.N').set_title('Product Importance')
sns.violinplot(y = df['Cost_of_the_Product'], ax=ax[2], kde=True, x = df['Reached.on.Time_Y.N']).set_title('Cost of the Product')
```

Out[16]: Text(0.5, 1.0, 'Cost of the Product')



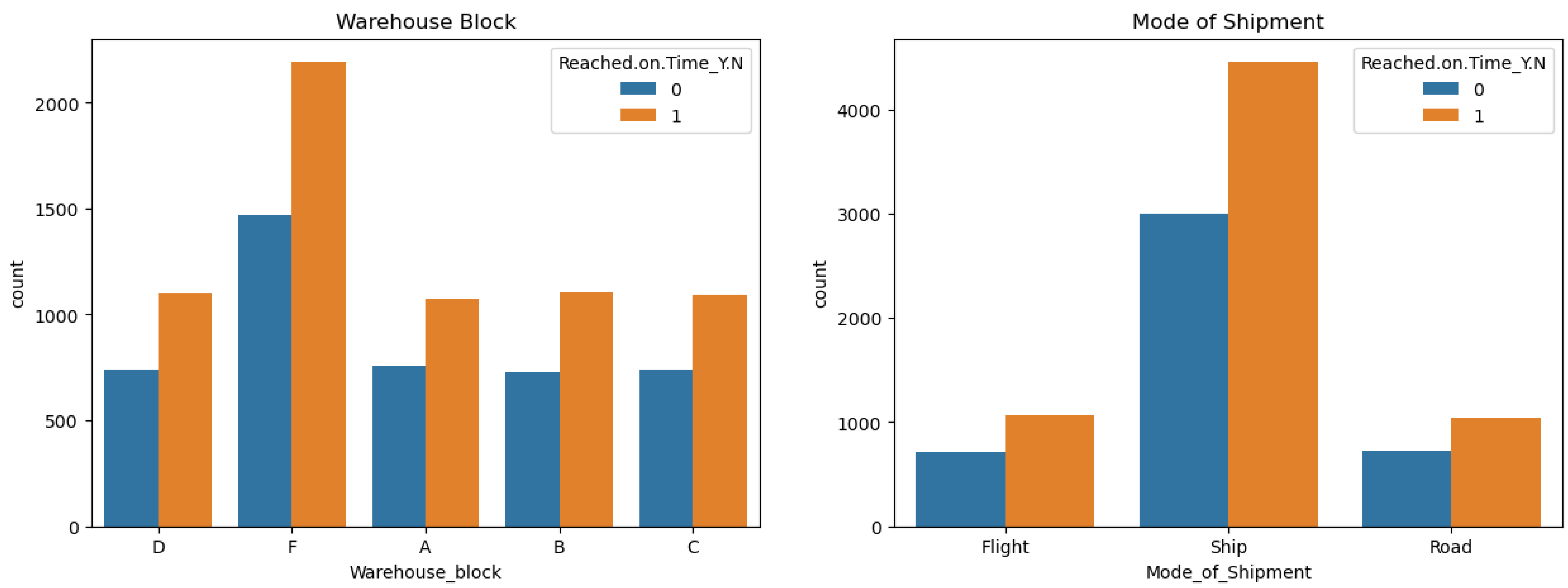
The above plots visualizes the relationship between product properties and product delivery. From the first graph, it is quite clear that product weight has an impact of timely delivery of the product. Products that weight more than 4500 grams are not delivered on time, in addition to that more products that weight between 2500 - 3500 grams are delivered timely. The second graph is about the product importance and product delivery, where we can see that there is no major difference between the product delivery based on the product importance. The third graph shows the relationship between the cost of the product and product delivery, where we can see that products that cost more than 250 have higher count of not delivered on time.

From this we conclude that product weight and cost has an impact on the product delivery.

Logistics and Product Delivery

In [17]:
```
fig, ax = plt.subplots(1,2,figsize=(15,5))
sns.countplot(x = 'Warehouse_block', data = df, ax=ax[0], hue = 'Reached.on.Time_Y.N').set_title('Warehouse Block')
sns.countplot(x = 'Mode_of_Shipment', data = df, ax=ax[1], hue = 'Reached.on.Time_Y.N').set_title('Mode of Shipment')
```

Out[17]: Text(0.5, 1.0, 'Mode of Shipment')

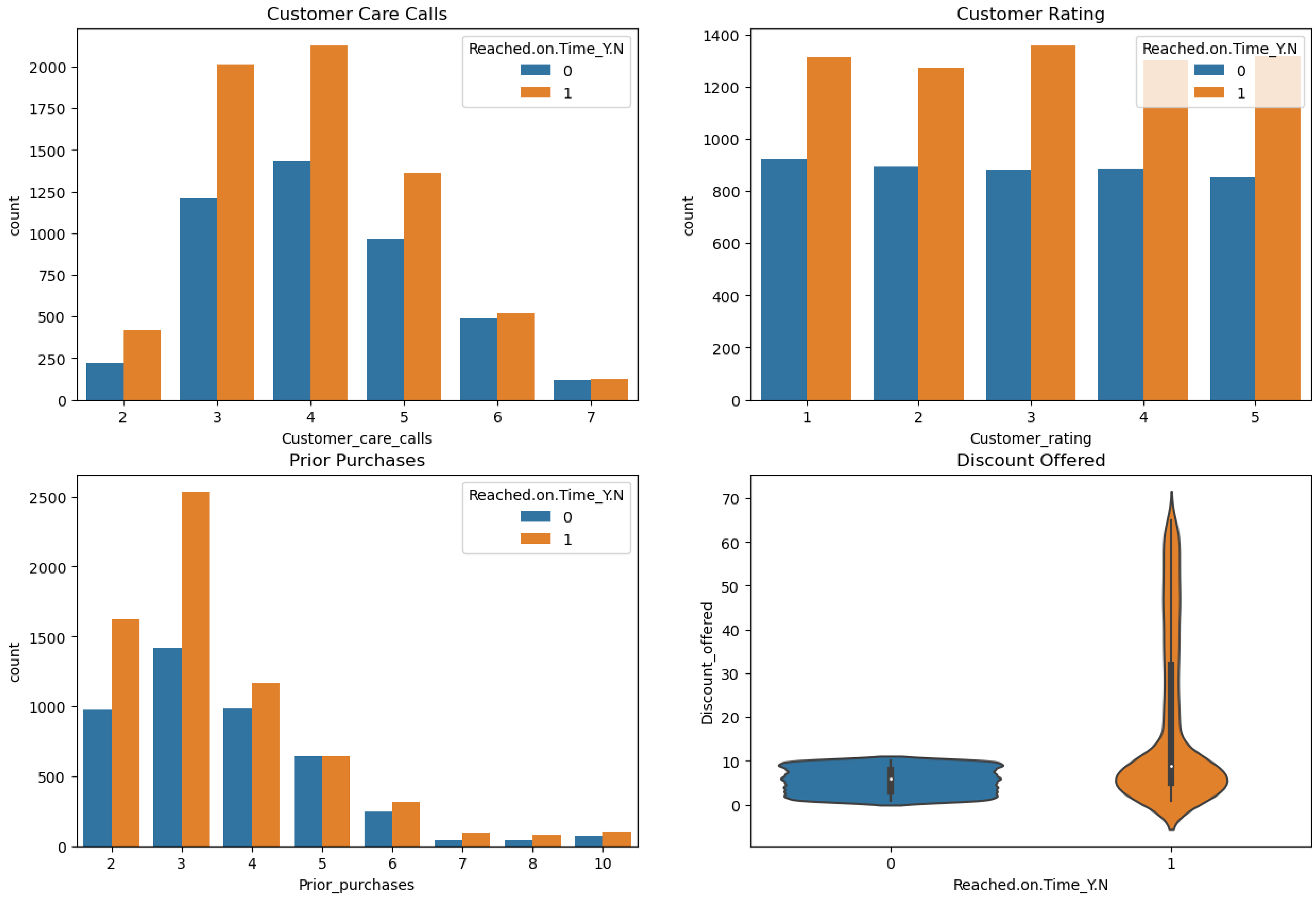


These graphs explain the relationship between the Logistic and timely delivery of the product. Since most of the products are shipped from warehouse F, we assumed that warehouse F is close to seaport, and most of the products are shipped via ship. In both the graphs, the difference between the number of products delivered on time and not delivered on time is constant across all the warehouse blocks and mode of shipment. This means that the logistic and mode of shipment has no impact on the product delivery.

Customer Experience and Product Delivery

In [18]:
```
fig, ax = plt.subplots(2,2,figsize=(15,10))
sns.countplot(x = 'Customer_care_calls', data = df, ax=ax[0,0],hue = 'Reached.on.Time_Y.N').set_title('Customer Care Calls')
sns.countplot(x = 'Customer_rating', data = df, ax=ax[0,1],hue = 'Reached.on.Time_Y.N').set_title('Customer Rating')
sns.countplot(x = 'Prior_purchases', data = df, ax=ax[1,0],hue = 'Reached.on.Time_Y.N').set_title('Prior Purchases')
sns.violinplot(x = 'Reached.on.Time_Y.N', y = 'Discount_offered' ,data = df, ax=ax[1,1]).set_title('Discount Offered')
```

Out[18]:
```
Text(0.5, 1.0, 'Discount Offered')
```



It is important to understand the customer experience and respond to services provided by the E-Commerce company. The above graphs explain the relationship between customer experience and product delivery. The first graph is about the customer care calls and product delivery, where we see that the difference in timely and late delivery of the product decreases with increase in the number of calls by the customer, which means that with the delay in product delivery the customer gets anxious about the product and calls the customer care. The second graph is about the customer rating and product delivery, where we can see that customers who rating have higher count of products delivered on time.

The third graph is about the customer's prior purchase, which also shows that customers who have done more prior purchases have higher count of products delivered on time and this is the reason that they are purchasing again from the company. The fourth graph is about the discount offered on the product and product delivery, where we can see that products that have 0-10% discount have higher count of products delivered late, whereas products that have discount more than 10% have higher count of products delivered on time.

Data Preprocessing 2

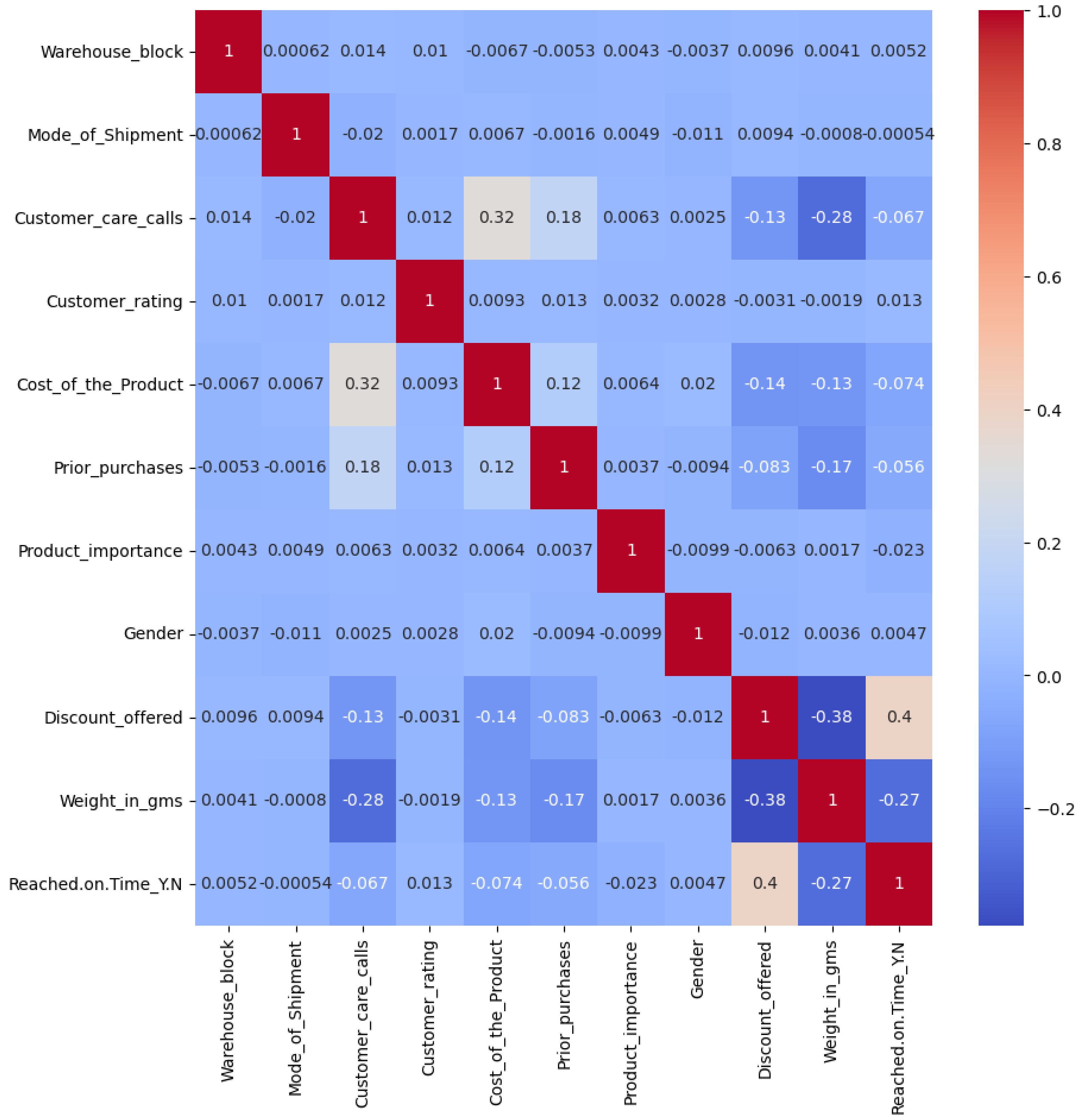
In [19]:
```
## Label encoding the categorical variables
from sklearn.preprocessing import LabelEncoder

#Label encoding object
le = LabelEncoder()

#columns for label encoding
cols = ['Warehouse_block','Mode_of_Shipment','Product_importance', 'Gender']

#label encoding
for i in cols:
    le.fit(df[i])
    df[i] = le.transform(df[i])
    print(i, df[i].unique())
```

```
Warehouse_block [3 4 0 1 2]
Mode_of_Shipment [0 2 1]
Product_importance [1 2 0]
Gender [0 1]
```

Correlation Matrix Heatmap

In [20]:
```
plt.figure(figsize=(10,10))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
```

Out[20]: <Axes: >

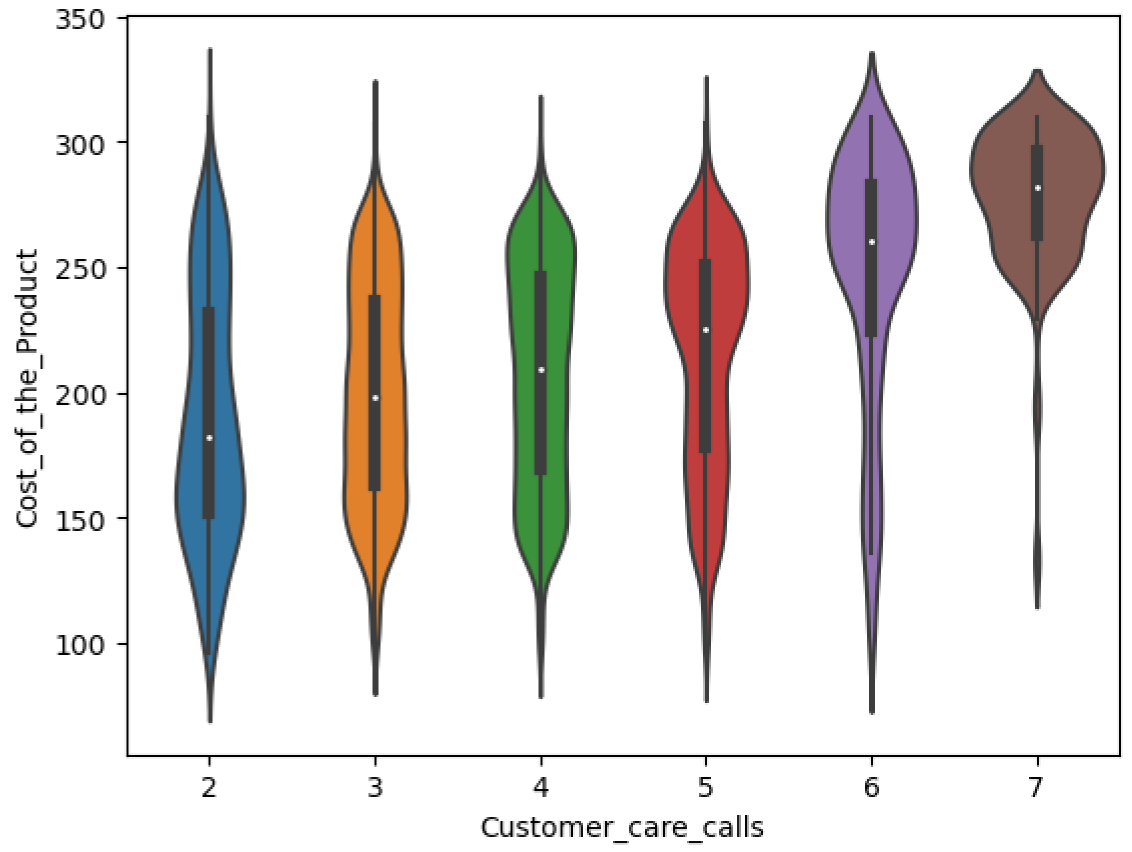


	Warehouse_block	Mode_of_Shipment	Customer_care_calls	Customer_rating	Cost_of_the_Product	Prior_purchases	Product_importance	Gender	Discount_offered	Weight_in_gms	Reached.on.Time_Y.N
Warehouse_block	1	0.00062	0.014	0.01	-0.0067	-0.0053	0.0043	-0.0037	0.0096	0.0041	0.0052
Mode_of_Shipment	0.00062	1	-0.02	0.0017	0.0067	-0.0016	0.0049	-0.011	0.0094	-0.0008	-0.00054
Customer_care_calls	0.014	-0.02	1	0.012	0.32	0.18	0.0063	0.0025	-0.13	-0.28	-0.067
Customer_rating	0.01	0.0017	0.012	1	0.0093	0.013	0.0032	0.0028	-0.0031	-0.0019	0.013
Cost_of_the_Product	-0.0067	0.0067	0.32	0.0093	1	0.12	0.0064	0.02	-0.14	-0.13	-0.074
Prior_purchases	-0.0053	-0.0016	0.18	0.013	0.12	1	0.0037	-0.0094	-0.083	-0.17	-0.056
Product_importance	0.0043	0.0049	0.0063	0.0032	0.0064	0.0037	1	-0.0099	-0.0063	0.0017	-0.023
Gender	-0.0037	-0.011	0.0025	0.0028	0.02	-0.0094	-0.0099	1	-0.012	0.0036	0.0047
Discount_offered	0.0096	0.0094	-0.13	-0.0031	-0.14	-0.083	-0.0063	-0.012	1	-0.38	0.4
Weight_in_gms	0.0041	-0.0008	-0.28	-0.0019	-0.13	-0.17	0.0017	0.0036	-0.38	1	-0.27
Reached.on.Time_Y.N	0.0052	-0.00054	-0.067	0.013	-0.074	-0.056	-0.023	0.0047	0.4	-0.27	1

The number of customer service calls and the cost of the product show a positive link in the correlation matrix heatmap.

In [21]:
```
sns.violinplot(x = 'Customer_care_calls', y = 'Cost_of_the_Product', data = df)
```

Out[21]: <Axes: xlabel='Customer_care_calls', ylabel='Cost_of_the_Product'>



Customers are clearly more concerned with product delivery when the product is expensive. This is why they called customer service to find out the status of the product. As a result, when the product is expensive, it is critical to ensure its timely delivery.

Train Test Split

In [22]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(df.drop('Reached.on.Time_Y.N', axis=1), df['Reached.on.Time_Y.N'], test_size=0.2, random_state=0)
```

Model Building

We will be using the following models to predict the product delivery:

- Random Forest Classifier
- Decision Tree Classifier
- Logistic Regression
- K Nearest Neighbors

Random Forest Classifier

In [23]:
```
from sklearn.ensemble import RandomForestClassifier

#Random Forest Classifier Object
rfc = RandomForestClassifier()
```

- **RandomForestClassifier** is an ensemble learning method that fits a number of decision tree classifiers on various sub-samples of the dataset.
- Import the **RandomForestClassifier** class from scikit-learn's ensemble module.

In [24]:
```
#Using GridSearchCV for hyperparameter tuning
from sklearn.model_selection import GridSearchCV

#Parameter grid
param_grid = {
    'max_depth': [4,8,12,16],
    'min_samples_leaf': [2,4,6,8],
    'min_samples_split': [2,4,6,8],
    'criterion': ['gini', 'entropy'],
    'random_state': [0,42]
}

#GridSearchCV object
grid = GridSearchCV(estimator=rfc, param_grid=param_grid, cv=5, n_jobs=-1, verbose=2, scoring='accuracy')

#Fitting the model
grid.fit(X_train, y_train)

#Best parameters
print('Best parameters: ', grid.best_params_)
```

```
Fitting 5 folds for each of 256 candidates, totalling 1280 fits
Best parameters:  {'criterion': 'entropy', 'max_depth': 8, 'min_samples_leaf': 6, 'min_samples_split': 2, 'random_state': 0}
```

- **GridSearchCV** is used for hyperparameter tuning by searching over a specified parameter grid.
- **param_grid** containing various hyperparameter values to be tested during grid search. This includes values for 'max_depth', 'min_samples_leaf', 'min_samples_split', 'criterion', and 'random_state'.The specific values for max_depth, min_samples_leaf, and min_samples_split are chosen to prevent the model from overfitting to the training data. These hyperparameters control the complexity of the individual trees, ensuring they don't become too deep or too specific to the training set.
- **GridSearchCV Object** takes the RandomForestClassifier as the estimator, the parameter grid defined earlier, performs 5-fold cross-validation (cv=5), uses all available processors for parallel execution (n_jobs=-1), provides verbose output during the search (verbose=2), and evaluates models based on accuracy (scoring='accuracy'). The GridSearchCV will evaluate the model's performance for each combination and return the best set of hyperparameters that maximize the specified scoring metric (in this case, accuracy).

In [25]:
```
#Random Forest Classifier Object
rfc = RandomForestClassifier(criterion='gini', max_depth=8, min_samples_leaf=8, min_samples_split=2, random_state=42)

#Fitting the model
rfc.fit(X_train, y_train)
```

Out[25]:
```
▾ RandomForestClassifier
RandomForestClassifier(max_depth=8, min_samples_leaf=8, random_state=42)
```

- **random_state** The random_state parameter ensures reproducibility. By setting a specific random seed, you make sure that the randomness introduced during the training process is consistent across different runs. This is important for result reproducibility and debugging.
- By using **rfc.fit:** Fit the RandomForestClassifier to the training data using the best hyperparameters.

In [26]:
```
#Training accuracy
print('Training accuracy: ', rfc.score(X_train, y_train))
```

```
Training accuracy:  0.7250823957267871
```

- **rfc.score** gives the training accuracy of the trained model on the training data.

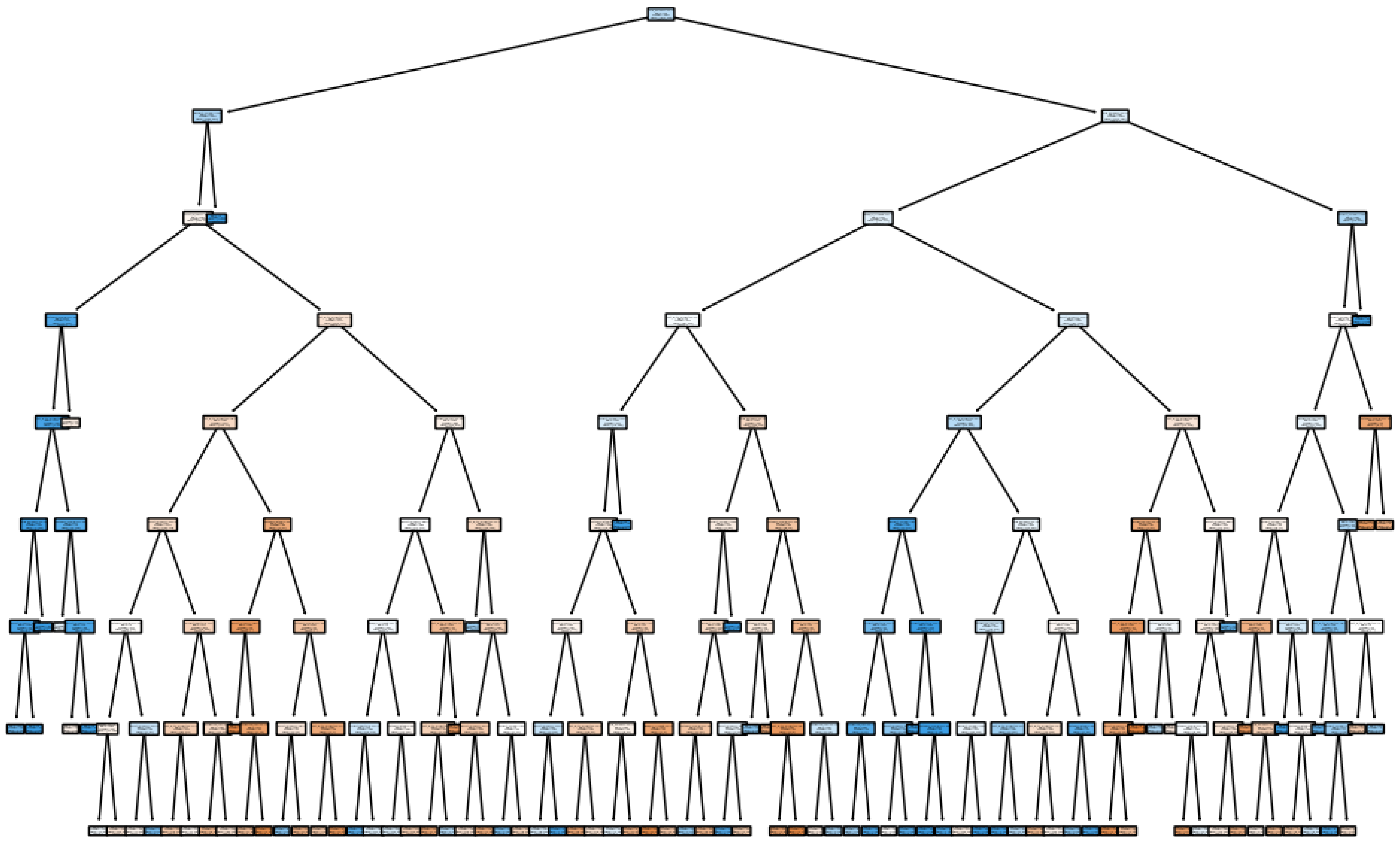
In [27]:
```
#predicting the test set results
rfc_pred = rfc.predict(X_test)
rfc_pred
```

Out[27]:
```
array([0, 1, 1, ..., 0, 1, 0])
```

- By using the trained RandomForestClassifier we can make the predictions(using **rfc.predict**) on the test set.

In [28]:
```
# Extract feature names as strings
feature_names = [str(feature) for feature in df.columns[:-1].tolist()]

# Extract class names as strings
class_names = [str(label) for label in df.iloc[:, -1].unique().tolist()]

# Print feature names and class names
print("Feature Names:", feature_names)
print("Class Names:", class_names)

# Import necessary libraries
import matplotlib.pyplot as plt
from sklearn.tree import plot_tree

# Visualize one tree from the RandomForestClassifier
plt.figure(figsize=(12, 8))
plot_tree(rfc.estimators_[1], feature_names=feature_names, class_names=class_names, filled=True, rounded=True)
plt.show()
```

```
Feature Names: ['Warehouse_block', 'Mode_of_Shipment', 'Customer_care_calls', 'Customer_rating', 'Cost_of_the_Product', 'Prior_purchases', 'Product_importance', 'G
ender', 'Discount_offered', 'Weight_in_gms']
Class Names: ['1', '0']
```



By employing the feature_names and class_names, we can visualize a tree, and the resultant tree visualization provides valuable insights into the decision-making process of the RandomForestClassifier. This aids in comprehending the hierarchical structure of the model's rules and the importance of different features.

Decision Tree Classifier

Here, we demonstrate the process of initializing, tuning, training, and evaluating a Decision Tree Classifier model using scikit-learn library in Python.

In [29]:
```
from sklearn.tree import DecisionTreeClassifier

#Decision Tree Classifier Object
dtc = DecisionTreeClassifier()
```

A Decision Tree Classifier model was trained using the training dataset. Hyperparameter tuning was performed using GridSearchCV to identify the best combination of parameters for optimal model performance. The following hyperparameters were tuned:

In [30]:
```
#Using GridSearchCV for hyperparameter tuning
from sklearn.model_selection import GridSearchCV
#Parameter grid
param_grid = {
    'max_depth': [2,4,6,8],
    'min_samples_leaf': [2,4,6,8],
    'min_samples_split': [2,4,6,8],
    'criterion': ['gini', 'entropy'],
    'random_state': [0,42]}

#GridSearchCV object
grid = GridSearchCV(estimator=dtc, param_grid=param_grid, cv=5, n_jobs=-1, verbose=2, scoring='accuracy')

#Fitting the model
grid.fit(X_train, y_train)

#Best parameters
print('Best parameters: ', grid.best_params_)
```

```
[CV] END criterion=entropy, max_depth=12, min_samples_leaf=2, min_samples_split=4, random_state=42; total time=   0.6s
[CV] END criterion=entropy, max_depth=12, min_samples_leaf=2, min_samples_split=6, random_state=42; total time=   0.6s
[CV] END criterion=entropy, max_depth=12, min_samples_leaf=2, min_samples_split=8, random_state=0; total time=   0.6s
[CV] END criterion=entropy, max_depth=12, min_samples_leaf=4, min_samples_split=2, random_state=0; total time=   0.5s
[CV] END criterion=entropy, max_depth=12, min_samples_leaf=4, min_samples_split=4, random_state=0; total time=   0.6s
[CV] END criterion=entropy, max_depth=12, min_samples_leaf=4, min_samples_split=4, random_state=42; total time=   0.5s
[CV] END criterion=entropy, max_depth=12, min_samples_leaf=4, min_samples_split=6, random_state=42; total time=   0.6s
[CV] END criterion=entropy, max_depth=12, min_samples_leaf=4, min_samples_split=8, random_state=42; total time=   0.6s
[CV] END criterion=entropy, max_depth=12, min_samples_leaf=6, min_samples_split=2, random_state=0; total time=   0.5s
[CV] END criterion=entropy, max_depth=12, min_samples_leaf=6, min_samples_split=4, random_state=0; total time=   0.5s
[CV] END criterion=entropy, max_depth=12, min_samples_leaf=6, min_samples_split=4, random_state=42; total time=   0.6s
[CV] END criterion=entropy, max_depth=12, min_samples_leaf=6, min_samples_split=6, random_state=42; total time=   0.6s
[CV] END criterion=entropy, max_depth=12, min_samples_leaf=6, min_samples_split=8, random_state=42; total time=   0.5s
[CV] END criterion=entropy, max_depth=12, min_samples_leaf=8, min_samples_split=2, random_state=0; total time=   0.5s
[CV] END criterion=entropy, max_depth=12, min_samples_leaf=8, min_samples_split=4, random_state=0; total time=   0.5s
[CV] END criterion=entropy, max_depth=12, min_samples_leaf=8, min_samples_split=4, random_state=42; total time=   0.6s
[CV] END criterion=entropy, max_depth=12, min_samples_leaf=8, min_samples_split=6, random_state=42; total time=   0.6s
[CV] END criterion=entropy, max_depth=12, min_samples_leaf=8, min_samples_split=8, random_state=0; total time=   0.6s

Best parameters:  {'criterion': 'gini', 'max_depth': 6, 'min_samples_leaf': 6, 'min_samples_split': 2, 'random_state': 0}
```

GridSearchCV from sklearn.model_selection is used for hyperparameter tuning. "param_grid" specifies the hyperparameters to be tuned along with their possible values. After evaluating 256 different combinations of hyperparameters, the best parameters are identified.

In [31]:
```
#Decision Tree Classifier Object
dtc = DecisionTreeClassifier(criterion='gini', max_depth=6, min_samples_leaf=6, min_samples_split=2, random_state=0, class_weight='balanced')

#Fitting the model
dtc.fit(X_train, y_train)
```

Out[31]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier(class_weight='balanced', max_depth=6, min_samples_leaf=6,
                       random_state=0)
```

A new instance of DecisionTreeClassifier is created with the best hyperparameters obtained from the grid search.

In [32]:
```
#Training accuracy
print('Training accuracy: ', dtc.score(X_train, y_train))
```

```
Training accuracy:  0.6913285600636436
```

The model achieved an accuracy score of approximately 69.13% on the training dataset using these tuned hyperparameters.

In [33]:
```
#predicting the test set results
dtc_pred = dtc.predict(X_test)
```

Logistic Regression

Logistic regression can be employed to predict the estimated delivery time for products based on various factors.

In [34]:
```
from sklearn.linear_model import LogisticRegression

#Logistic Regression Object
lr = LogisticRegression()
```

In [35]:
```
#fitting the model
lr.fit(X_train, y_train)
```

Out[35]:
```
▾ LogisticRegression
LogisticRegression()
```

In [36]:
```
#Training accuracy
lr.score(X_train, y_train)
```

Out[36]:
```
0.6356404136833731
```

In [37]:
```
#predicting the test set results
lr_pred = lr.predict(X_test)
print(lr_pred)
```

```
[0 0 1 ... 0 1 1]
```

K Nearest Neighbors

K-Nearest Neighbors (KNN) is a simple, instance-based learning algorithm used for classification and regression tasks in machine learning. It works by finding the K closest training examples in the feature space to a given input, and then predicts the output based on the majority class (for classification) or average value (for regression) of those K neighbors.

In [38]:
```
from sklearn.neighbors import KNeighborsClassifier

#KNN Classifier Object
knn = KNeighborsClassifier()
```

In [40]:
```
#fitting the model
knn.fit(X_train, y_train)
```

Out[40]:
```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

In [41]:
```
#training accuracy
knn.score(X_train, y_train)
```

Out[41]:
```
0.7778156608705534
```

In [42]:
```
#predicting the test set results
knn_pred = knn.predict(X_test)
```

Model Evaluation

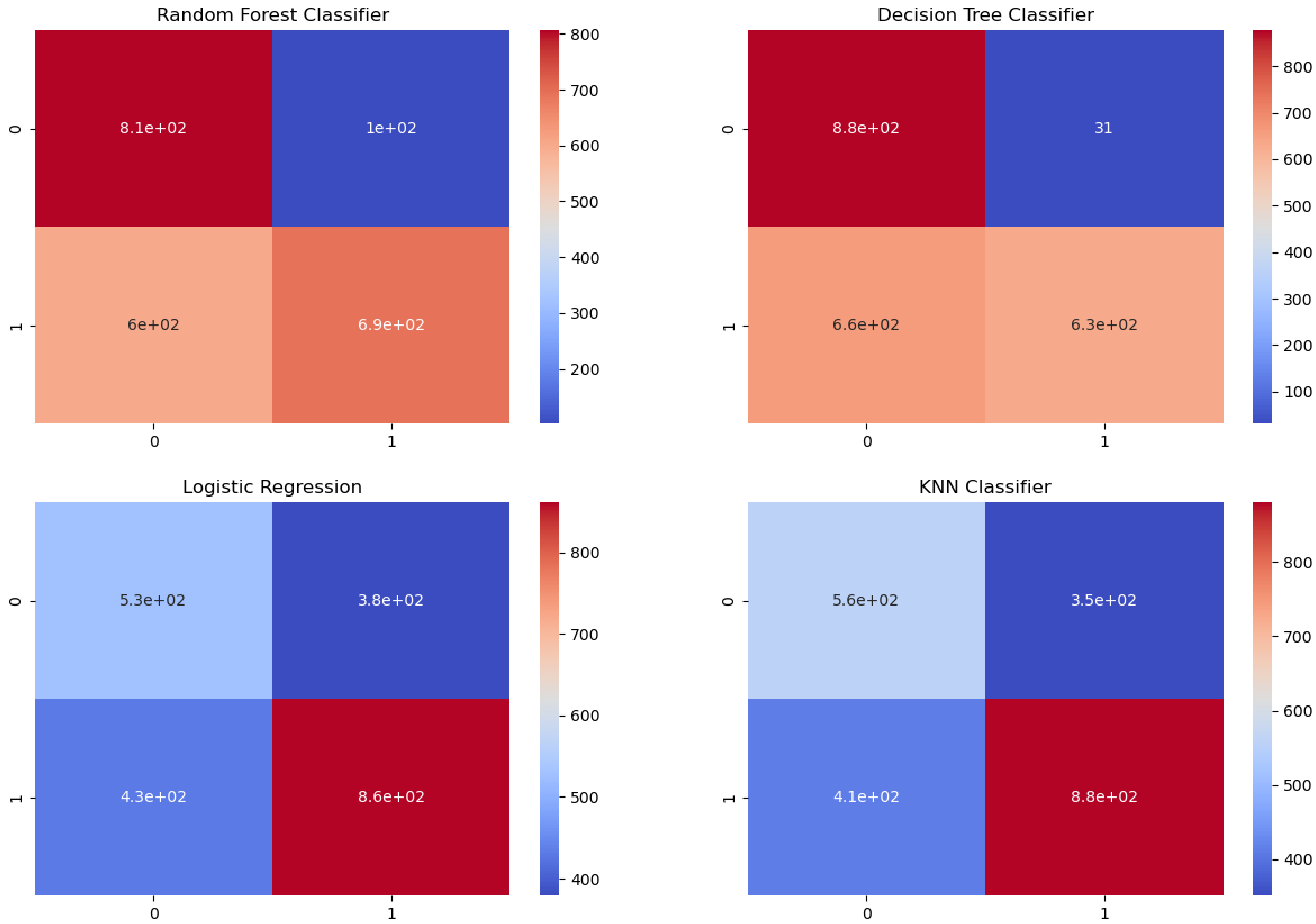
Model evaluation is a crucial step in machine learning with multifaceted importance. It quantitatively measures a model's performance, assessing metrics like accuracy, precision, and recall. This evaluation guides decision-making, aiding in selecting the best model or determining if the current one meets performance standards. Diagnostic metrics such as the confusion matrix identify errors, offering insights for improvement. When dealing with multiple models, evaluation metrics enable direct comparisons for optimal model selection. Additionally, it plays a key role in hyperparameter tuning and optimization, guiding parameter adjustments. Overall, model evaluation provides actionable insights, supports decision-making, and drives continuous improvement in predictive performance.

In [43]:
```
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, mean_absolute_error, r2_score, mean_squared_error
```

- This heatmap represents the confusion matrix of predictions (`rfc_pred`) made by a particular model on the test data (`y_test`). The 'coolwarm' colormap is used, and the matrix is annotated with actual counts.
- The resulting visualizations will provide a comparative view of the classification performance of four different classifiers (Random Forest, Decision Tree, Logistic Regression, and KNN) on the test data. The confusion matrices will show the true positive, true negative, false positive, and false negative values, enabling a qualitative assessment of each model's ability to correctly classify instances and identify areas of improvement or optimization.

In [44]:
```
fig, ax = plt.subplots(2,2,figsize=(15,10))
sns.heatmap(confusion_matrix(y_test, rfc_pred), annot=True, cmap='coolwarm', ax=ax[0,0]).set_title('Random Forest Classifier')
sns.heatmap(confusion_matrix(y_test, dtc_pred), annot=True, cmap='coolwarm', ax=ax[0,1]).set_title('Decision Tree Classifier')
sns.heatmap(confusion_matrix(y_test, lr_pred), annot=True, cmap='coolwarm', ax=ax[1,0]).set_title('Logistic Regression')
sns.heatmap(confusion_matrix(y_test, knn_pred), annot=True, cmap='coolwarm', ax=ax[1,1]).set_title('KNN Classifier')
```

Out[44]:
```
Text(0.5, 1.0, 'KNN Classifier')
```



Classification report

The classification report for four different classifiers (Random Forest, Decision Tree, Logistic Regression, and KNN) applied to the test data. The classification report includes metrics such as precision, recall, F1-score, and support for each class

In [45]:
```
#classification report
print('Random Forest Classifier: \n', classification_report(y_test, rfc_pred))
print('Decision Tree Classifier: \n', classification_report(y_test, dtc_pred))
print('Logistic Regression: \n', classification_report(y_test, lr_pred))
print('KNN Classifier: \n', classification_report(y_test, knn_pred))
```

```
Random Forest Classifier: 
               precision    recall  f1-score   support

           0       0.57      0.89      0.70       908
           1       0.87      0.53      0.66      1292

    accuracy                           0.68      2200
   macro avg       0.72      0.71      0.68      2200
weighted avg       0.75      0.68      0.68      2200

Decision Tree Classifier: 
               precision    recall  f1-score   support

           0       0.57      0.97      0.72       908
           1       0.95      0.49      0.65      1292

    accuracy                           0.69      2200
   macro avg       0.76      0.73      0.68      2200
weighted avg       0.80      0.69      0.68      2200

Logistic Regression: 
               precision    recall  f1-score   support

           0       0.55      0.58      0.57       908
           1       0.69      0.67      0.68      1292

    accuracy                           0.63      2200
   macro avg       0.62      0.62      0.62      2200
weighted avg       0.64      0.63      0.63      2200

KNN Classifier: 
               precision    recall  f1-score   support

           0       0.57      0.61      0.59       908
           1       0.71      0.68      0.70      1292

    accuracy                           0.65      2200
   macro avg       0.64      0.65      0.65      2200
weighted avg       0.66      0.65      0.65      2200
```

- **Precision:** The ability of the classifier not to label as positive a sample that is negative.
- **Recall:** The ability of the classifier to find all the positive samples.
- **F1-score:** The harmonic mean of precision and recall, providing a balanced measure.
- **Support:** The number of actual occurrences of the class in the specified dataset.

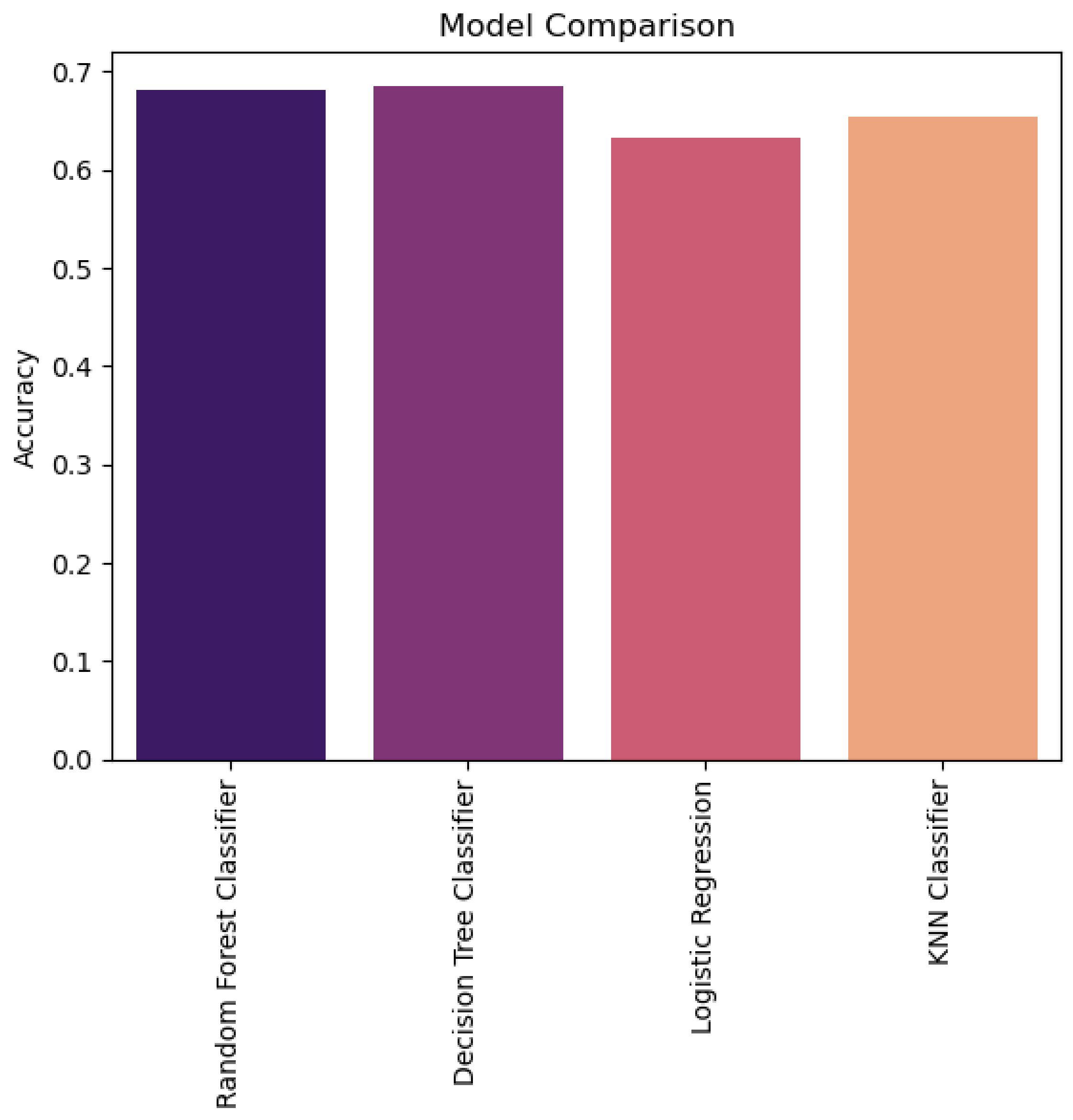
By comparing the classification reports for each classifier, you can gain insights into how well each model performs in terms of precision, recall, and overall accuracy for different classes. This information is valuable for understanding the strengths and weaknesses of each classifier, helping in the selection of the most appropriate model for the specific task at hand. It also aids in identifying whether a particular model excels in certain classes but struggles with others, providing guidance for further model improvement or refinement.

Model Comparison

Let's visualize a model comparison using a bar plot, which showcases the accuracy of four distinct classifiers (Random Forest, Decision Tree, Logistic Regression, and KNN) on the test dataset. The height of each bar represents the accuracy of the corresponding model. This visualization allows us to easily compare the performance of different models and identify which one achieves the highest accuracy. It provides insights into which classifier is most effective for the specific classification task, helping in the selection and evaluation of machine learning models.

In [46]:
```
models = ['Random Forest Classifier', 'Decision Tree Classifier', 'Logistic Regression', 'KNN Classifier']
accuracy = [accuracy_score(y_test, rfc_pred), accuracy_score(y_test, dtc_pred), accuracy_score(y_test, lr_pred), accuracy_score(y_test, knn_pred)]
sns.barplot(x=models, y=accuracy, palette='magma').set_title('Model Comparison')
plt.xticks(rotation=90)
plt.ylabel('Accuracy')
```

Out[46]:
```
Text(0, 0.5, 'Accuracy')
```



Conclusion

The primary objective of this project was to forecast the punctuality of product deliveries from an e-commerce company. The analysis delved into various factors influencing delivery times and examined customer behavior patterns. Through exploratory data analysis, it was observed that product weight and cost significantly impact delivery outcomes. Products weighing between 2500 - 3500 grams and costing less than 250 dollars exhibited a higher likelihood of on-time delivery. Warehouse F, presumably located near a seaport, emerged as the primary shipping point.

Customer behavior emerged as a key predictor of timely deliveries. Increased customer inquiries correlated with delayed deliveries, while customers with a history of prior purchases showed a higher incidence of on-time deliveries, indicating their loyalty to the company. Notably, products with discounts below 10% tended to experience delayed deliveries, whereas those with discounts exceeding 10% were more likely to be delivered punctually.

Turning to machine learning models, the decision tree classifier achieved the highest accuracy at 69%, outperforming other models. The random forest classifier and logistic regression followed closely with accuracies of 68% and 67%, respectively. The K Nearest Neighbors model recorded the lowest accuracy at 65%. These findings offer valuable insights for optimizing delivery operations and refining customer interactions in the e-commerce domain.

References

1)https://www.geeksforgeeks.org/random-forest-classifier-using-scikit-learn/ (https://www.geeksforgeeks.org/random-forest-classifier-using-scikit-learn/)

2)https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html (https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html)

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6)Breiman L, Friedman J, Stone CJ, Olshen RA (1984) Classification and regression trees, chapter 10, 279–294 (CRC press).

7)Exploratory Data Analysis:

- "Exploratory Data Analysis" by John W. Tukey: https://www.amazon.com/Exploratory-Data-Analysis-John-Tukey/dp/0201076160 (https://www.amazon.com/Exploratory-Data-Analysis-John-Tukey/dp/0201076160)
- "Python Data Science Handbook" by Jake VanderPlas: https://jakevdp.github.io/PythonDataScienceHandbook/ (https://jakevdp.github.io/PythonDataScienceHandbook/)

8)Model Predictions:

- "Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow" by Aurélien Géron: https://www.oreilly.com/library/view/hands-on-machine-learning/9781492032632/ (https://www.oreilly.com/library/view/hands-on-machine-learning/9781492032632/)
- "Introduction to Statistical Learning" by Gareth James, Daniela Witten, Trevor Hastie, Robert Tibshirani: http://faculty.marshall.usc.edu/gareth-james/ISL/ (http://faculty.marshall.usc.edu/gareth-james/ISL/)

Haiku:

Data streams intertwine,

Predicting the delivery line,

Machine's foresight shines.