E-retail factors for customer activation and retention:

*A case study from Indian e-commerce customers

```
*Customer satisfaction has emerged as one of the most important factors that
 guarantee the success of online store.
*A comprehensive review of the literature, theories and models have been
 carried out to propose the models for customer activation and customer
retention.
*Five major factors that contributed to the success of an e-commerce store
have been
 identified as: service quality, system quality, information quality, trust
and net benefit.
*The research furthermore investigated the factors that influence the online
customers
 repeat purchase intention. The combination of both utilitarian value and
hedonistic values
 are needed to affect the repeat purchase intention (loyalty) positively.
*The data is collected from the Indian online shoppers.
*Results indicate the e-retail success factors, which are very much critical
for customer satisfaction.
```

```
#Importing the libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

```
!pip install openpyxl
```

```
Requirement already satisfied: openpyxl in c:\users\satya\anaconda3\lib\site-
packages (3.0.9)
Requirement already satisfied: et-xmlfile in c:\users\satya\anaconda3\lib\sit
e-packages (from openpyxl) (1.1.0)
# Reading the data
Dt=pd.read_excel('D:\Data Trained - Excel
links\customer_retention_dataset.xlsx')
Dt.head()
```

```
# Now Setting option to show max rows and max columns
pd.set_option("display.max_columns",None)
pd.set_option("display.max_rows", None)
```

In [7]:

```
from string import digits

#Removing tab spaces
Dt.columns = Dt.columns.str.replace('\t','')
```

EXPLORATORY DATA ANALYTICS :

```
# looking at the sahpe of the data
Dt.shape
```

```
(269, 71)
```

```
# looking at all data types
Data.dtypes



#Removing digits
remove_digits = str.maketrans('', '', digits)
Dt.columns = Dt.columns.str.translate(remove_digits)

#Removing leading and traillling spaces
Dt.columns = Dt.columns.str.strip()
```

```
# looking at the head of the data
Dt.head()
```

```
# Let see the null count for each column, but will not count
Dt.isnull().sum().any()
```

```
False
```

```
# Let see the the uniqueness of the data
Dt.nunique(
```

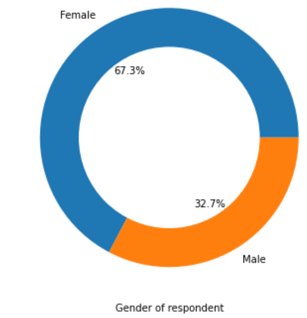
IMPLEMENTING UNIVARIATE ANALYSIS

In [15]:

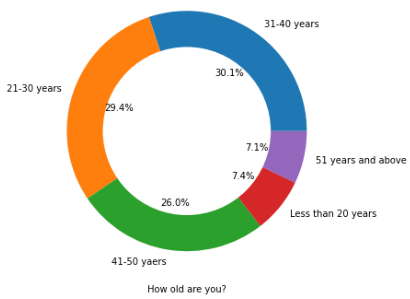
```
personal_info=['Gender of respondent','How old are you?','Which city do you
shop online from?',
               'What is the Pin Code of where you shop online from?','Since
How Long You are Shopping Online ?',
               'How many times you have made an online purchase in the past
year?']
```

Checking Personal information

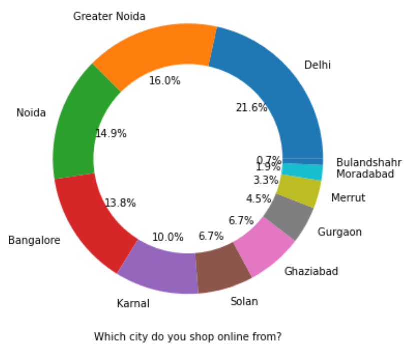
```
for i in personal_info:
    if i!='What is the Pin Code of where you shop online from?':
        plt.figure(figsize=(8,6))
        Dt[i].value_counts().plot.pie(autopct='%1.1f%%')
        centre=plt.Circle((0,0),0.7,fc='white')
        fig=plt.gcf()
        fig.gca().add_artist(centre)
        plt.xlabel(i)
        plt.ylabel('')
        plt.figure()


plt.figure()
```



<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



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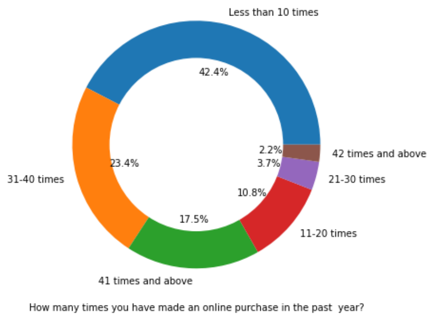


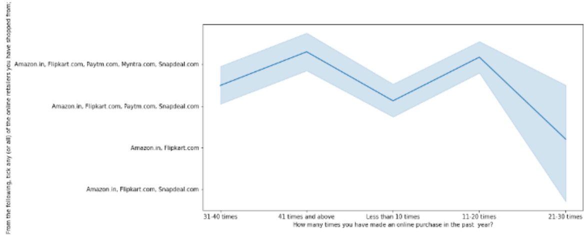

```
<Figure size 432x288 with 0 Axes>
```

Here **in** the analysis, there are double the number of women than men who took the survey**.**
-Most of the people are **in** the 30's followed by 20's,senior citizen **and** teenagers are the least **in** number**.**
-Most of the people belongs to Banglore, delhi, noida ambiguity can also be seen **as** noida has two categories(noida **and** greater noida) which need to be handled**.**
-Most of the people shopping online been shopping **from** a long time**.**
-Majority of people shop online 10 times a year, ambiguity can also be seen **for** range 42 times **and** above which needs are to be handeled**.**

Analysing on the basis of Various following factors

Intention of Repeat purchase:

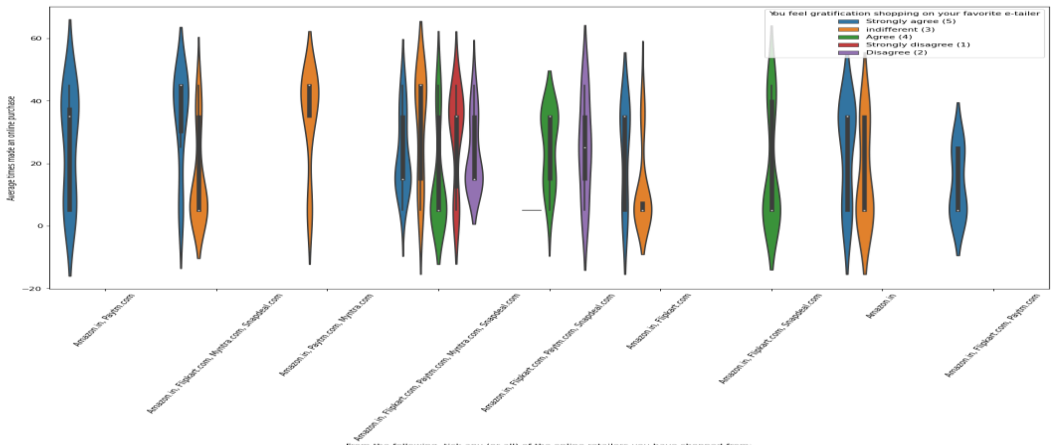
```
#Resolving ambiguity of column
#Changing 42 times and above to 41 times and above
Dt['How many times you have made an online purchase in the past 
year?'].replace('42 times and above','41 times and above',

inplace=True)
plt.figure(figsize=(12,6))
sns.lineplot(Dt['How many times you have made an online purchase in the past 
year?'],
               Dt['From the following, tick any (or all) of the online 
retailers you have shopped from;'])
```



Most of the shoppers who shop more than 41 times a year shop from all the online brands, some of the people who shop for 32-40 and less than 10 times a year seem to exclude myntra. People shop from flipkart and Amazon whatever be the case.

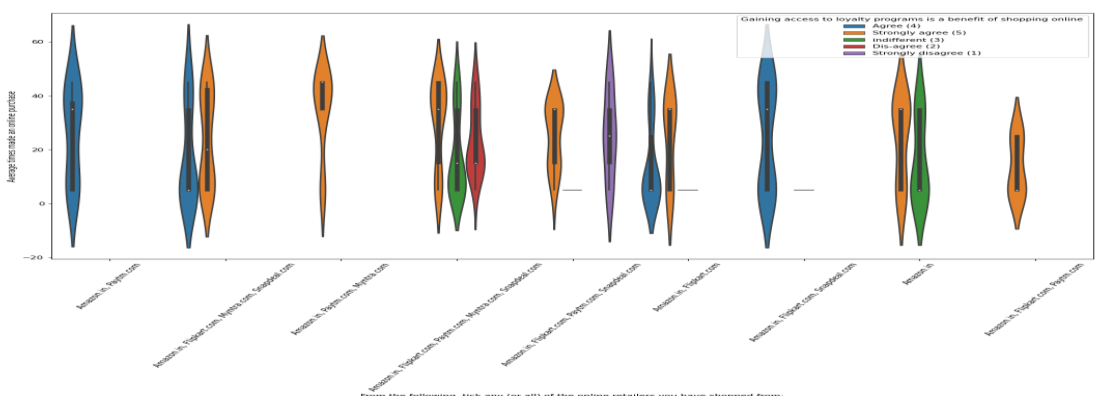
<u>*Now doing Convertion of years to numbers for better analysis</u>

```
dict={'31-40 times':35,'41 times and above':45,'Less than 10 times':5,'11-20 
times':15,'21-30 times':25}

Dt['Average times made an online purchase']=Dt['How many times you have made 
an online purchase in the past  year?'].replace(dict)


plt.figure(figsize=(18,10))
sns.violinplot(Dt['From the following, tick any (or all) of the online 
retailers you have shopped from;'],
               Dt['Average times made an online purchase'],hue=Dt['You feel 
gratification shopping on your favorite e-tailer'])
plt.xticks(rotation=60)
```



From the graph analysis,All the people who have shopped from amazon,paytm, flipkart are satisfied. People who shop from a more number of online brands dosnot get satisfied.

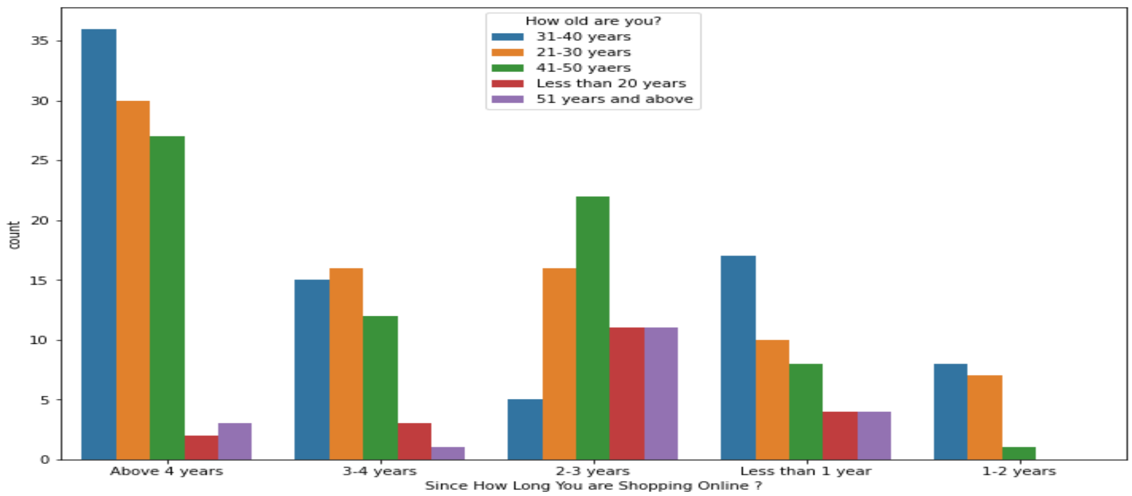
```
plt.figure(figsize=(18,10))
sns.violinplot(Dt['From the following, tick any (or all) of the online 
retailers you have shopped from;'],
               Dt['Average times made an online purchase'],hue=Dt['Gaining 
access to loyalty programs is a benefit of shopping online'])
plt.xticks(rotation=60)
```



From the Grapgh analysis, people shopping from flipkart and sanpdeal seems to give such benefits but people who shop from almost everywhere disagree with this statement too. Moreover, People of Amazon and paytm are getting benefits from the loyalty points

Getting Online Retailing Analysis:

```
plt.figure(figsize=(12,8))
sns.countplot(Dt['Since How Long You are Shopping Online ?'],hue=Dt['How old are you?'])
```



More and Highest number of people have been shopping online for above 4 years except for the age group below 20 years and above 50 years. People who are shopping online for 1-2 years does not include teenagers and elder people.

#Converting Years to numbers for better analysis

In [31]:

```
# Getting data about the age groups
Dt['Since How Long You are Shopping Online ?'].unique()
```

Out[31]:

```
array(['Above 4 years', '3-4 years', '2-3 years', 'Less than 1 year',
       '1-2 years'], dtype=object)
```

In [32]:

```
dict={'Above 4 years':4.5,'3-4 years':3.5,'2-3 years':2.5,'1-2 years':1.5,'Less than 1 year':0.5}
Dt['Average years of shopping online']=Dt['Since How Long You are Shopping Online ?'].replace(dict)
```

In [34]:

```
# Getting data about the cities
Dt['Which city do you shop online from?'].unique()
```

Out[34]:

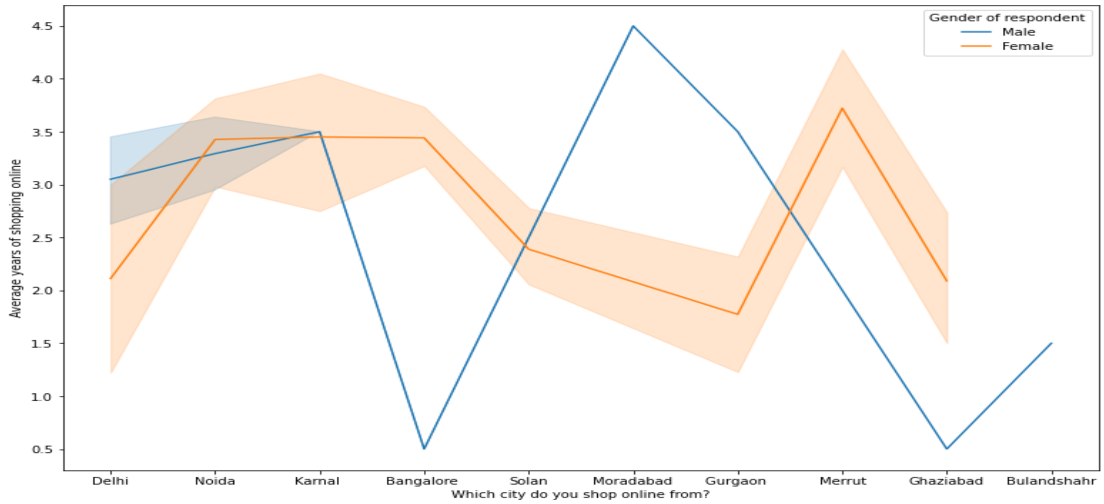
```
array(['Delhi', 'Greater Noida', 'Karnal ', 'Bangalore ', 'Noida',
       'Solan', 'Moradabad', 'Gurgaon ', 'Merrut', 'Ghaziabad',
       'Bulandshahr'], dtype=object)
#Changing Greater noida to noida
Dt['Which city do you shop online from?'].replace({'Greater Noida':'Noida'},inplace=True)
```

In [37]:

```
plt.figure(figsize=(13,9))
sns.lineplot(Dt['Which city do you shop online from?'],Dt['Average years of
shopping online'],hue=Dt['Gender of respondent'])
```

Out[37]:

```
<AxesSubplot:xlabel='Which city do you shop online from?', ylabel='Average ye
ars of shopping online'>
```

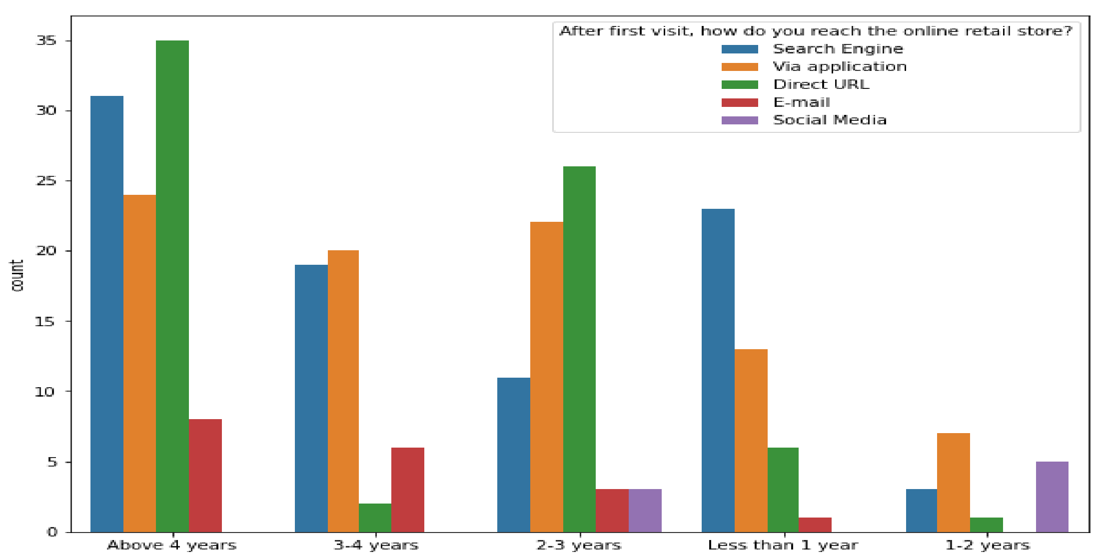


In the above given data lines,one can say that, the density of female customers is more than male. *Highest number of men shopping online belong from delhi and noida,* whereas, men from moradabad have been shopping online for the longest. *Men living in banglore and ghaziabad shop have shopped online for less than 1 year.* Women from meerut and noida have shopped the longest.

In [38]:

```
plt.figure(figsize=(10,8))
sns.countplot(Dt['Since How Long You are Shopping Online ?'],
              hue=Dt['After first visit, how do you reach the online retail
store?'])
```

```
<AxesSubplot:xlabel='Since How Long You are Shopping Online ?', ylabel='count
'>
```



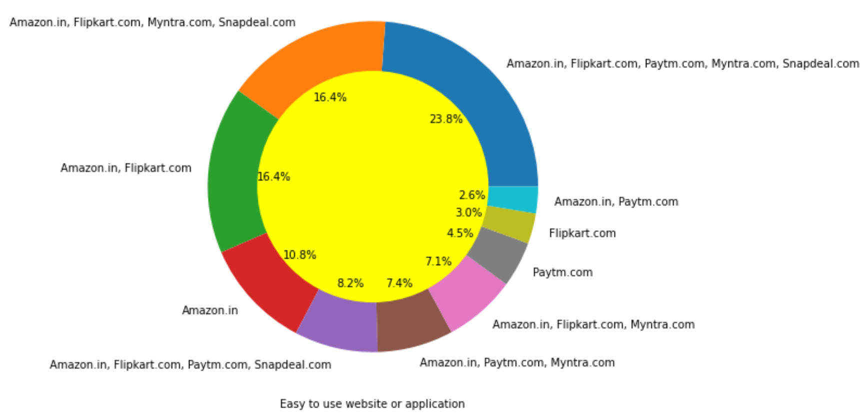
Moreover, people who are shopping online for more than 3 years donot use the application rather use search engine and direct url's in large number which indicates that online brands should update all their platforms rather than just application.

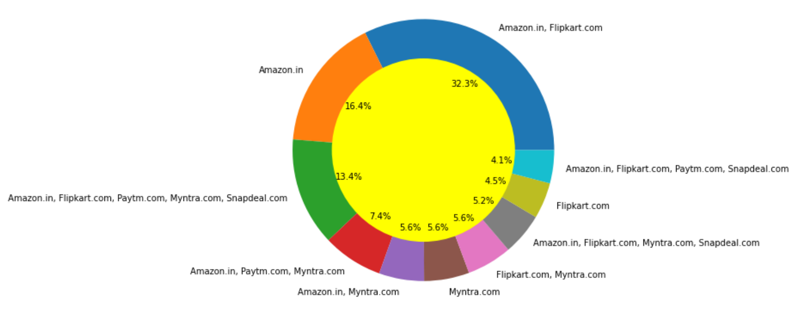
Checking for Brand image

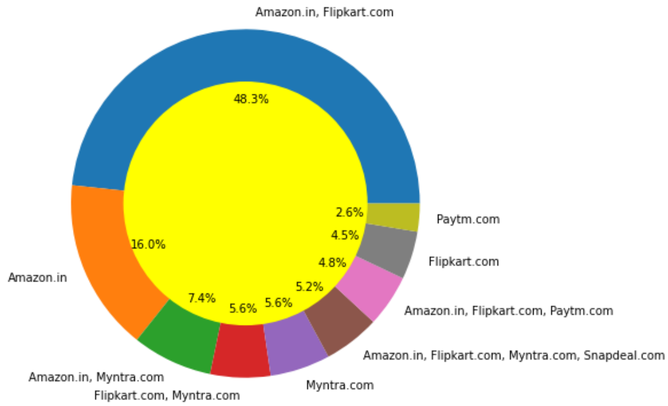
```
performance=['Easy to use website or application',
        'Visual appealing web-page layout', 'Wild variety of product on
offer',
        'Complete, relevant description information of products',
        'Fast loading website speed of website and application',
        'Reliability of the website or application',
        'Quickness to complete purchase',
        'Availability of several payment options', 'Speedy order delivery',
        'Privacy of customers’ information',
        'Security of customer financial information',
        'Perceived Trustworthiness',
        'Presence of online assistance through multi-channel']
```

In [41]:

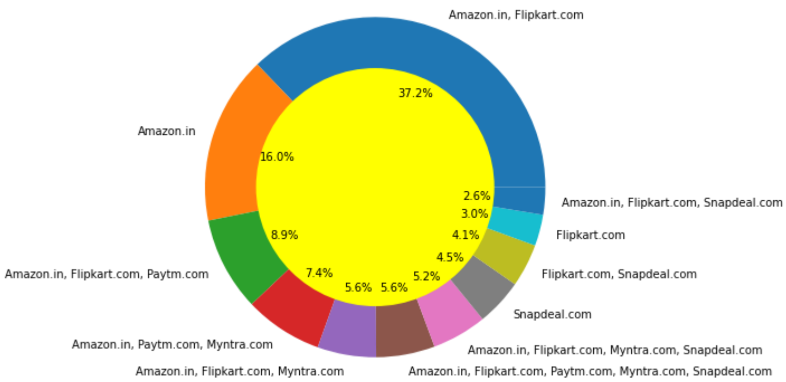
```
for i in performance:
         plt.figure(figsize=(9,7))
         Dt[i].value_counts().plot.pie(autopct='%1.1f%%')
         centre=plt.Circle((0,0),0.7,fc='yellow')
         fig=plt.gcf()
         fig.gca().add_artist(centre)
         plt.xlabel(i)
         plt.ylabel('')
         plt.figure()
```



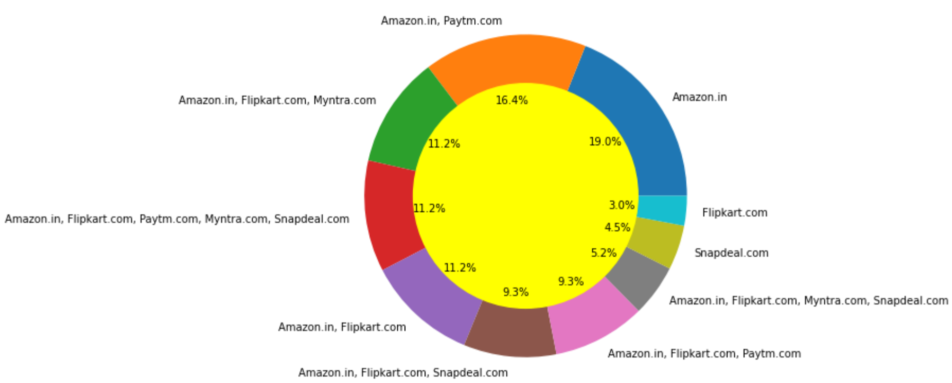




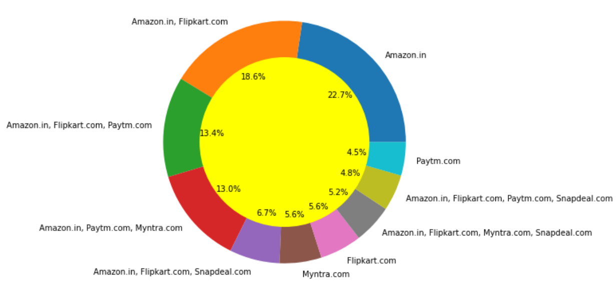
Wild variety of product on offer



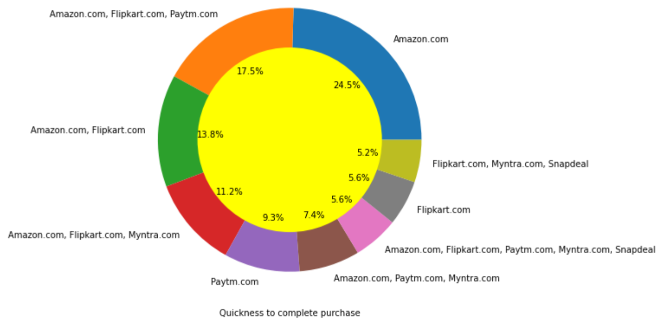
Complete, relevant description information of products



Fast loading website speed of website and application



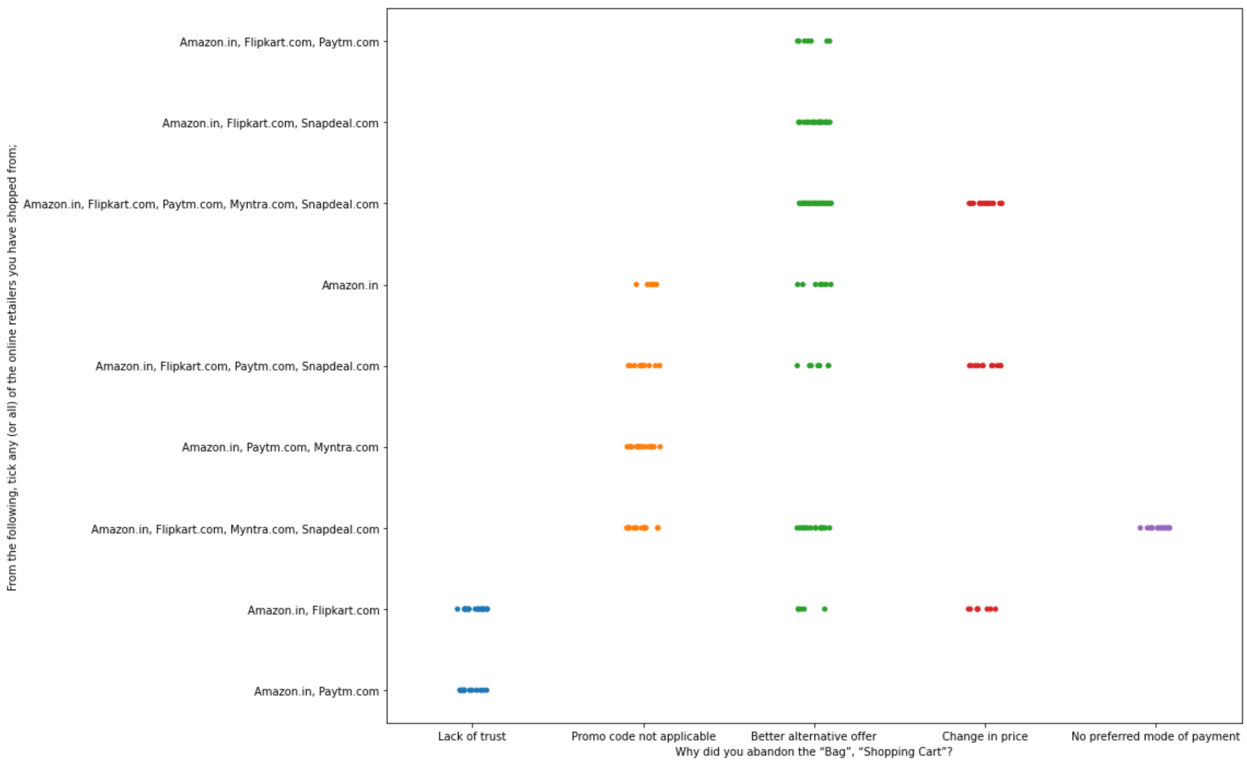
Reliability of the website or application



Flipkart,Amazon have been the highest votes for having all the positive points and have maintained a very good brand image followed by paytm and the myntra.

In [42]:

```
plt.figure(figsize=(14,12))
sns.stripplot(Dt['Why did you abandon the “Bag”, “Shopping Cart”?'],
              Dt['From the following, tick any (or all) of the online
retailers you have shopped from;'])
```



We can clearly see that most of the time people avoid the bag is beacuse they get a better alternative offer or promo code not applicable. There is also lack of trust seen in flipkart,amazon and paytm by some people.

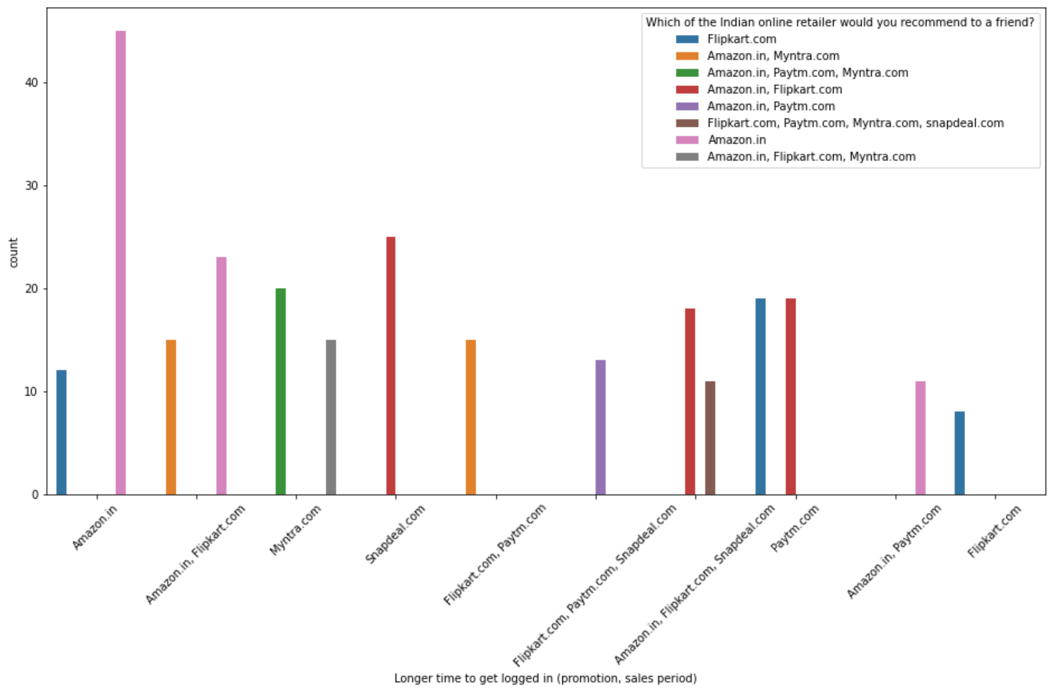
Checking Loyalty

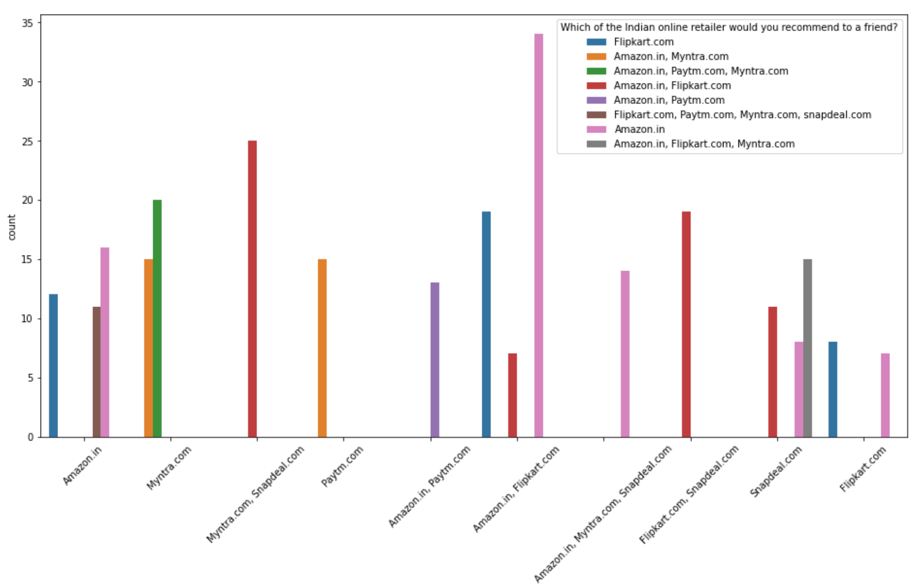
The people who are Loyal customers keep using the same brand even if it is not good as other brands

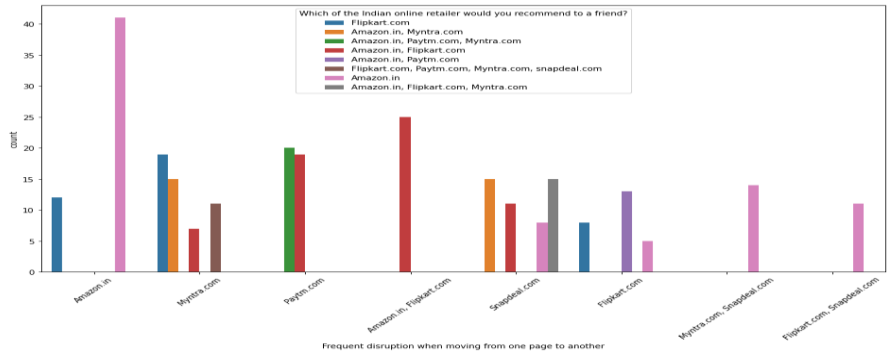
In [43]:

```
#Collecting all the negative remarks about a brand
bad=['Longer time to get logged in (promotion, sales period)',
```

```
       'Longer time in displaying graphics and photos (promotion, sales
period)',
       'Late declaration of price (promotion, sales period)',
       'Longer page loading time (promotion, sales period)',
       'Limited mode of payment on most products (promotion, sales period)',
       'Longer delivery period', 'Change in website/Application design',
       'Frequent disruption when moving from one page to another']


for i in bad:
        plt.figure(figsize=(16,8))
        sns.countplot(Dt[i],hue=Dt['Which of the Indian online retailer would
you recommend to a friend?'])
        plt.xticks(rotation=45)
        plt.figure()
```








```
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```

*Customers seem to be more loyal to amazon, flipkart and paytm as even though many of them have given negative remarks about them still they would recommend these platforms to their friend.

Processing the dataframe

*Separating the label from rest of the features

In [45]:

```
x=Dt.copy()
x.drop('Which of the Indian online retailer would you recommend to a friend?',axis=1,inplace=True)
y=Dt['Which of the Indian online retailer would you recommend to a friend?']
```

Encoding Categorical Features

In [46]:

```
cat=[i for i in x.columns if x[i].dtypes=='O']
```

In [47]:

```
# Getting the libraries
from sklearn.preprocessing import OrdinalEncoder,LabelEncoder
encode=OrdinalEncoder()
labe=LabelEncoder()

#using ordinal encoder for independent features
for i in cat:
    x[i]=encode.fit_transform(x[i].values.reshape(-1,1))

#Using label encoder for Label Column
y=labe.fit_transform(y)
```

Doing Scaling Process:

In [49]:

```
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()

xd=scaler.fit_transform(x)
x=pd.DataFrame(xd,columns=x.columns)
```

Using chi2 test

```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
```

In [59]:

```
selection = SelectKBest(score_func=chi2)
fit = selection.fit(x,y)
```

In [60]:

```
#Naming the dataframe columns
Datascores = pd.DataFrame(fit.scores_)
Datacolumns = pd.DataFrame(x.columns)
featureScores = pd.concat([Datacolumns,Datascores],axis=1)
featureScores.columns = ['Features','Score']
```

In [61]:

```
 # print 10 best features
print(featureScores.nlargest(10,'Score'))
feat=list(featureScores.nlargest(10,'Score')['Features'])
```

```
Features      Score
16    Why did you abandon the “Bag”, “Shopping Cart”?  75.754028
22                         Loading and processing speed  59.810983
42  Shopping on the website gives you the sense of...  59.253569
10  What browser do you run on your device to acce...  57.171099
67                Change in website/Application design  55.301526
49                    Visual appealing web-page layout  54.245760
65  Limited mode of payment on most products (prom...  53.269266
61  Longer time to get logged in (promotion, sales...  48.222655
62  Longer time in displaying graphics and photos ...  48.130643
50                    Wild variety of product on offer  47.605973
```

Using various feature selection method which affects the most

#Using Feature importance of random forrest

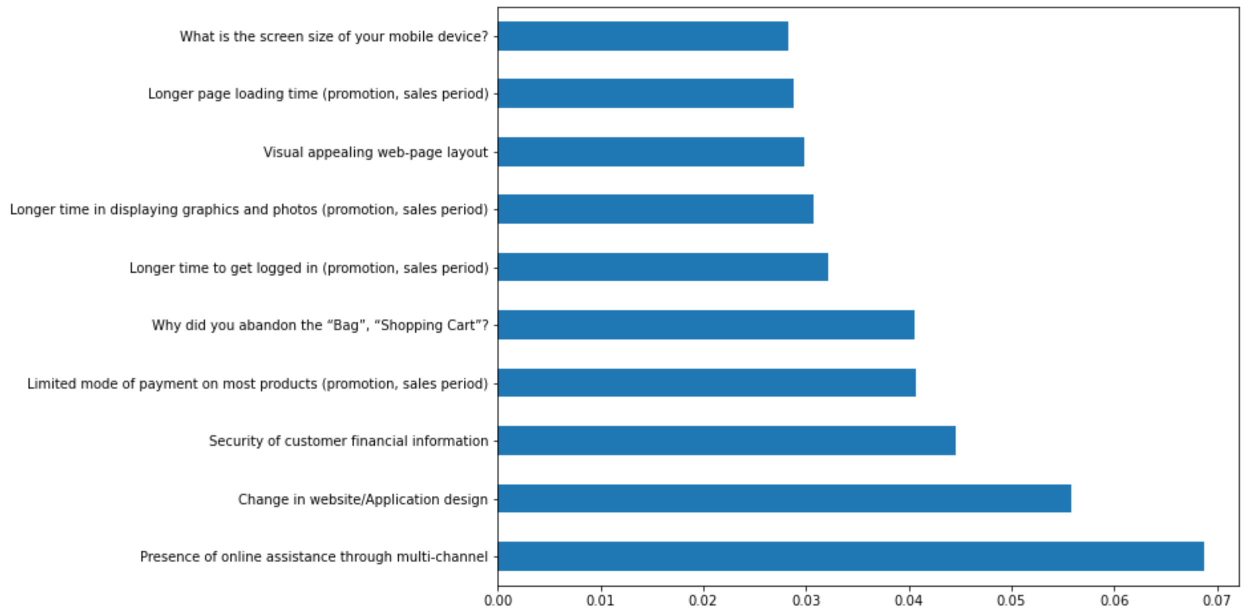
In [51]:

```
from sklearn.ensemble import RandomForestClassifier
m=RandomForestClassifier()
m.fit(x,y)
```

```
andomForestClassifier()
```

In [52]:

```
# Now plot graph of feature importances for better visualization
feat_importances = pd.Series(m.feature_importances_, index=x.columns)
plt.figure(figsize=(10,8))
feat_importances.nlargest(10).plot(kind='barh')
plt.show()
```



From the above chart we can see that above features are of most importance in determining whhich platform will a ciustomer recommend to his friend.

#PCA Anaysis

In [62]:

```
from sklearn.decomposition import PCA
pca = PCA().fit(x)
```

In [63]:

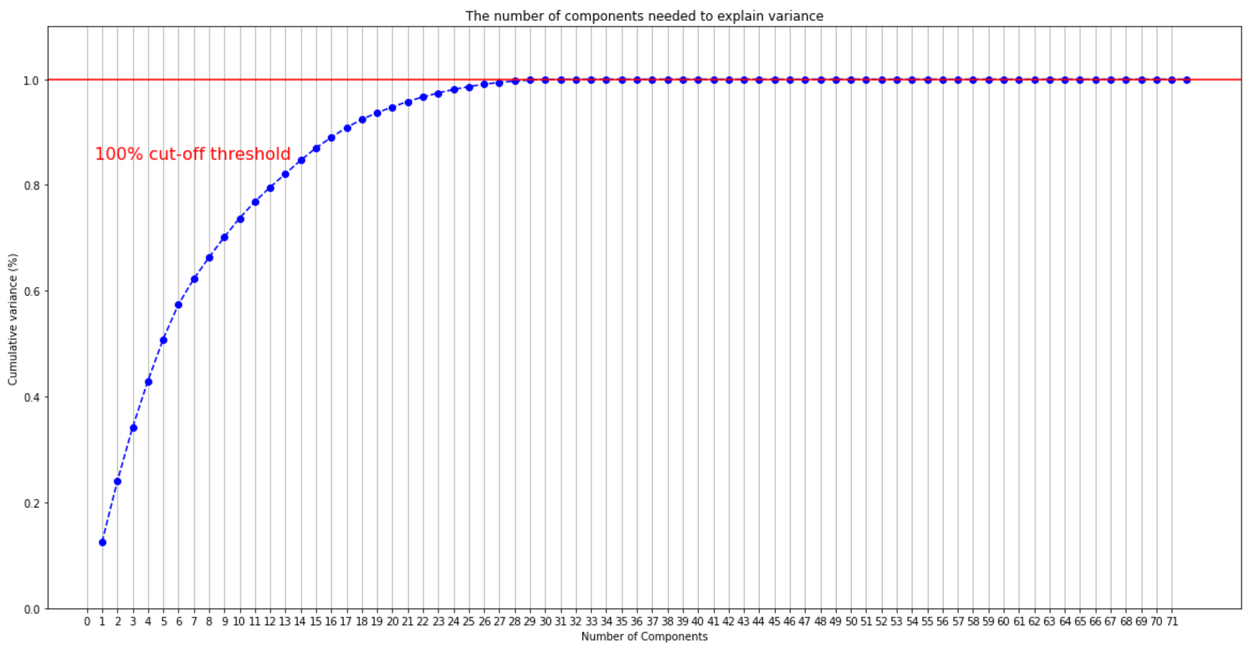
```
fig, ax = plt.subplots(figsize=(20,10))
xi = np.arange(1, 73, step=1)
yi = np.cumsum(pca.explained_variance_ratio_)

plt.ylim(0.0,1.1)
plt.plot(xi, yi, marker='o', linestyle='--', color='b')

plt.xlabel('Number of Components')
plt.xticks(np.arange(0, 72, step=1)) #change from 0-based array index to 1-
based human-readable label
plt.ylabel('Cumulative variance (%)')
plt.title('The number of components needed to explain variance')

plt.axhline(y=1, color='r', linestyle='-')
plt.text(0.5, 0.85, '100% cut-off threshold', color = 'red', fontsize=16)

ax.grid(axis='x')
plt.show()
```



- The grapgh shows number of components are increased from 0.1 to 1.0 and growing constantly

In [64]:

```
pca=PCA(n_components=29)
x=pca.fit_transform(x)
x=pd.DataFrame(x)
x.head()
```

- From the Table- the values what we get are both nagative and positve results

Modelling Phase

In [66]:

```
from sklearn.model_selection import train_test_split,cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import
accuracy_score,confusion_matrix,classification_report,roc_auc_score,roc_curve
```

In [67]:

```
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.3,random_state=7)
```

Random Forest Analysis

```
model=RandomForestClassifier()
model.fit(xtrain,ytrain)
p=model.predict(xtest)
s=cross_val_score(model,x,y,cv=10)
print('Accuracy',np.round(accuracy_score(p,ytest),4))
print('----------------------------------------------------------')
print('Mean of Cross Validation Score',np.round(s.mean(),4))
print('----------------------------------------------------------')
print('Confusion Matrix')
```

```
print(confusion_matrix(p,ytest))
print('-----------------------------------------------------------------')
print('Classification Report')
print(classification_report(p,ytest))
Accuracy 1.0
-----------------------------------------------------------------
Mean of Cross Validation Score 0.9889
-----------------------------------------------------------------
Confusion Matrix
[[26  0  0  0  0  0  0  0]
 [ 0 22  0  0  0  0  0  0]
 [ 0  0  4  0  0  0  0  0]
 [ 0  0  0  4  0  0  0  0]
 [ 0  0  0  0  5  0  0  0]
 [ 0  0  0  0  0  7  0  0]
 [ 0  0  0  0  0  0 11  0]
 [ 0  0  0  0  0  0  0  2]]
-----------------------------------------------------------------
Classification Report
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        26
           1       1.00      1.00      1.00        22
           2       1.00      1.00      1.00         4
           3       1.00      1.00      1.00         4
           4       1.00      1.00      1.00         5
           5       1.00      1.00      1.00         7
           6       1.00      1.00      1.00        11
           7       1.00      1.00      1.00         2
accuracy                           1.00        81
   macro avg       1.00      1.00      1.00        81
weighted avg       1.00      1.00      1.00        81
```

- The Accuracy what we have got is 1.0

  and the Mean of Cross Validation Score 0.9889, which is good in condition.

```
model=XGBClassifier(verbosity=0)
model.fit(xtrain,ytrain)
p=model.predict(xtest)
s=cross_val_score(model,x,y,cv=10)
```

Hyperparameter Tuning

In [71]:

```
from sklearn.model_selection import RandomizedSearchCV
```

Random Forest

In [72]:

```
params={'n_estimators':[100, 300, 500, 700],
        'min_samples_split':[1,2,3,4],
        'min_samples_leaf':[1,2,3,4],
        'max_depth':[None,1,2,3,4,5,6,7,8,9,10,15,20,25,30,35,40]}
```

In [76]:

```
g=RandomizedSearchCV(RandomForestClassifier(),params,cv=10)
g.fit(xtrain,ytrain)
```

Out[79]:

```
RandomizedSearchCV(cv=10, estimator=RandomForestClassifier(),
                   param_distributions={'max_depth': [None, 1, 2, 3, 4, 5, 6,
7,
                                                      8, 9, 10, 15, 20, 25, 3
0,
                                                      35, 40],
                                        'min_samples_leaf': [1, 2, 3, 4],
                                        'min_samples_split': [1, 2, 3, 4],
                                        'n_estimators': [100, 300, 500, 700]}
)
```

In [78]:

```
print(g.best_estimator_)
print(g.best_params_)
print(g.best_score_)
```

```
RandomForestClassifier(max_depth=30, min_samples_leaf=4, n_estimators=500)
{'n_estimators': 500, 'min_samples_split': 2, 'min_samples_leaf': 4, 'max_dep
th': 30}
0.9947368421052631
m=RandomForestClassifier(max_depth=20, min_samples_leaf=4,
min_samples_split=4,n_estimators=700)
m.fit(xtrain,ytrain)
p=m.predict(xtest)
score=cross_val_score(m,x,y,cv=10)
```

In [81]:

```
print('Accuracy',np.round(accuracy_score(p,ytest),4))
print('-----------------------------------------------------------')
print('Mean of Cross Validation Score',np.round(s.mean(),4))
print('-----------------------------------------------------------')
print('Confusion Matrix')
print(confusion_matrix(p,ytest))
print('-----------------------------------------------------------')
print('Classification Report')
print(classification_report(p,ytest))
```

```
Accuracy 1.0
-----------------------------------------------------------
Mean of Cross Validation Score 0.9889
-----------------------------------------------------------
Confusion Matrix
[[26  0  0  0  0  0  0  0]
 [ 0 22  0  0  0  0  0  0]
 [ 0  0  4  0  0  0  0  0]
 [ 0  0  0  4  0  0  0  0]
 [ 0  0  0  0  5  0  0  0]
 [ 0  0  0  0  0  7  0  0]
 [ 0  0  0  0  0  0 11  0]
 [ 0  0  0  0  0  0  0  2]]
-----------------------------------------------------------
Classification Report
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        26
```

```
           1       1.00      1.00      1.00        22
           2       1.00      1.00      1.00         4
           3       1.00      1.00      1.00         4
           4       1.00      1.00      1.00         5
           5       1.00      1.00      1.00         7
           6       1.00      1.00      1.00        11
           7       1.00      1.00      1.00         2

    accuracy                           1.00        81
   macro avg       1.00      1.00      1.00        81
weighted avg       1.00      1.00      1.00        81
```

- Herwe the Accuracy is 1.0 and the Mean of Cross Validation Score 0.9889, which is same for both the analysis

Xgboost

In [82]:

```
params={'n_estimators':[100,200,300,400,500],
      'learning_rate':[0.001,0.01,0.10,],
      'subsample':[0.5,1],
      'max_depth':[1,2,3,4,5,6,7,8,9,10]}
```

In [ ]:

```
g=RandomizedSearchCV(XGBClassifier(),params,cv=10)
g.fit(xtrain,ytrain)
```

In [ ]:

```
print(g.best_estimator_)
print(g.best_params_)
print(g.best_score_)
```

Finalizing the best Model

In [ ]:

```
model=XGBClassifier(max_depth=2,learning_rate=0.01,n_estimators=500,subsample
=1)
model.fit(xtrain,ytrain)
p=model.predict(xtest)
score=cross_val_score(model,x,y,cv=10)
```

Saving the Model

In [85]:

```
import joblib
joblib.dump(model,'Retention.obj')
```

Out[85]:

```
['Retention.obj']
```

Conclusion

***All the websites were **not** equally preferred by online customers.

***Amazon was the most preferred followed by Flipkart.

***These two companies are most trusted **in** the industry **and** hence, have a huge reliability. Also, the sellers listed on these websites are generally **from** Tier 1 cities **as** compared to Snapdeal **and** PayTM which have more sellers **from** tier 2 **and** 3 cities.

***The cost of the product, the reliability of the E-commerce company **and** the **return** policiesall play an equally important role **in** deciding the buying behaviour of online customers.
***The cost **is** an important factor **as** it was the basic criteria used by online retailers to attract customers. The reliability of the E-commerce company **is** also important, **as** it **is** even required **in** offline retail. It **is** important because customers are paying online, so they need to be sure of security of the online transaction. The **return** policies are important because **in** online retail customer does **not** get to feel the product. Thus, he wants to be surethat it will be possible to **return** the product **if** he does **not** like it **in** real. Whereas, the logistics factor, which included Cash on delivery option, One day delivery **and** the quality of packaging plays a secondary role **in** this process though these are Must-be-quality.
***This **is** so because these all does **not** interfere **with** the real product **and** people believe that this **is** the basic value that E-commerce websitesprovide.
***Also, these websites have the most lenient **return** policies **as** compared to others **and** also the time required to process a **return** **is** low.
-------------------------------------End-----------------------------