

# Exploratory Data Analysis

In [1]:

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

import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
pip install openpyxl

Requirement already satisfied: openpyxl in c:\users\hema\anaconda3\lib\site-packages (3.0.7)
Requirement already satisfied: et-xmlfile in c:\users\hema\anaconda3\lib\site-packages (from openpyxl) (1.0.1)
Note: you may need to restart the kernel to use updated packages.
```

In [3]:

```
pip install nbconvert

Requirement already satisfied: nbconvert in c:\users\hema\anaconda3\lib\site-packages (6.0.7)
Requirement already satisfied: mistune<2,>=0.8.1 in c:\users\hema\anaconda3\lib\site-packages (from nbconvert) (0.8.4)
Requirement already satisfied: nbformat>=4.4 in c:\users\hema\anaconda3\lib\site-packages (from nbconvert) (5.1.3)
Requirement already satisfied: pandocfilters>=1.4.1 in c:\users\hema\anaconda3\lib\site-packages (from nbconvert) (1.4.3)
Requirement already satisfied: jinja2>=2.4 in c:\users\hema\anaconda3\lib\site-packages (from nbconvert) (2.11.3)
Requirement already satisfied: nbclient<0.6.0,>=0.5.0 in c:\users\hema\anaconda3\lib\site-packages (from nbconvert) (0.5.3)
Requirement already satisfied: entrypoints>=0.2.2 in c:\users\hema\anaconda3\lib\site-packages (from nbconvert) (0.3)
Requirement already satisfied: traitlets>=4.2 in c:\users\hema\anaconda3\lib\site-packages (from nbconvert) (5.0.5)
Requirement already satisfied: defusedxml in c:\users\hema\anaconda3\lib\site-packages (from nbconvert) (0.7.1)
Requirement already satisfied: jupyterlab-pygments in c:\users\hema\anaconda3\lib\site-packages (from nbconvert) (0.1.2)
Requirement already satisfied: jupyter-core in c:\users\hema\anaconda3\lib\site-packages (from nbconvert) (4.7.1)
Requirement already satisfied: testpath in c:\users\hema\anaconda3\lib\site-packages (from nbconvert) (0.4.4)
Requirement already satisfied: pygments>=2.4.1 in c:\users\hema\anaconda3\lib\site-packages (from nbconvert) (2.8.1)
```

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Requirement already satisfied: jupyter-client>=6.1.5 in c:\users\hema\anaconda3\lib\site-packages (from nbclient<0.6.0,>=0.5.0->nbconvert) (6.1.12)

Requirement already satisfied: async-generator in c:\users\hema\anaconda3\lib\site-packages (from nbclient<0.6.0,>=0.5.0->nbconvert) (1.10)

Requirement already satisfied: nest-asyncio in c:\users\hema\anaconda3\lib\site-packages (from nbclient<0.6.0,>=0.5.0->nbconvert) (1.5.1)

Requirement already satisfied: pyzmq>=13 in c:\users\hema\anaconda3\lib\site-packages (from jupyter-client>=6.1.5->nbclient<0.6.0,>=0.5.0->nbconvert) (20.0.0)

Requirement already satisfied: tornado>=4.1 in c:\users\hema\anaconda3\lib\site-packages (from jupyter-client>=6.1.5->nbclient<0.6.0,>=0.5.0->nbconvert) (6.1)

Requirement already satisfied: python-dateutil>=2.1 in c:\users\hema\anaconda3\lib\site-packages (from jupyter-client>=6.1.5->nbclient<0.6.0,>=0.5.0->nbconvert) (2.8.1)

Requirement already satisfied: pywin32>=1.0 in c:\users\hema\anaconda3\lib\site-packages (from jupyter-core->nbconvert) (227)

Requirement already satisfied: ipython-genutils in c:\users\hema\anaconda3\lib\site-packages (from nbformat>=4.4->nbconvert) (0.2.0)

Requirement already satisfied: jsonschema!=2.5.0,>=2.4 in c:\users\hema\anaconda3\lib\site-packages (from nbformat>=4.4->nbconvert) (3.2.0)

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Requirement already satisfied: six>=1.11.0 in c:\users\hema\anaconda3\lib\site-packages (from jsonschema!=2.5.0,>=2.4->nbformat>=4.4->nbconvert) (1.15.0)

Requirement already satisfied: setuptools in c:\users\hema\anaconda3\lib\site-packages (from jsonschema!=2.5.0,>=2.4->nbformat>=4.4->nbconvert) (52.0.0.post20210125)

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Requirement already satisfied: packaging in c:\users\hema\anaconda3\lib\site-packages (from bleach->nbconvert) (20.9)

Requirement already satisfied: pyparsing>=2.0.2 in c:\users\hema\anaconda3\lib\site-packages (from packaging->bleach->nbconvert) (2.4.7)

Note: you may need to restart the kernel to use updated packages.

In [4]:

```
pip install nbconvert[webpdf]
```

Requirement already satisfied: nbconvert[webpdf] in c:\users\hema\anaconda3\lib\site-packages (6.0.7)

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Requirement already satisfied: urllib3<2.0.0,>=1.25.8 in c:\users\hema\anaconda3\lib\site-packages (from pyppeteer==0.2.2->nbconvert[webpdf]) (1.26.4)

Requirement already satisfied: pyee<8.0.0,>=7.0.1 in c:\users\hema\anaconda3\lib\site-packages (from pyppeteer==0.2.2->nbconvert[webpdf]) (7.0.4)

Requirement already satisfied: websockets<9.0,>=8.1 in c:\users\hema\anaconda3\lib\site-packages (from pyppeteer==0.2.2->nbconvert[webpdf]) (8.1)

Requirement already satisfied: appdirs<2.0.0,>=1.4.3 in c:\users\hema\anaconda3\lib\site-packages (from pyppeteer==0.2.2->nbconvert[webpdf]) (1.4.4)

Requirement already satisfied: tqdm<5.0.0,>=4.42.1 in c:\users\hema\anaconda3\lib\site-packages (from pyppeteer==0.2.2->nbconvert[webpdf]) (4.59.0)

Requirement already satisfied: MarkupSafe>=0.23 in c:\users\hema\anaconda3\lib\site-packages (from Jinja2>=2.4->nbconvert[webpdf]) (1.1.1)

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Requirement already satisfied: async-generator in c:\users\hema\anaconda3\lib\site-packages (from nbclient<0.6.0,>=0.5.0->nbconvert[webpdf]) (1.10)

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Requirement already satisfied: python-dateutil>=2.1 in c:\users\hema\anaconda3\lib\site-packages (from jupyter-client>=6.1.5->nbclient<0.6.0,>=0.5.0->nbconvert[webpdf]) (2.8.1)

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Requirement already satisfied: ipython-genutils in c:\users\hema\anaconda3\lib\site-packages (from nbformat>=4.4->nbconvert[webpdf]) (0.2.0)

Requirement already satisfied: pyparsing>=2.0.2 in c:\users\hema\anaconda3\lib\site-packages (from packaging->bleach->nbconvert[webpdf]) (2.4.7)

Requirement already satisfied: attrs>=17.4.0 in c:\users\hema\anaconda3\lib\site-packages (from jsonschema!=2.5.0,>=2.4->nbformat>=4.4->nbconvert[webpdf]) (20.3.0)

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Requirement already satisfied: pyparsing>=2.0.2 in c:\users\hema\anaconda3\lib\site-packages (from packaging->bleach->nbconvert[webpdf]) (2.4.7)

Note: you may need to restart the kernel to use updated packages.

In [5]:

```
file = ('customer_retention_dataset.xlsx')
```

In [6]:

```
#extract the data from excel
```

In [7]:

```
newdata=pd.read_excel(file,sheet_name='datasheet')
```

In [8]:

```
newdata.head()
```

Out[8]:

	1 Gender of respondent	2 How old are you?	3 Which city do you live from?	4 What is the Pin Code of where you shop online from?	5 Since How Long You are Shopping Online?	6 How many times you have made an online purchase in the past 1 year?	7 How do you access the internet while shopping online?	8 Which device do you use to access the online shopping?	9 What is the screen size of your mobile device?	10 What is the operating system (OS) of your device?	11 Long time to get logged in (profile, sales period)	12 Long time in displaying graphics and photos (profile, sales period)	13 Late declaration of price (promotion, sales period)	14 Long page loading time (profile, sales period)	15 Limited mode of payment on most products (profile, sales period)	16 Long delivery period	17 Change in website/Application design	18 Frequent disruption when moving from one page to another	19 Website is as efficient as before	20 Which of the Indian online retailer would you recommend to a friend?
0	Male	31-40 years	Delhi	110009	Above 4 years	31-40 times	Dial-up	Desktop	Others	Windows/Mobile	Amazon.in	Amazon.in	Flipkart.com	Flipkart.com	Amazon.in	Paytm.com	Flipkart.com	Amazon.in	Amazon.in	Flipkart.com

		1Gender of respondent	2How old are you?	3Which city do you shop online from?	4What is the Pin Code of where you shop online from?	5Since How Long You are Shopping Online?	6How many times you have made an online purchase in the past 1 year?	7How do you access the internet while shopping online?	8Which device do you use to access the online shopping?	9What is the screen size of your mobile device?	10What is the operating system (OS) of your device?	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	Website is as efficient as before	Which of the Indian online retailer would you recommend to a friend?
1	Female		21-30 years	Delhi	110030	Above 4 years	41 times and above	Wi-Fi	Smartphone	4.7 inches	IOS/Mac	Amazon.in, Flipkart.com	Myntra.com	snapdeal.com	Snapdeal.com	Snapdeal.com	Snapdeal.com	Amazon.in	Myntra.com	Amazon.in, Flipkart.com	Amazon.in, Myntara.com
2	Female		21-30 years	Greater Noida	201308	3-4 years	41 times and	Mobile Internet	Smartphone	5.5 inches	Android	Myntra.com	Myntra.com	Myntra.com	Myntra.com	Amazon.in	Paytm.com	Paytm.com	Paytm.com	Amazon.in	Amazon.in, Paytm.com,

1Gender of respondent	2How old are you?	3Which city do you shop online from?	4What is the Pin Code of where you shop online from?	5Since How Long You are Shopping Online?	6How many times have you made an online purchase in the past 1 year?	7How do you access the internet while shopping online?	8Which device do you use to access the online shopping?	9What is the screen size of your mobile device?	10What is the operating system (OS) of your device?	11Longer time to get logged in (promotion, sales period)	12Longer time in displaying graphics and photos (promotion, sales period)	13Late declaration of price (promotion, sales period)	14Longer page loading time (promotion, sales period)	15Limited mode of payment on most products (promotion, sales period)	16Longer delivery period	17Change in website/Application design	18Frequent disruption when moving from one page to another	19Website is as efficient as before	20Which of the Indian online retailer would you recommend to a friend?
3	Male	21-30 years	Karnal	13-20 years	3-4 years	Less than 10 times	Mobile Internet	Smartphone	5.5 inches	IOS/Mac	.	Snapple.com	Myntra.com	Paytm.com	Paytm.com	Paytm.com	Amazon.in, Flipkart.com	Amazon.in, Flipkart.com	Amazon.in, Flipkart.com

1Gender of respondent	2How old are you?	3Which city do you shop online from?	4What is the Pin Code of where you shop online from?	5Since How Long are you shopping online?	6How many times have you made an online purchase in the past 1 year?	7How do you access the internet while shopping online?	8Which device do you use to access the online shopping?	9What is the screen size of your mobile device?	10What is the operating system (OS) of your device?	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	Website is as efficient as before	Which of the Indian online retailer would you recommend to a friend?
Female	21-30 years	Bangalore	530068	2-3 years	11-20 times	Wi-Fi	Smartphone	4.7 inches	IOS/Mac	Flipkart.com, Paytm.com	Paytm.com	Paytm.com	Paytm.com	Snapdeal.com	Paytm.com	Amazon.in	Snapdeal.com	Paytm.com	Amazon.in, Mynt, ra.com

5 rows × 71 columns

#Setting option to show max rows and max columns

pd.set\_option('display.max\_columns', None)

In [9]:



```
pd.set_option('display.max_rows', None)
```

## Pre-processing the columns names

```
from string import digits
```

```
#Removing tab spaces
```

```
newdata.columns = newdata.columns.str.replace('/t', '')
```

```
#Removing digits
```

```
remove_digits =str.maketrans('', '', digits)
```

```
newdata.columns = newdata.columns.str.translate(remove_digits)
```

```
#Removing trailing and leading spaces
```

```
newdata.columns = newdata.columns.str.strip()
```

```
newdata.head()
```

In [10]:

In [11]:

In [12]:

In [13]:

In [14]:

Out[14]:

Longer time to get logs in (promotions, salaries)  
Security of customer information  
Privacy of customer information  
Speedy order delivery

Availability of services  
Quality of service  
Reliability of the website or application

Fast loading times  
Compliance with regulations  
Willingness to provide customer support

From the website, click on the product or service you want  
Visit the website and click on the product or service you want  
Easy to use website with clear navigation

Shop online with ease  
Shop online with ease  
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Online shopping gives monetary benefit and discounts	object
Enjoyment is derived from shopping online	object
Shopping online is convenient and flexible	object
Return and replacement policy of the e-tailer is important for purchase decision	object
Gaining access to loyalty programs is a benefit of shopping online	object
Displaying quality Information on the website improves satisfaction of customers	object
User derive satisfaction while shopping on a good quality website or application	object
Net Benefit derived from shopping online can lead to users satisfaction	object
User satisfaction cannot exist without trust	object
Offering a wide variety of listed product in several category	object
Provision of complete and relevant product information	object
Monetary savings	object
The Convenience of patronizing the online retailer	object
Shopping on the website gives you the sense of adventure	object
Shopping on your preferred e-tailer enhances your social status	object
You feel gratification shopping on your favorite e-tailer	object
Shopping on the website helps you fulfill certain roles	object
Getting value for money spent	object
From the following, tick any (or all) of the online retailers you have shopped from;	object
Easy to use website or application	object
Visual appealing web-page layout	object
Wild variety of product on offer	object
Complete, relevant description information of products	object
Fast loading website speed of website and application	object
Reliability of the website or application	object
Quickness to complete purchase	object
Availability of several payment options	object
Speedy order delivery	object
Privacy of customers' information	object
Security of customer financial information	object
Perceived Trustworthiness	object
Presence of online assistance through multi-channel	object
Longer time to get logged in (promotion, sales period)	object
Longer time in displaying graphics and photos (promotion, sales period)	object
Late declaration of price (promotion, sales period)	object
Longer page loading time (promotion, sales period)	object
Limited mode of payment on most products (promotion, sales period)	object
Longer delivery period	object
Change in website/Application design	object

```
Frequent disruption when moving from one page to another
Website is as efficient as before
Which of the Indian online retailer would you recommend to a friend?
dtype: object
```

```
object
object
object
```

In [17]:

```
newdata.isnull().sum()
```

Out[17]:

```
Gender of respondent      0
How old are you?         0
Which city do you shop online from?  0
What is the Pin Code of where you shop online from?  0
Since How Long You are Shopping Online ?  0
How many times you have made an online purchase in the past year?  0
How do you access the internet while shopping on-line?  0
Which device do you use to access the online shopping?  0
What is the screen size of your mobile device?  0
What is the operating system (OS) of your device?  0
What browser do you run on your device to access the website?  0
Which channel did you follow to arrive at your favorite online store for the first time?  0
After first visit, how do you reach the online retail store?  0
How much time do you explore the e- retail store before making a purchase decision?  0
What is your preferred payment Option?  0
How frequently do you abandon (selecting an items and leaving without making payment) your shopping cart?  0
Why did you abandon the "Bag", "Shopping Cart"?  0
The content on the website must be easy to read and understand  0
Information on similar product to the one highlighted is important for product comparison  0
Complete information on listed seller and product being offered is important for purchase decision.  0
All relevant information on listed products must be stated clearly  0
Ease of navigation in website  0
Loading and processing speed  0
User friendly Interface of the website  0
Convenient Payment methods  0
Trust that the online retail store will fulfill its part of the transaction at the stipulated time  0
Empathy (readiness to assist with queries) towards the customers  0
Being able to guarantee the privacy of the customer  0
Responsiveness, availability of several communication channels (email, online rep, twitter, phone etc.)  0
Online shopping gives monetary benefit and discounts  0
Enjoyment is derived from shopping online  0
```

Shopping online is convenient and flexible	0
Return and replacement policy of the e-tailer is important for purchase decision	0
Gaining access to loyalty programs is a benefit of shopping online	0
Displaying quality Information on the website improves satisfaction of customers	0
User derive satisfaction while shopping on a good quality website or application	0
Net Benefit derived from shopping online can lead to users satisfaction	0
User satisfaction cannot exist without trust	0
Offering a wide variety of listed product in several category	0
Provision of complete and relevant product information	0
Monetary savings	0
The Convenience of patronizing the online retailer	0
Shopping on the website gives you the sense of adventure	0
Shopping on your preferred e-tailer enhances your social status	0
You feel gratification shopping on your favorite e-tailer	0
Shopping on the website helps you fulfill certain roles	0
Getting value for money spent	0
From the following, tick any (or all) of the online retailers you have shopped from;	0
Easy to use website or application	0
Visual appealing web-page layout	0
Wild variety of product on offer	0
Complete, relevant description information of products	0
Fast loading website speed of website and application	0
Reliability of the website or application	0
Quickness to complete purchase	0
Availability of several payment options	0
Speedy order delivery	0
Privacy of customers' information	0
Security of customer financial information	0
Perceived Trustworthiness	0
Presence of online assistance through multi-channel	0
Longer time to get logged in (promotion, sales period)	0
Longer time in displaying graphics and photos (promotion, sales period)	0
Late declaration of price (promotion, sales period)	0
Longer page loading time (promotion, sales period)	0
Limited mode of payment on most products (promotion, sales period)	0
Longer delivery period	0
Change in website/Application design	0
Frequent disruption when moving from one page to another	0
Website is as efficient as before	0



Which of the Indian online retailer would you recommend to a friend?  
dtype: int64

0

In [18]:

newdata.nunique()

Out[18]:

Gender of respondent	2
How old are you?	5
Which city do you shop online from?	11
What is the Pin Code of where you shop online from?	39
Since How Long You are Shopping Online ?	5
How many times you have made an online purchase in the past year?	6
How do you access the internet while shopping on-line?	4
Which device do you use to access the online shopping?	4
What is the screen size of your mobile device?	4
What is the operating system (OS) of your device?	3
What browser do you run on your device to access the website?	4
Which channel did you follow to arrive at your favorite online store for the first time?	3
After first visit, how do you reach the online retail store?	5
How much time do you explore the e- retail store before making a purchase decision?	5
What is your preferred payment Option?	3
How frequently do you abandon (selecting an items and leaving without making payment) your shopping cart?	4
Why did you abandon the "Bag", "Shopping Cart"?	5
The content on the website must be easy to read and understand	4
Information on similar product to the one highlighted is important for product comparison	4
Complete information on listed seller and product being offered is important for purchase decision.	5
All relevant information on listed products must be stated clearly	4
Ease of navigation in website	4
Loading and processing speed	5
User friendly Interface of the website	5
Convenient Payment methods	3
Trust that the online retail store will fulfill its part of the transaction at the stipulated time	4
Empathy (readiness to assist with queries) towards the customers	4
Being able to guarantee the privacy of the customer	3
Responsiveness, availability of several communication channels (email, online rep, twitter, phone etc.)	4
Online shopping gives monetary benefit and discounts	5
Enjoyment is derived from shopping online	5
Shopping online is convenient and flexible	4
Return and replacement policy of the e-tailer is important for purchase decision	3

Gaining access to loyalty programs is a benefit of shopping online	5
Displaying quality Information on the website improves satisfaction of customers	3
User derive satisfaction while shopping on a good quality website or application	3
Net Benefit derived from shopping online can lead to users satisfaction	4
User satisfaction cannot exist without trust	5
Offering a wide variety of listed product in several category	4
Provision of complete and relevant product information	4
Monetary savings	4
The Convenience of patronizing the online retailer	3
Shopping on the website gives you the sense of adventure	5
Shopping on your preferred e-tailer enhances your social status	5
You feel gratification shopping on your favorite e-tailer	5
Shopping on the website helps you fulfill certain roles	5
Getting value for money spent	3
From the following, tick any (or all) of the online retailers you have shopped from;	9
Easy to use website or application	10
Visual appealing web-page layout	10
Wild variety of product on offer	9
Complete, relevant description information of products	11
Fast loading website speed of website and application	10
Reliability of the website or application	10
Quickness to complete purchase	9
Availability of several payment options	11
Speedy order delivery	6
Privacy of customers' information	11
Security of customer financial information	11
Perceived Trustworthiness	9
Presence of online assistance through multi-channel	10
Longer time to get logged in (promotion, sales period)	10
Longer time in displaying graphics and photos (promotion, sales period)	10
Late declaration of price (promotion, sales period)	8
Longer page loading time (promotion, sales period)	11
Limited mode of payment on most products (promotion, sales period)	8
Longer delivery period	6
Change in website/Application design	7
Frequent disruption when moving from one page to another	8
Website is as efficient as before	8
Which of the Indian online retailer would you recommend to a friend?	8
dtype: int64	

In [19]:

```
newdata.isnull().sum()/newdata.shape[0]*100
```

Out[19]:

Gender of respondent	0.0
How old are you?	0.0
Which city do you shop online from?	0.0
What is the Pin Code of where you shop online from?	0.0
Since How Long You are Shopping Online ?	0.0
How many times you have made an online purchase in the past year?	0.0
How do you access the internet while shopping on-line?	0.0
Which device do you use to access the online shopping?	0.0
What is the screen size of your mobile device?	0.0
What is the operating system (OS) of your device?	0.0
What browser do you run on your device to access the website?	0.0
Which channel did you follow to arrive at your favorite online store for the first time?	0.0
After first visit, how do you reach the online retail store?	0.0
How much time do you explore the e- retail store before making a purchase decision?	0.0
What is your preferred payment Option?	0.0
How frequently do you abandon (selecting an items and leaving without making payment) your shopping cart?	0.0
Why did you abandon the "Bag", "Shopping Cart"?	0.0
The content on the website must be easy to read and understand	0.0
Information on similar product to the one highlighted is important for product comparison	0.0
Complete information on listed seller and product being offered is important for purchase decision.	0.0
All relevant information on listed products must be stated clearly	0.0
Ease of navigation in website	0.0
Loading and processing speed	0.0
User friendly Interface of the website	0.0
Convenient Payment methods	0.0
Trust that the online retail store will fulfill its part of the transaction at the stipulated time	0.0
Empathy (readiness to assist with queries) towards the customers	0.0
Being able to guarantee the privacy of the customer	0.0
Responsiveness, availability of several communication channels (email, online rep, twitter, phone etc.)	0.0
Online shopping gives monetary benefit and discounts	0.0
Enjoyment is derived from shopping online	0.0
Shopping online is convenient and flexible	0.0
Return and replacement policy of the e-tailer is important for purchase decision	0.0
Gaining access to loyalty programs is a benefit of shopping online	0.0
Displaying quality Information on the website improves satisfaction of customers	0.0

User derive satisfaction while shopping on a good quality website or application	0.0
Net Benefit derived from shopping online can lead to users satisfaction	0.0
User satisfaction cannot exist without trust	0.0
Offering a wide variety of listed product in several category	0.0
Provision of complete and relevant product information	0.0
Monetary savings	0.0
The Convenience of patronizing the online retailer	0.0
Shopping on the website gives you the sense of adventure	0.0
Shopping on your preferred e-tailer enhances your social status	0.0
You feel gratification shopping on your favorite e-tailer	0.0
Shopping on the website helps you fulfill certain roles	0.0
Getting value for money spent	0.0
From the following, tick any (or all) of the online retailers you have shopped from;	0.0
Easy to use website or application	0.0
Visual appealing web-page layout	0.0
Wild variety of product on offer	0.0
Complete, relevant description information of products	0.0
Fast loading website speed of website and application	0.0
Reliability of the website or application	0.0
Quickness to complete purchase	0.0
Availability of several payment options	0.0
Speedy order delivery	0.0
Privacy of customers' information	0.0
Security of customer financial information	0.0
Perceived Trustworthiness	0.0
Presence of online assistance through multi-channel	0.0
Longer time to get logged in (promotion, sales period)	0.0
Longer time in displaying graphics and photos (promotion, sales period)	0.0
Late declaration of price (promotion, sales period)	0.0
Longer page loading time (promotion, sales period)	0.0
Limited mode of payment on most products (promotion, sales period)	0.0
Longer delivery period	0.0
Change in website/Application design	0.0
Frequent disruption when moving from one page to another	0.0
Website is as efficient as before	0.0
Which of the Indian online retailer would you recommend to a friend?	0.0
dtype: float64	

# Univariate Analysis

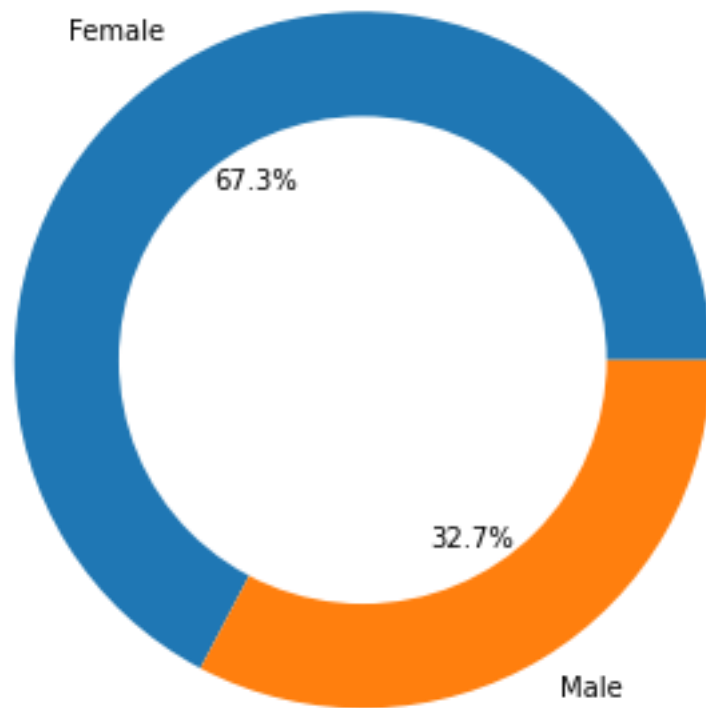
In [20]:

```
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?']
```

Personal Info

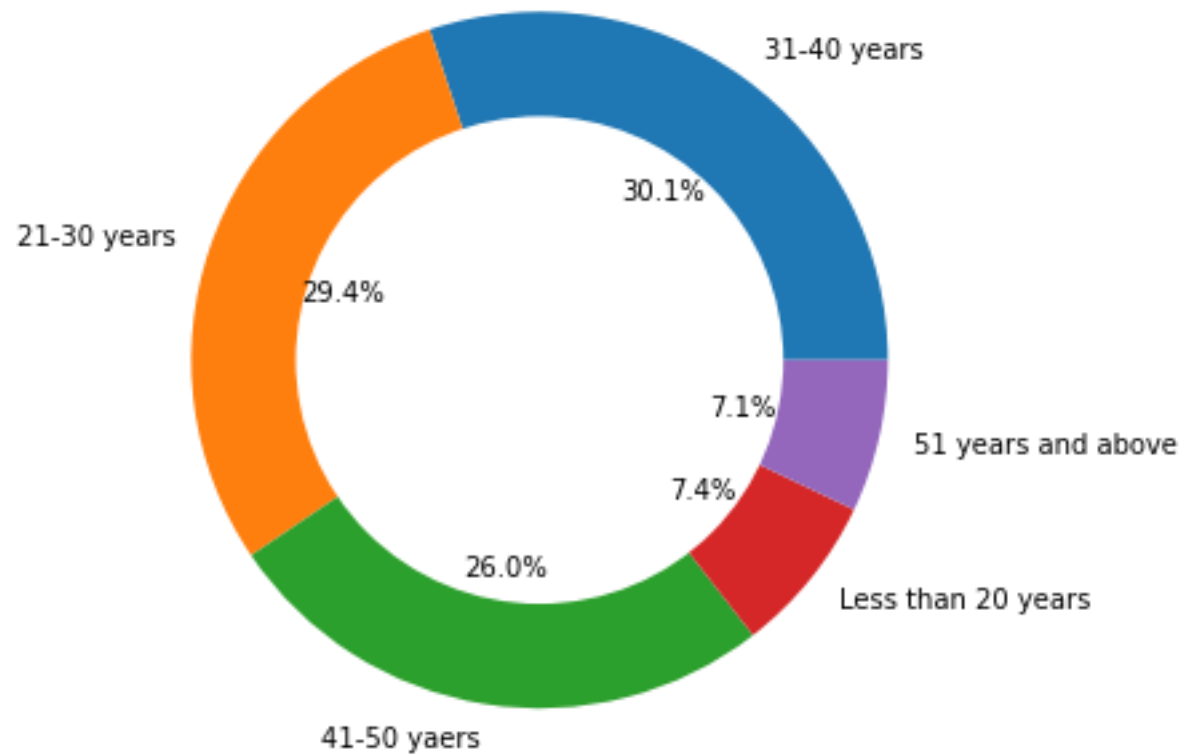
In [21]:

```
for i in personal_info:  
    if i!='What is the Pin Code of where you shop online from':  
        plt.figure(figsize=(8,6))  
        newdata[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()
```



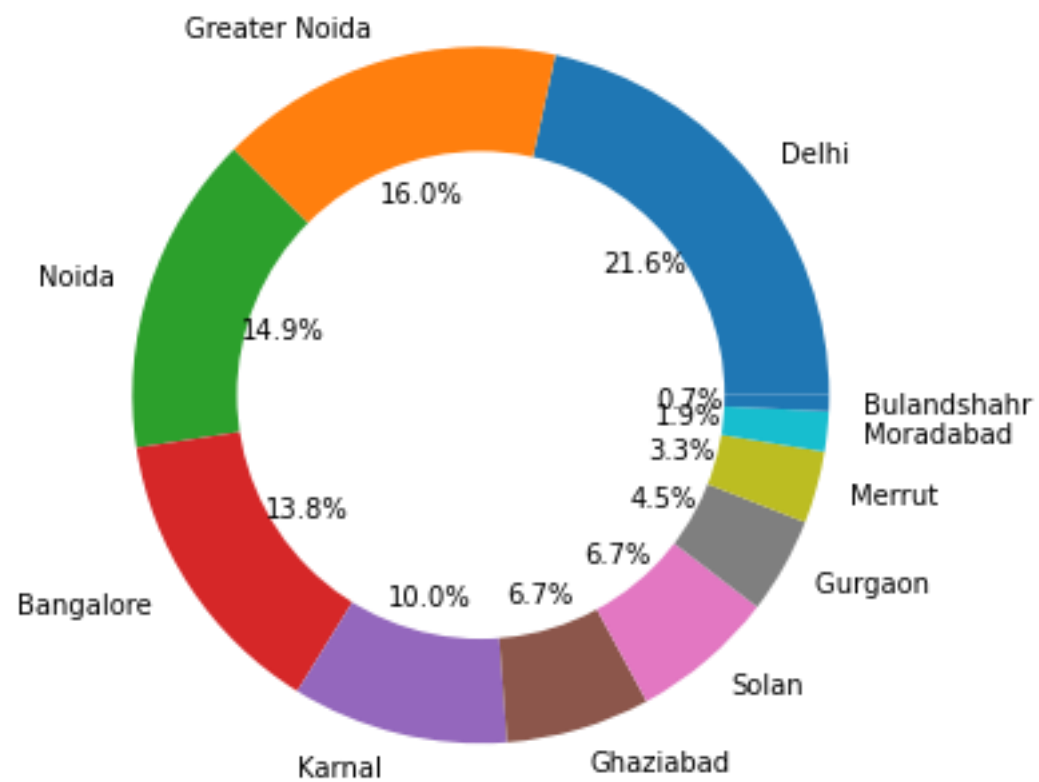
Gender of respondent

<Figure size 432x288 with 0 Axes>



How old are you?

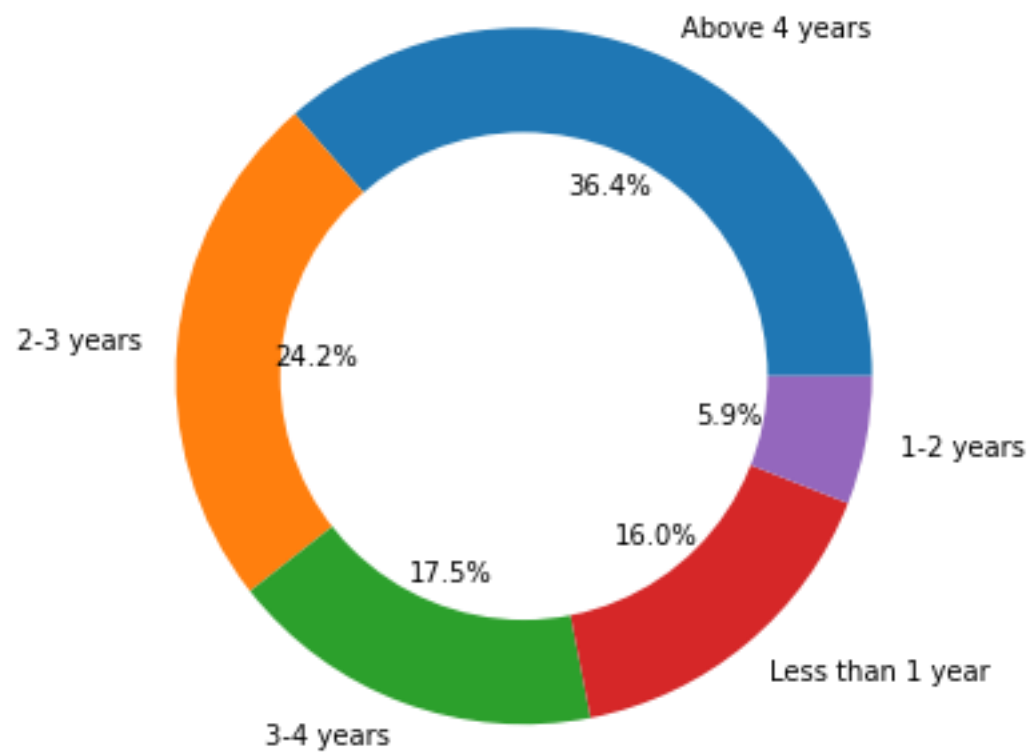
<Figure size 432x288 with 0 Axes>



Which city do you shop online from?

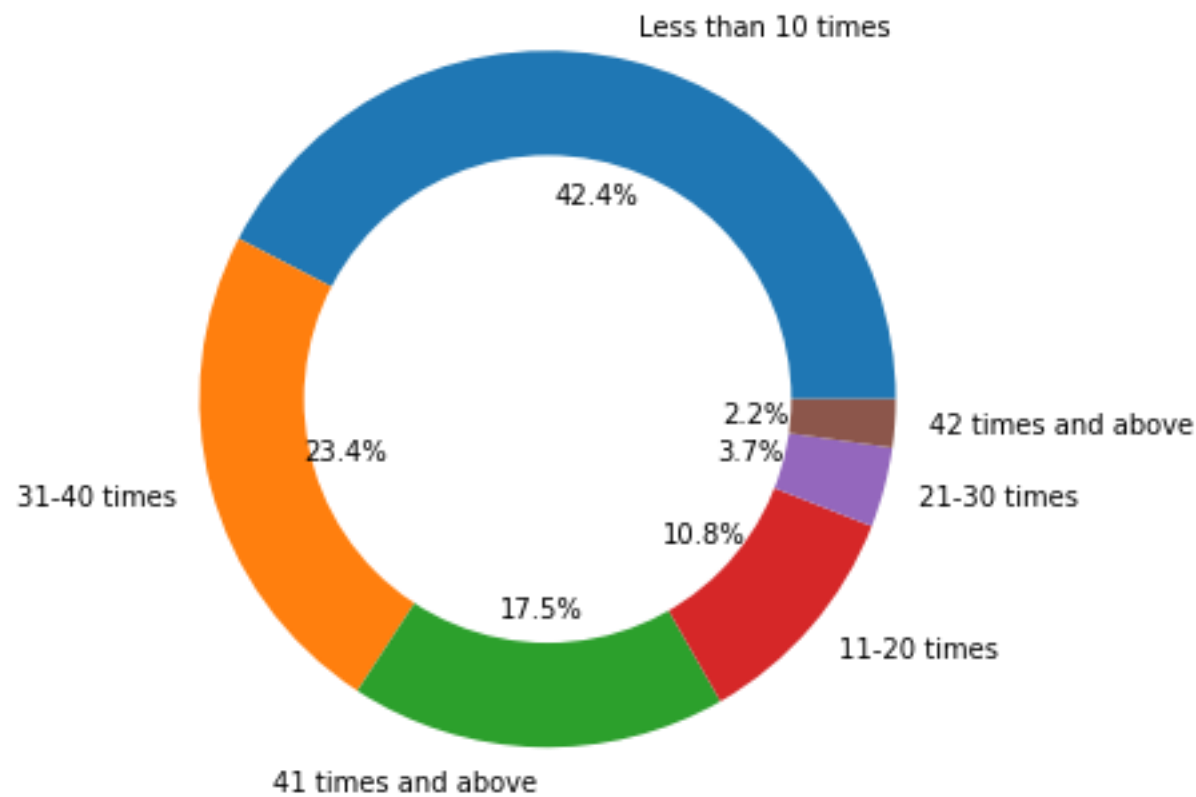
<Figure size 432x288 with 0 Axes>





Since How Long You are Shopping Online ?

<Figure size 432x288 with 0 Axes>



How many times you have made an online purchase in the past year?

<Figure size 432x288 with 0 Axes>

## Analysis on the basis of various following factors

Intention of Repeat purchase

In [22]:

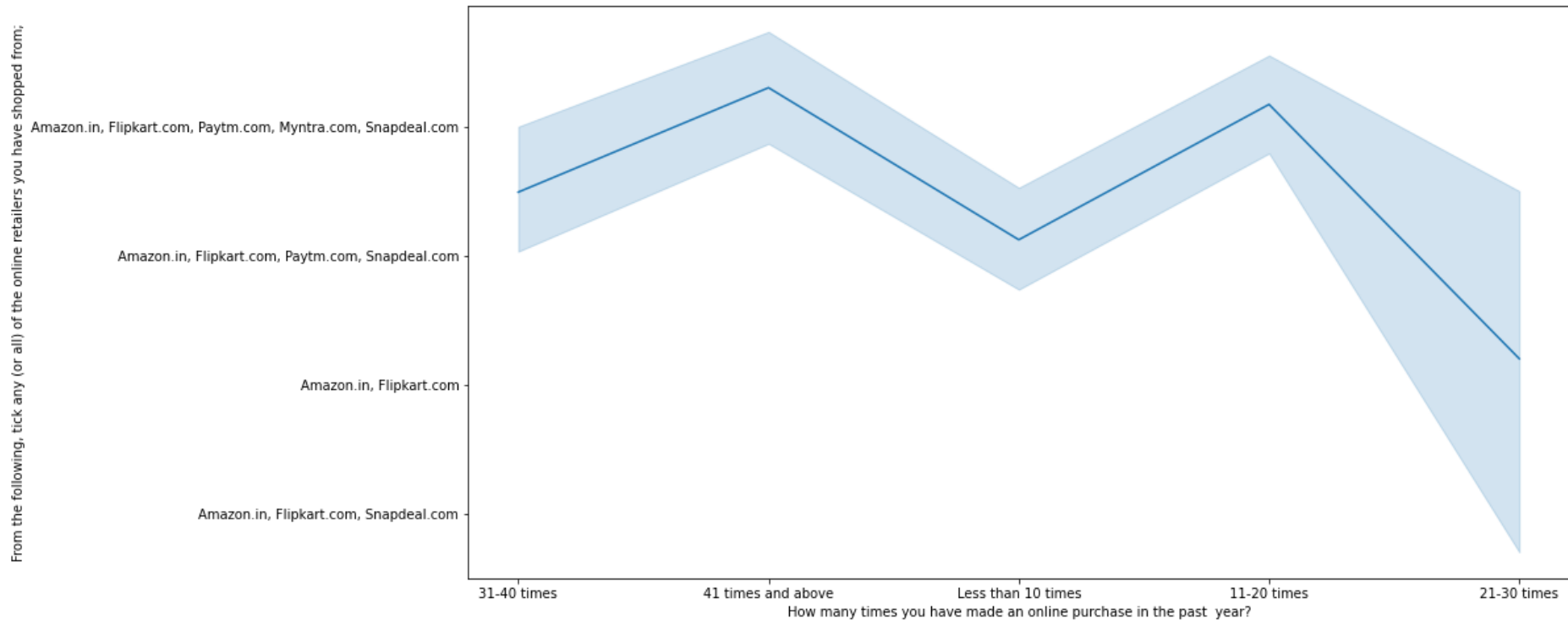
```
#Resolving ambiguity of column  
#changing 42 times and above to 41 times and above  
  
newdata['How many times you have made an online purchase in the past year?'].replace('42 times and above','41 times  
and above',  
  
                                         inplace=True)
```

In [23]:

```
plt.figure(figsize=(15,8))  
sns.lineplot(newdata['How many times you have made an online purchase in the past year?'],  
             newdata['From the following, tick any (or all) of the online retailers you have shopped from;'])
```

Out[23]:

```
<AxesSubplot:xlabel='How many times you have made an online purchase in the past year?', ylabel='From the following  
, tick any (or all) of the online retailers you have shopped from;'>
```



Converting years to numbers for better analysis

In [24]:

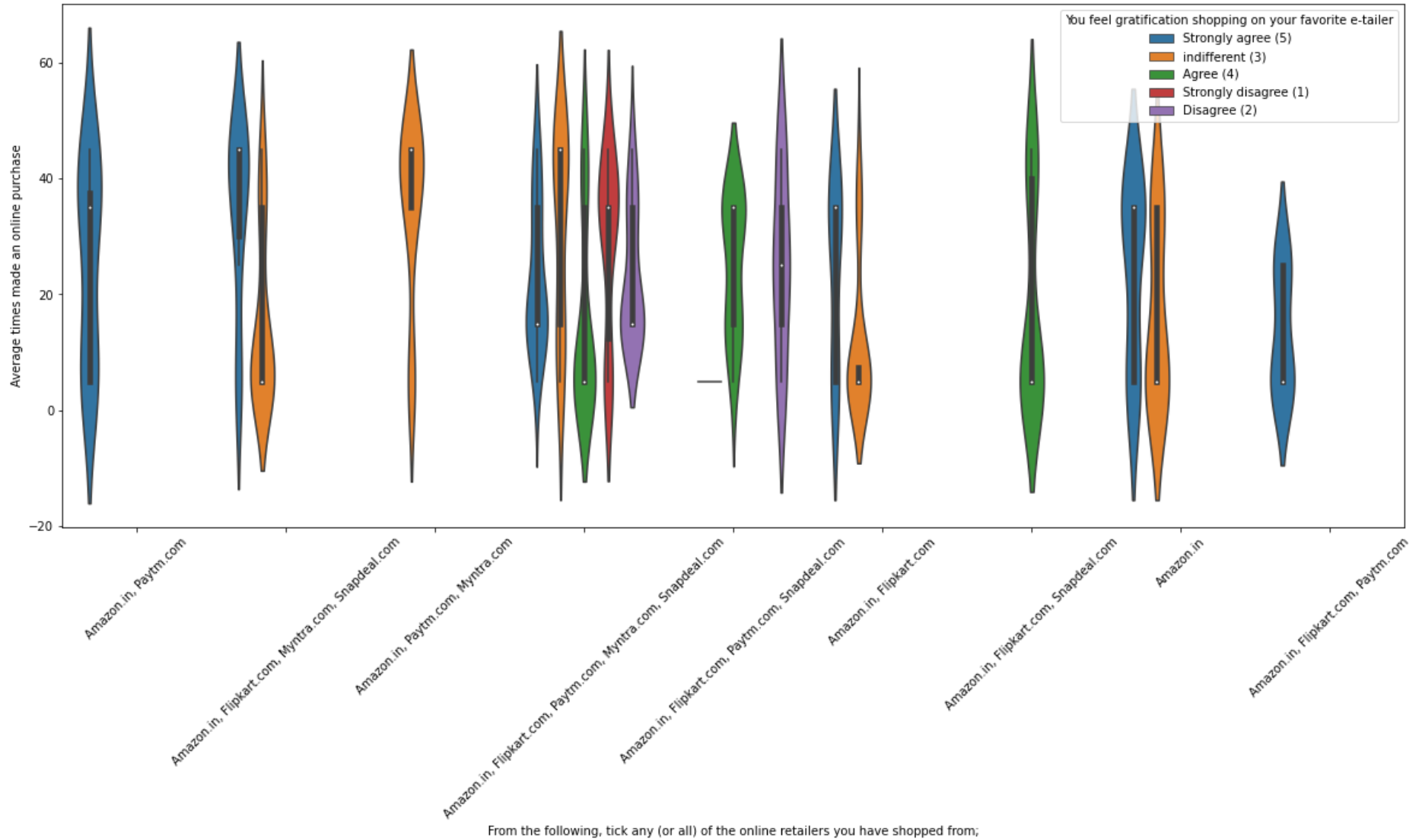
```
dict={'31-40 times':35,'41 times and above':45,'Less than 10 times':5,'11-20 times':15,'21-30 times':25}
newdata['Average times made an online purchase']=newdata['How many times you have made an online purchase in the
past year?'].replace(dict)
```

In [25]:

```
plt.figure(figsize=(20,8))
sns.violinplot(newdata['From the following, tick any (or all) of the online retailers you have shopped from;'],
               newdata['Average times made an online purchase'],hue=newdata['You feel gratification shopping on your
favorite e-tailer'])
plt.xticks(rotation=45)
```

Out[25]:

```
(array([0, 1, 2, 3, 4, 5, 6, 7, 8]),  
[Text(0, 0, 'Amazon.in, Paytm.com'),  
Text(1, 0, 'Amazon.in, Flipkart.com, Myntra.com, Snapdeal.com'),  
Text(2, 0, 'Amazon.in, Paytm.com, Myntra.com'),  
Text(3, 0, 'Amazon.in, Flipkart.com, Paytm.com, Myntra.com, Snapdeal.com'),  
Text(4, 0, 'Amazon.in, Flipkart.com, Paytm.com, Snapdeal.com'),  
Text(5, 0, 'Amazon.in, Flipkart.com'),  
Text(6, 0, 'Amazon.in, Flipkart.com, Snapdeal.com'),  
Text(7, 0, 'Amazon.in'),  
Text(8, 0, 'Amazon.in, Flipkart.com, Paytm.com')])
```



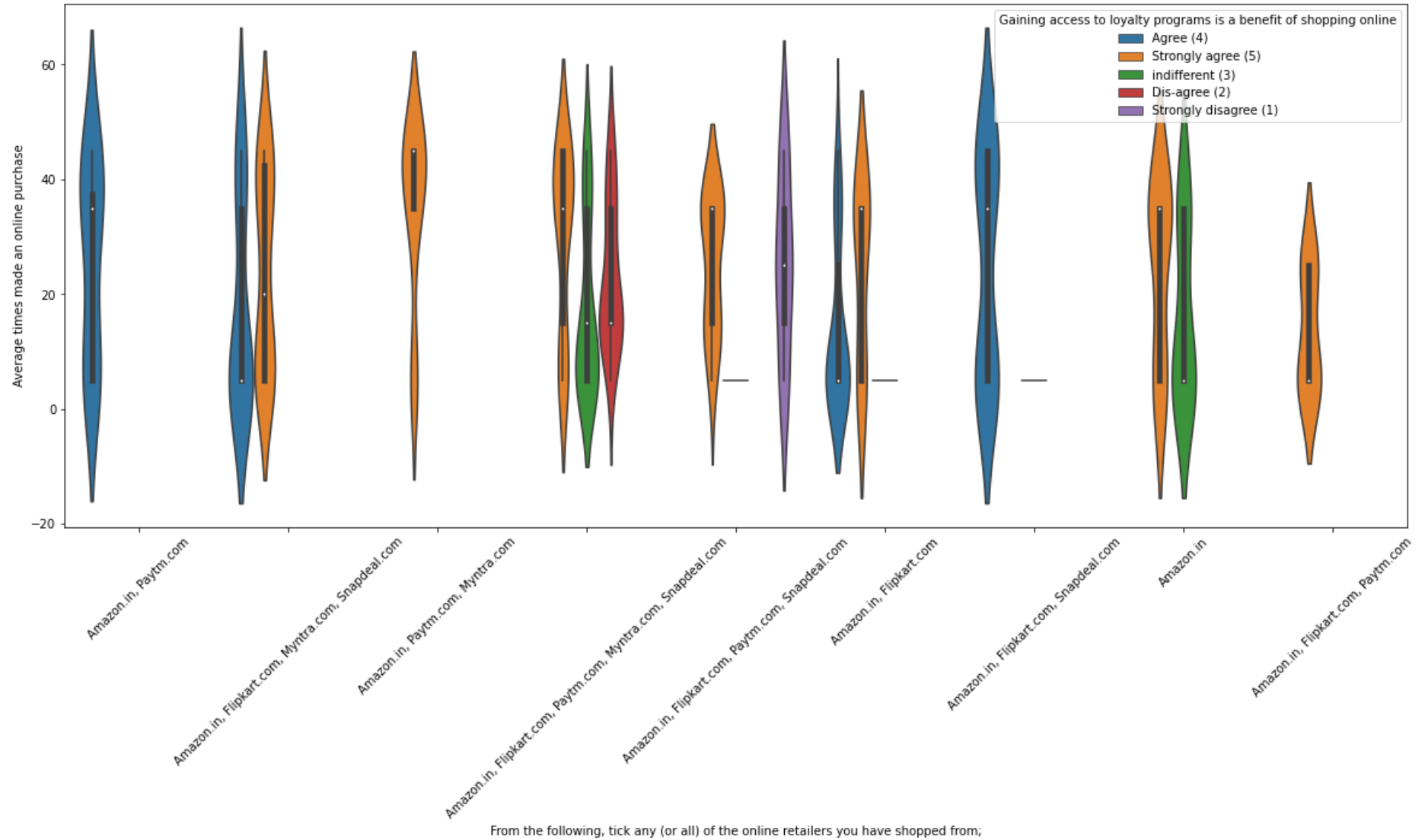
In [26]:

```
plt.figure(figsize=(20,8))
```

```
sns.violinplot(newdata['From the following, tick any (or all) of the online retailers you have shopped from;'],
               newdata['Average times made an online purchase'],hue=newdata['Gaining access to loyalty programs is a
benefit of shopping online'])
plt.xticks(rotation=45)
```

Out[26]:

```
(array([0, 1, 2, 3, 4, 5, 6, 7, 8]),
 [Text(0, 0, 'Amazon.in, Paytm.com'),
  Text(1, 0, 'Amazon.in, Flipkart.com, Myntra.com, Snapdeal.com'),
  Text(2, 0, 'Amazon.in, Paytm.com, Myntra.com'),
  Text(3, 0, 'Amazon.in, Flipkart.com, Paytm.com, Myntra.com, Snapdeal.com'),
  Text(4, 0, 'Amazon.in, Flipkart.com, Paytm.com, Snapdeal.com'),
  Text(5, 0, 'Amazon.in, Flipkart.com'),
  Text(6, 0, 'Amazon.in, Flipkart.com, Snapdeal.com'),
  Text(7, 0, 'Amazon.in'),
  Text(8, 0, 'Amazon.in, Flipkart.com, Paytm.com')])
```





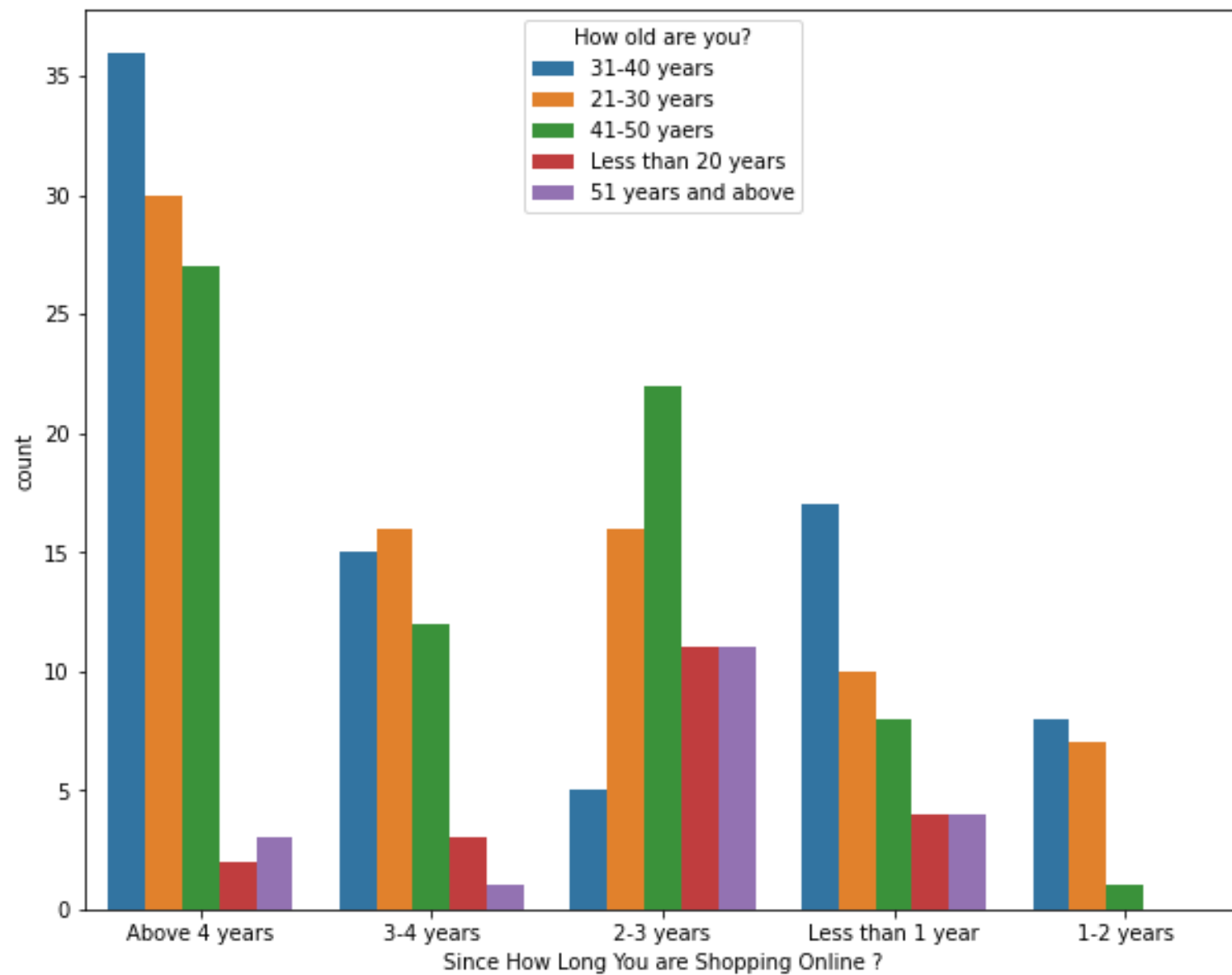
# Online Retailing

```
plt.figure(figsize=(10,8))  
sns.countplot(newdata['Since How Long You are Shopping Online ?'],hue=newdata['How old are you?'])
```

In [27]:

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

Out[27]:



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 [28]:

```
newdata['Since How Long You are Shopping Online ?'].unique()
```

Out[28]:

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

In [29]:

```
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}  
newdata['Average years of shopping online']=newdata['Since How Long You are Shopping Online ?'].replace(dict)
```

In [30]:

```
newdata['Which city do you shop online from?'].unique()
```

Out[30]:

```
array(['Delhi', 'Greater Noida', 'Karnal ', 'Bangalore ', 'Noida',  
      'Solan', 'Moradabad', 'Gurgaon ', 'Merrut', 'Ghaziabad',  
      'Bulandshahr'], dtype=object)
```

In [31]:

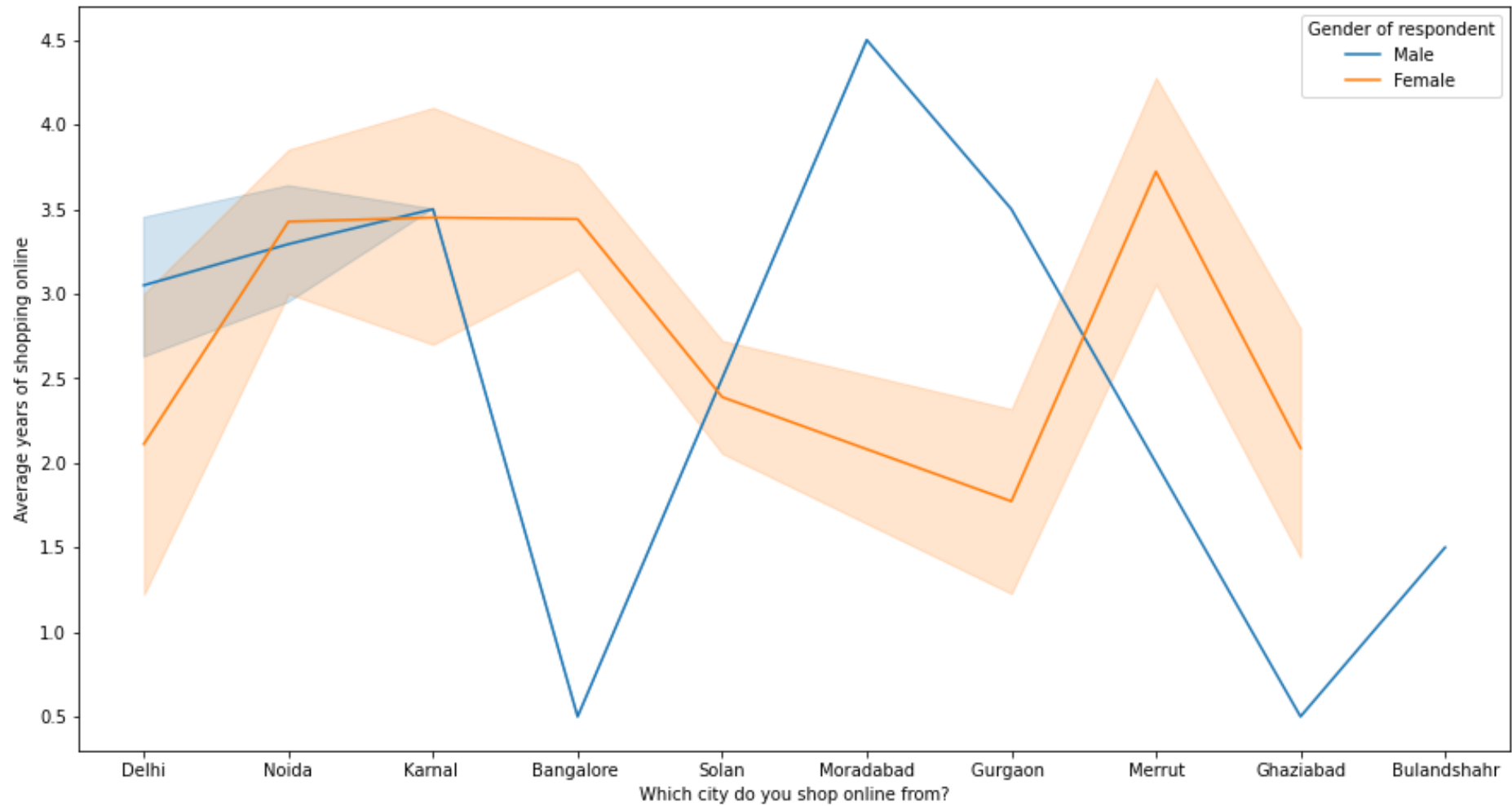
```
#Changing Greater noida to noida  
newdata['Which city do you shop online from?'].replace({'Greater Noida':'Noida'},inplace=True)
```

In [32]:

```
plt.figure(figsize=(15,8))  
sns.lineplot(newdata['Which city do you shop online from?'],newdata['Average years of shopping  
online'],hue=newdata['Gender of respondent'])
```

Out[32]:

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



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

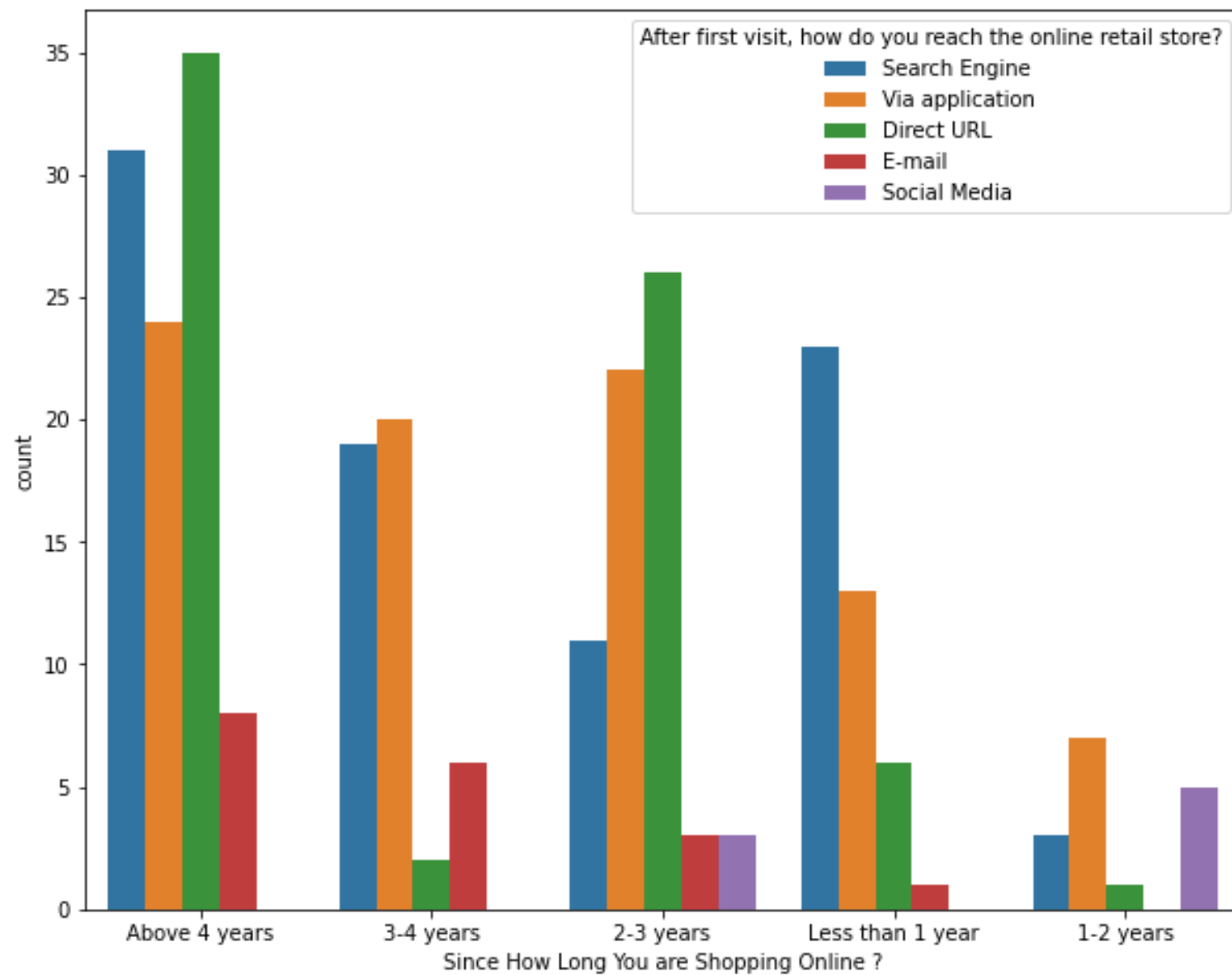
In [33]:

```
plt.figure(figsize=(10,8))
```

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

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

Out[33]:



Even though 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

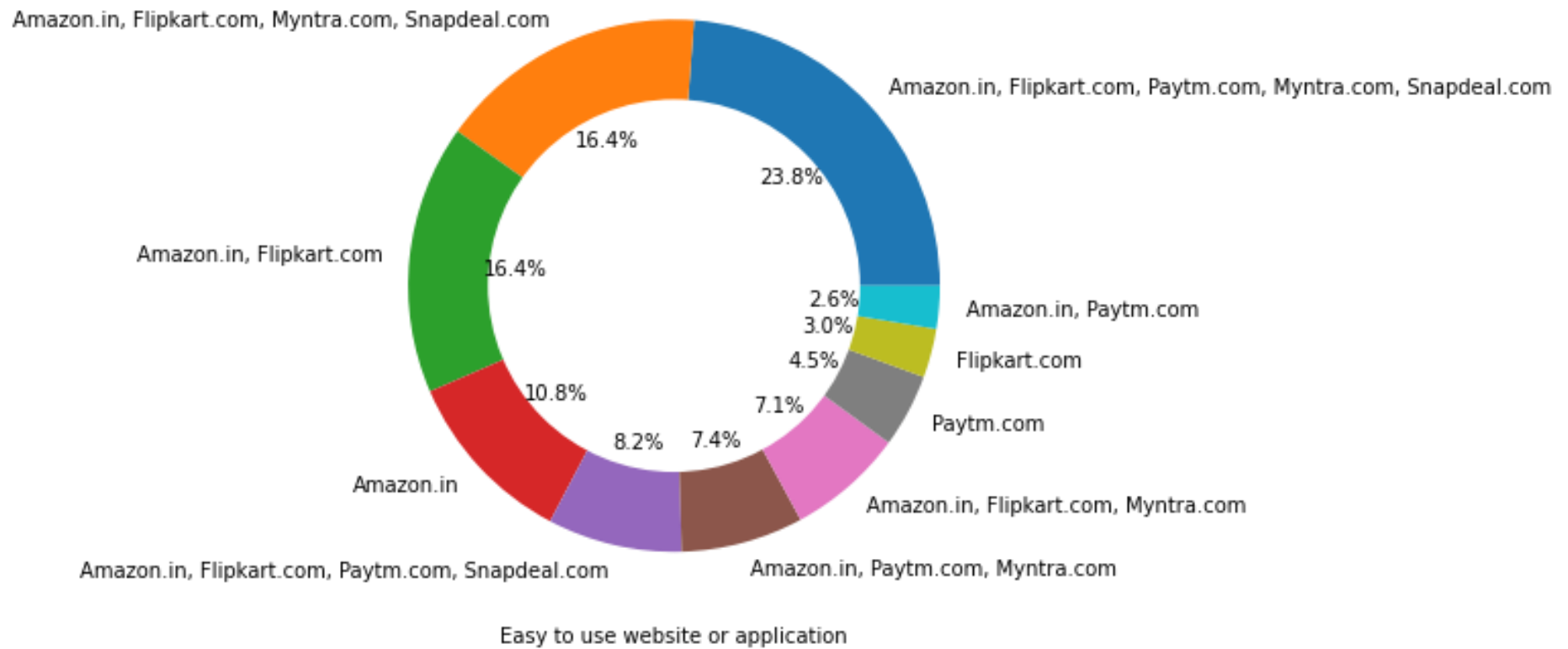
## Brand Image

In [34]:

```
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']
```

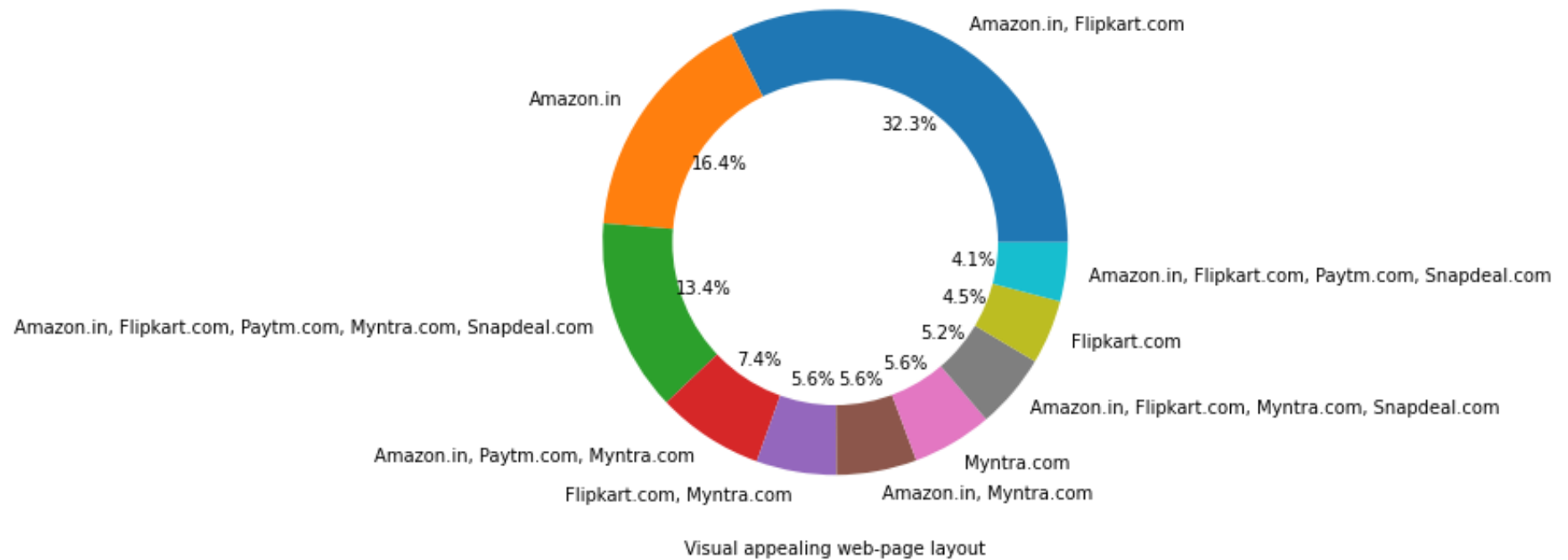
In [35]:

```
for i in performance:
    plt.figure(figsize=(8,6))
    newdata[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()
```

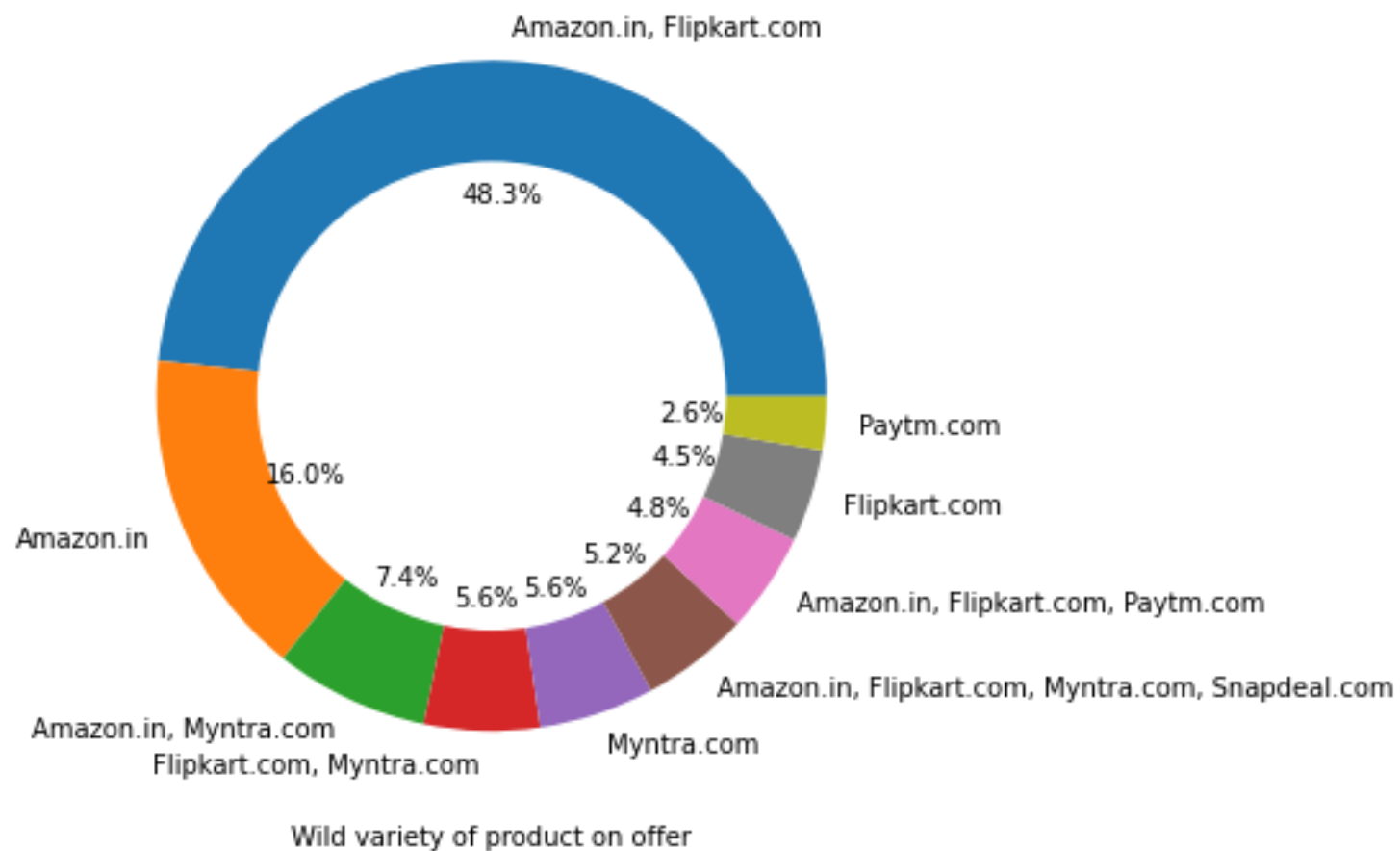


<Figure size 432x288 with 0 Axes>

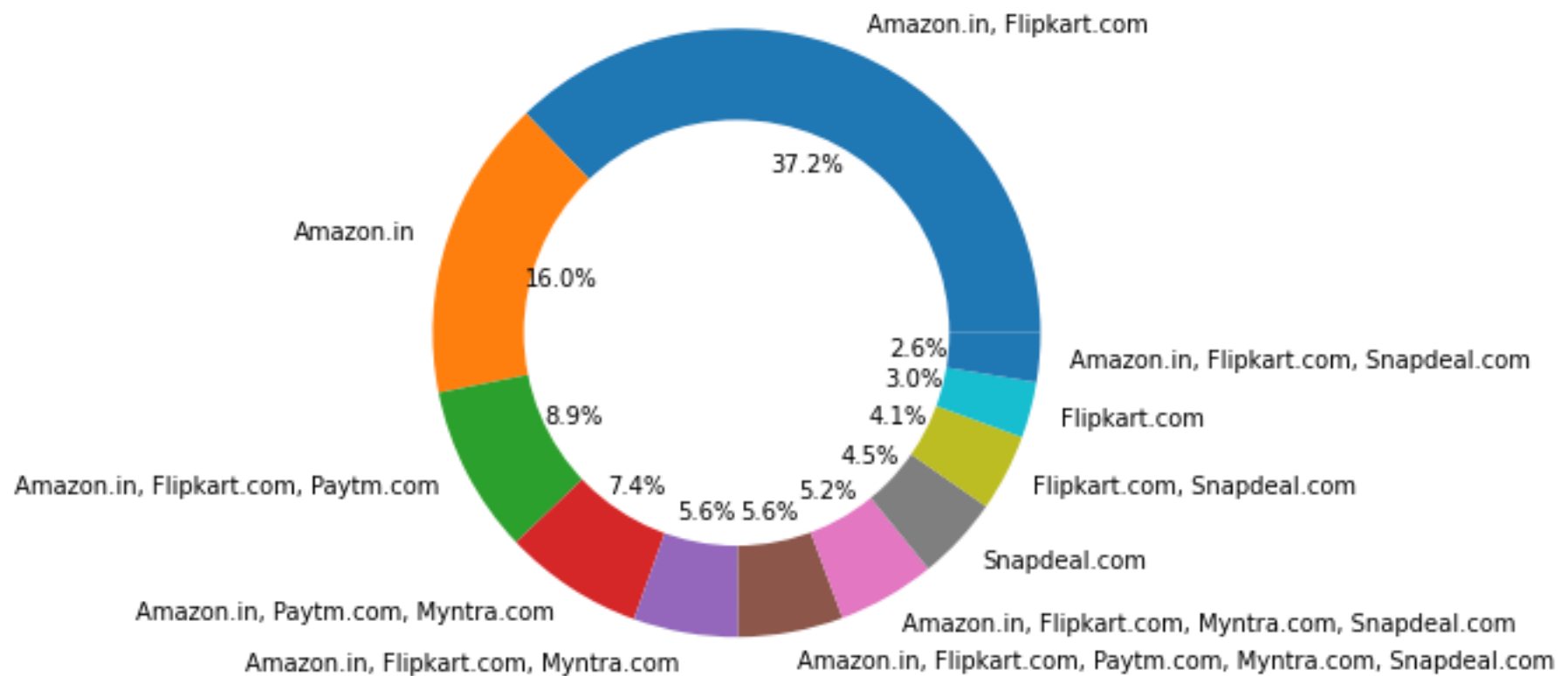




<Figure size 432x288 with 0 Axes>

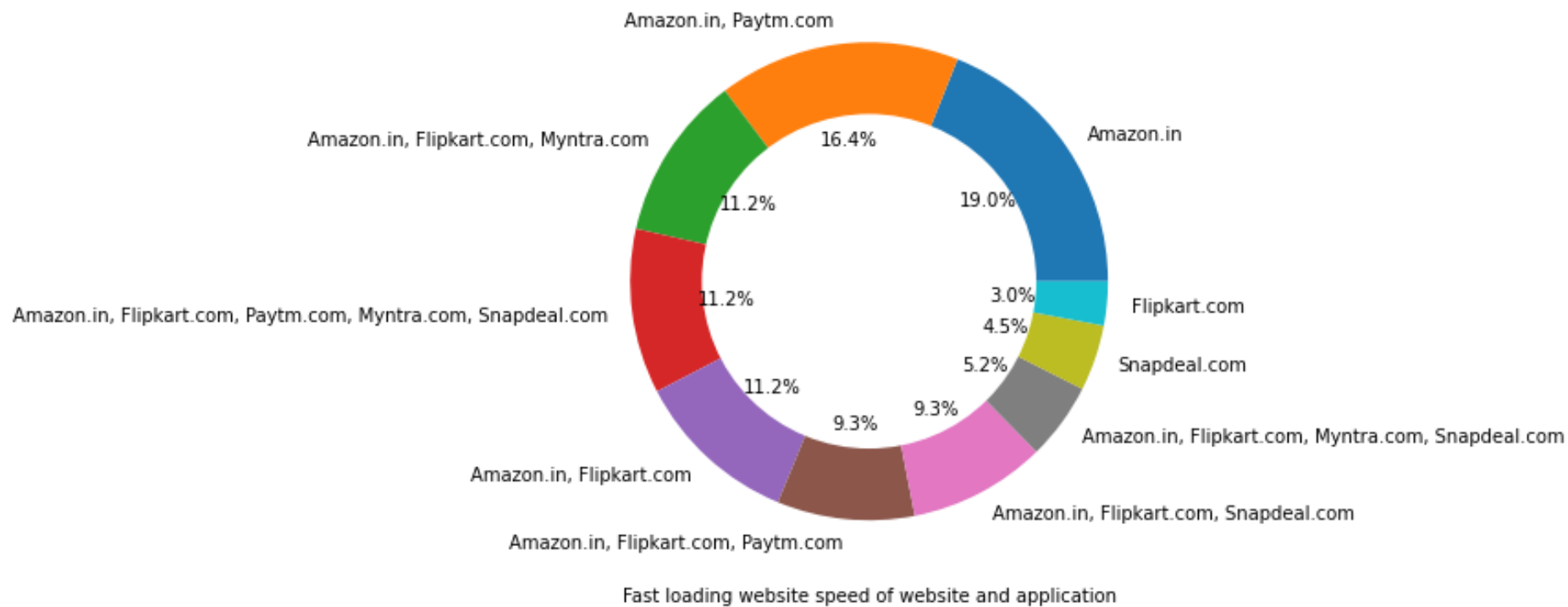


<Figure size 432x288 with 0 Axes>

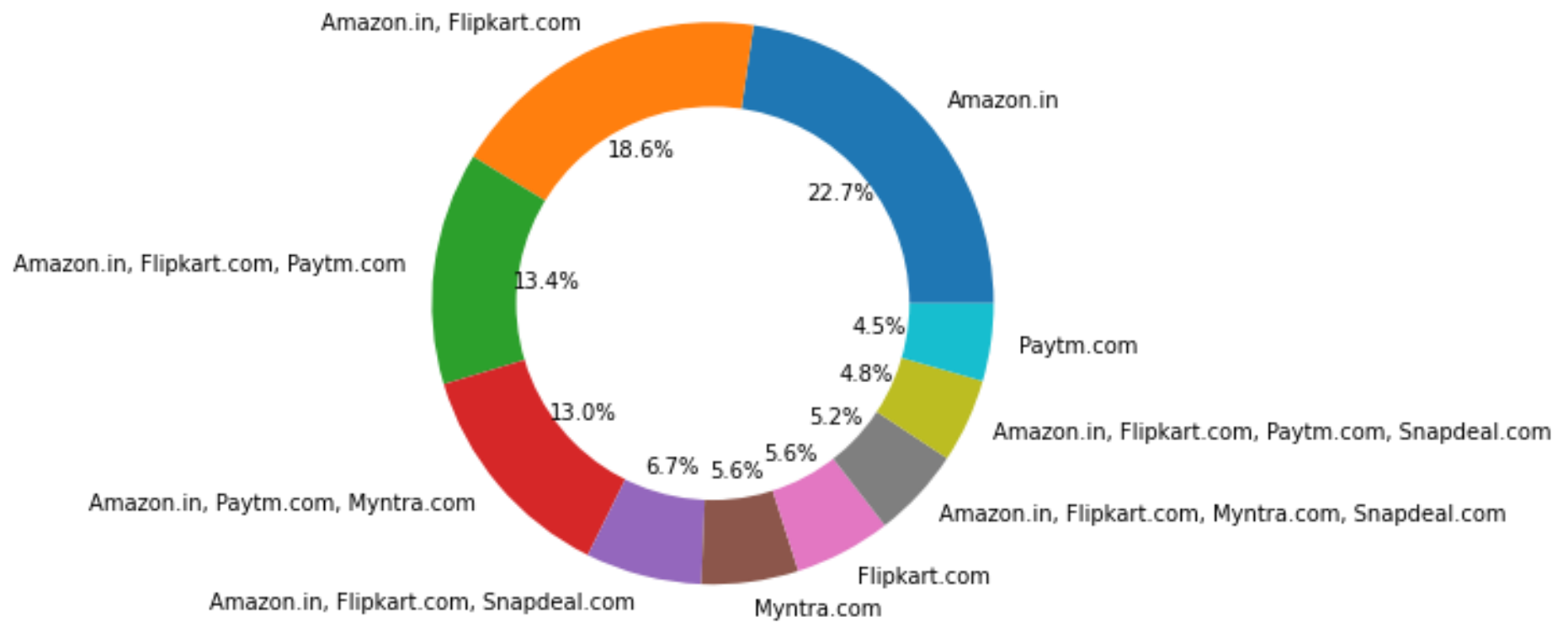


Complete, relevant description information of products

<Figure size 432x288 with 0 Axes>

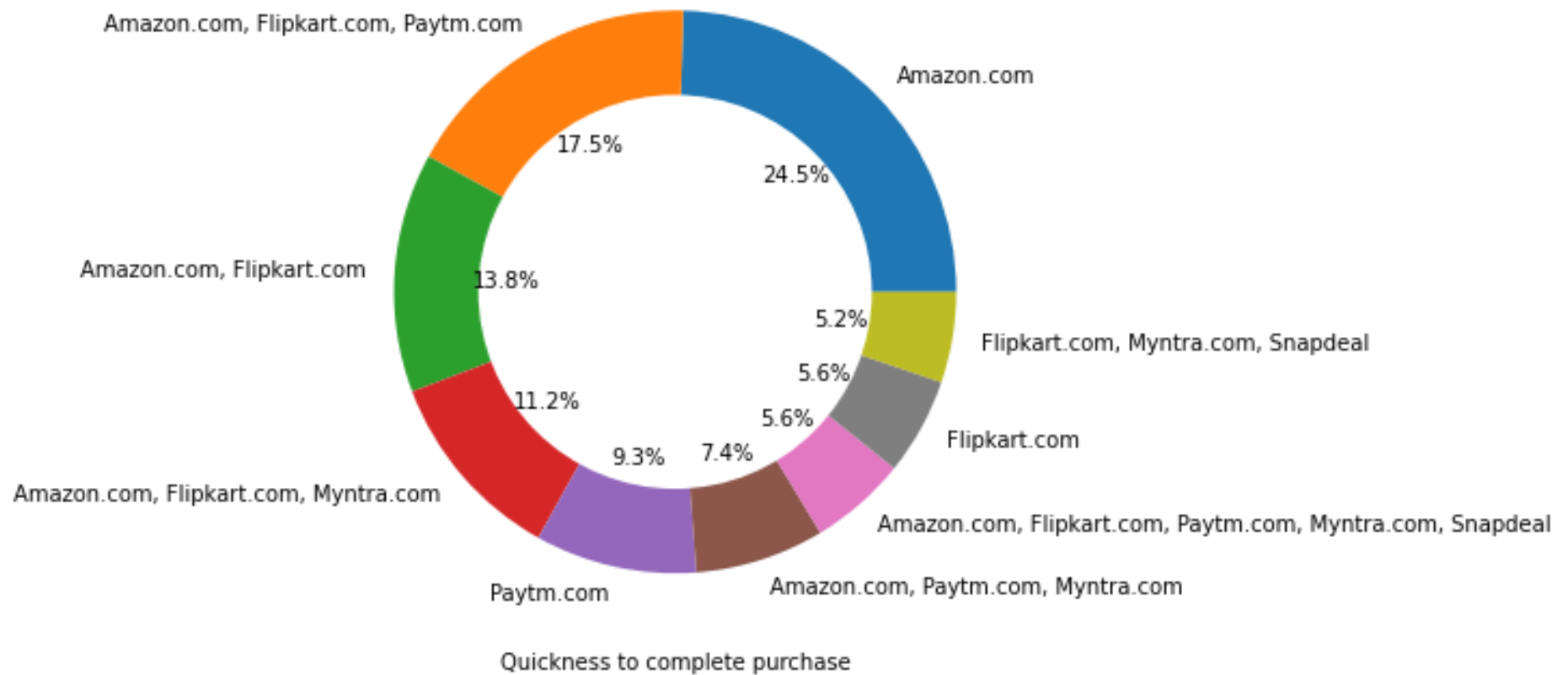


<Figure size 432x288 with 0 Axes>

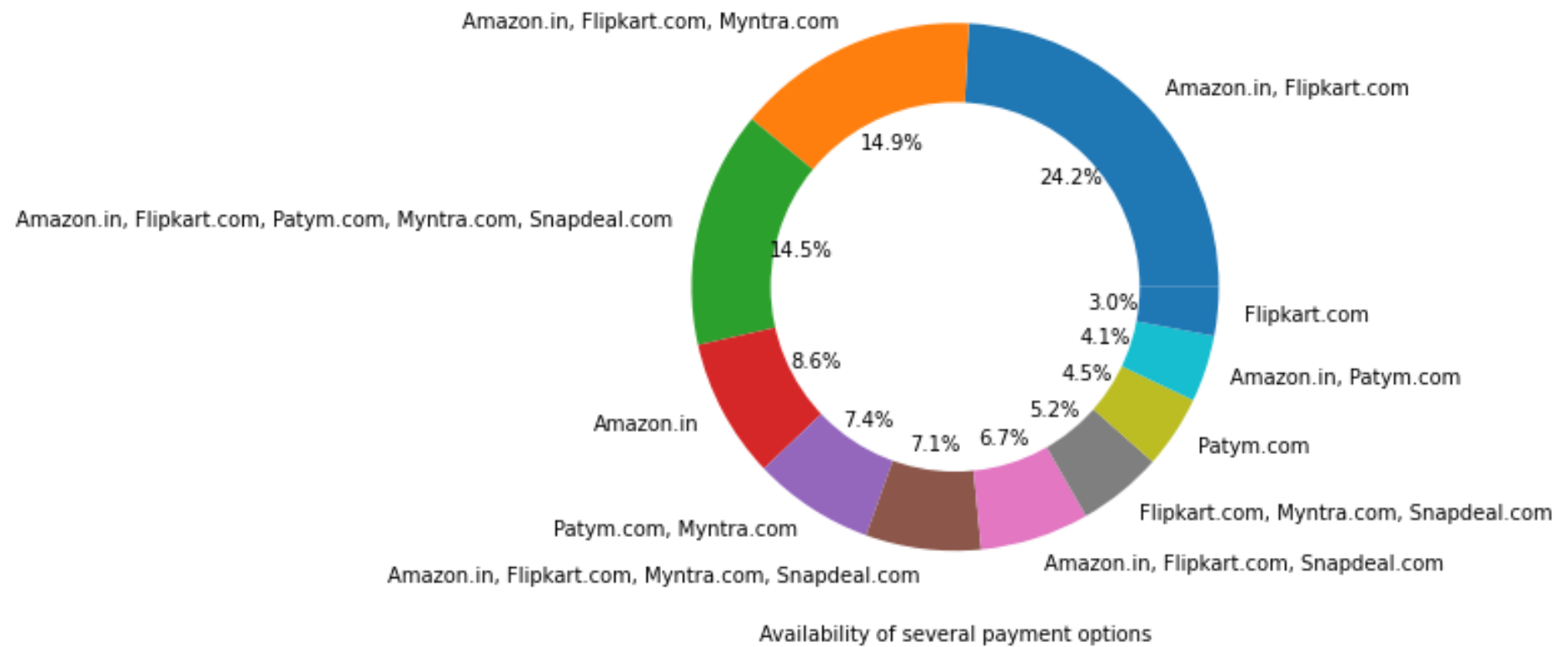


Reliability of the website or application

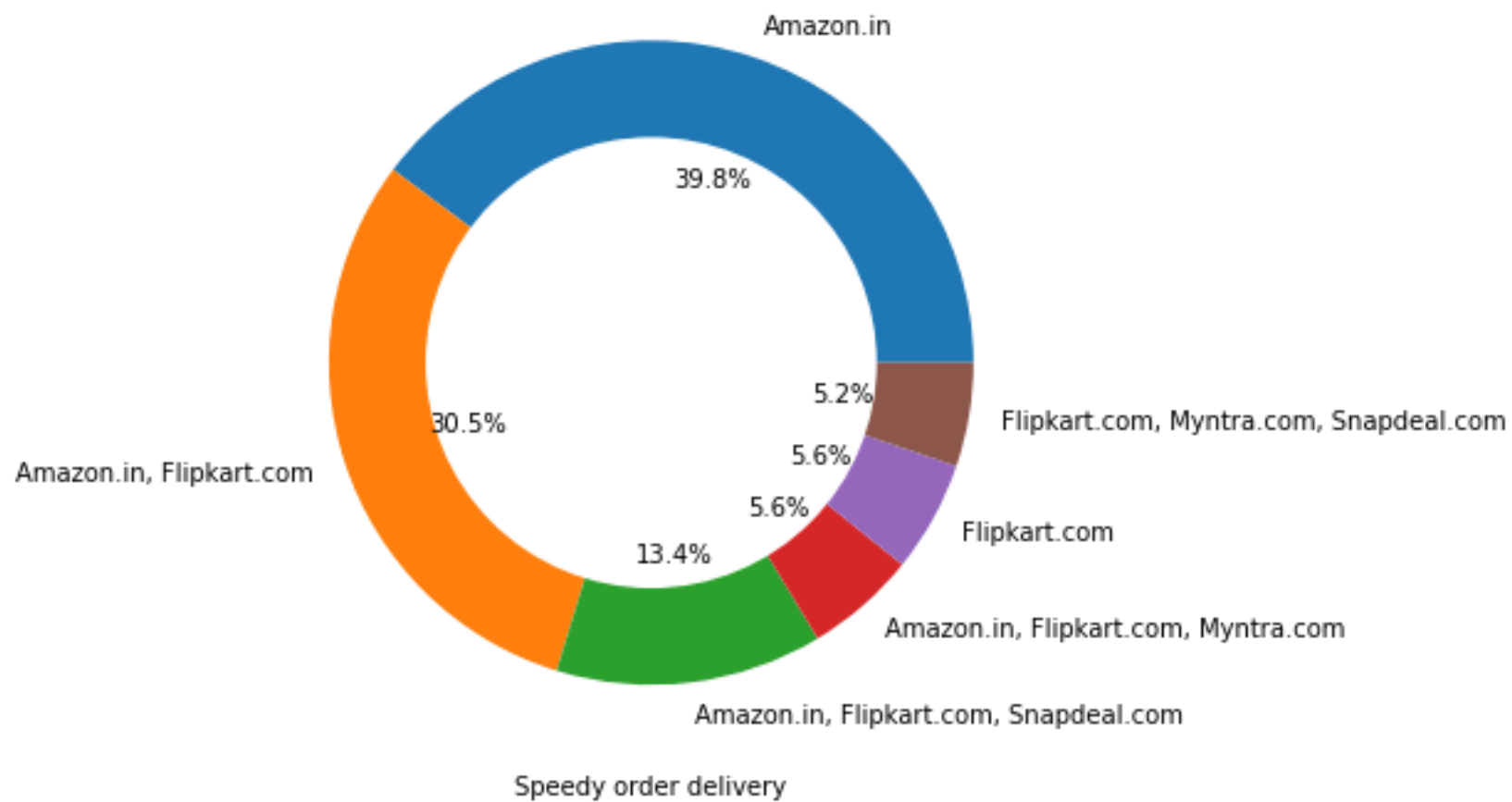
<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>

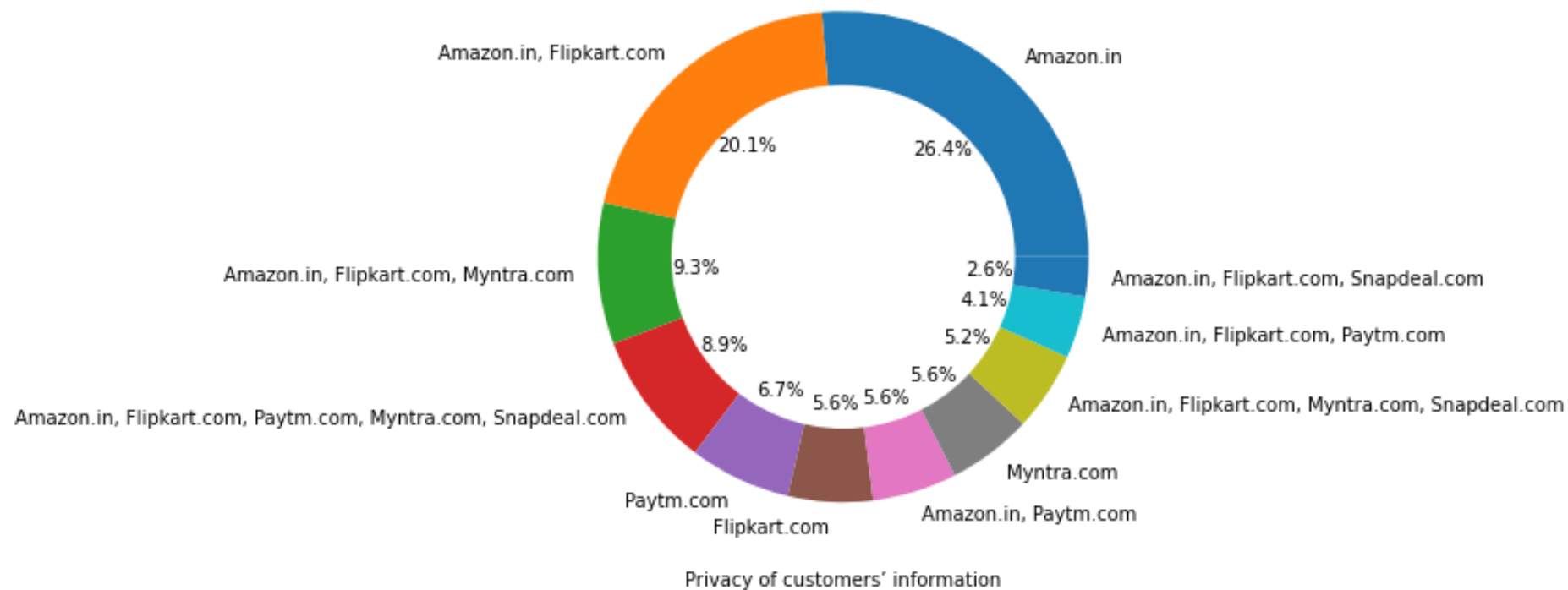


<Figure size 432x288 with 0 Axes>



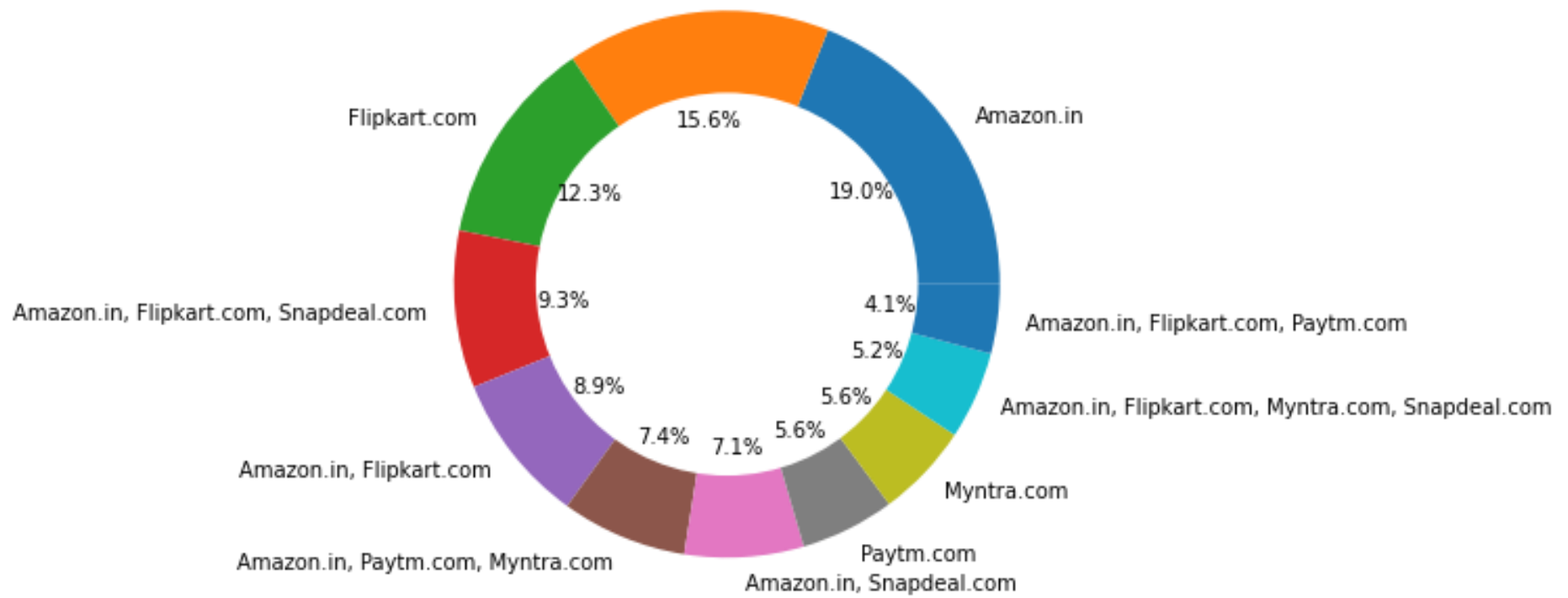
<Figure size 432x288 with 0 Axes>





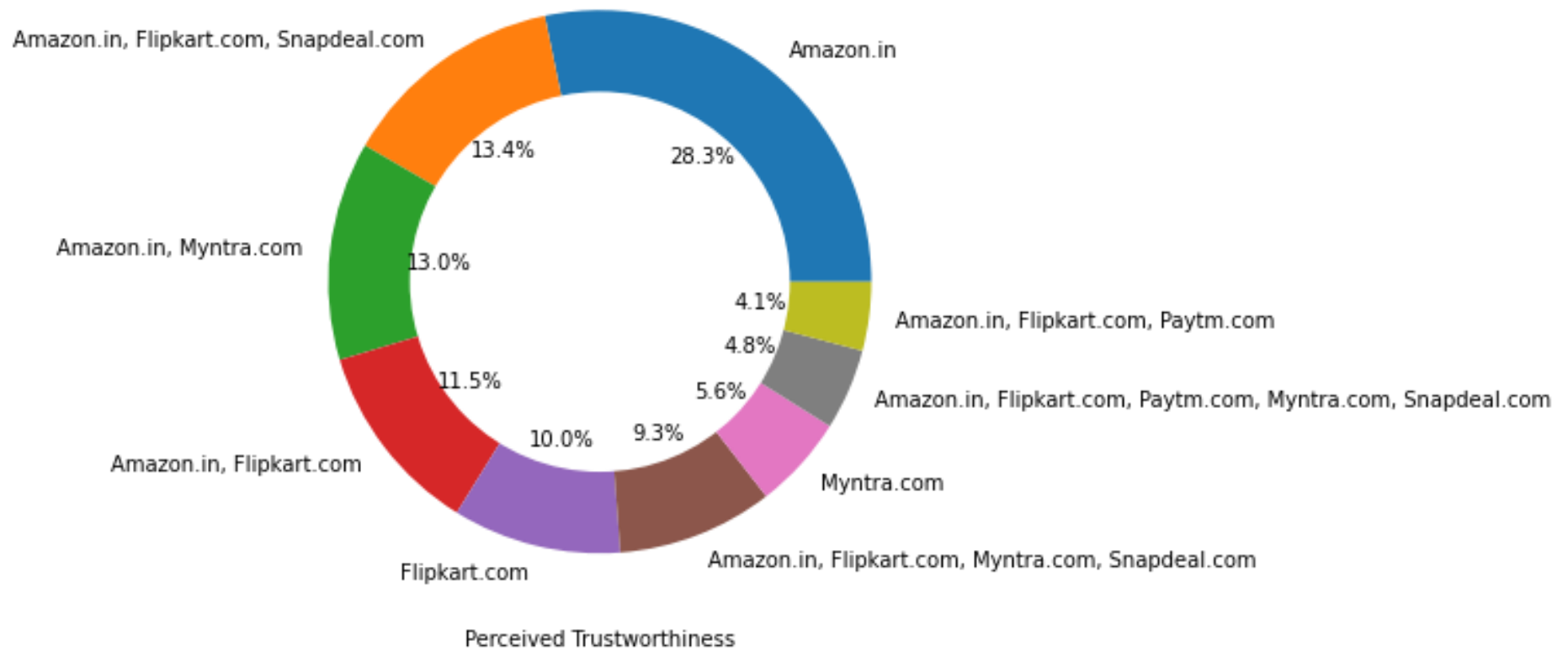
<Figure size 432x288 with 0 Axes>

Amazon.in, Flipkart.com, Paytm.com, Myntra.com, Snapdeal.com

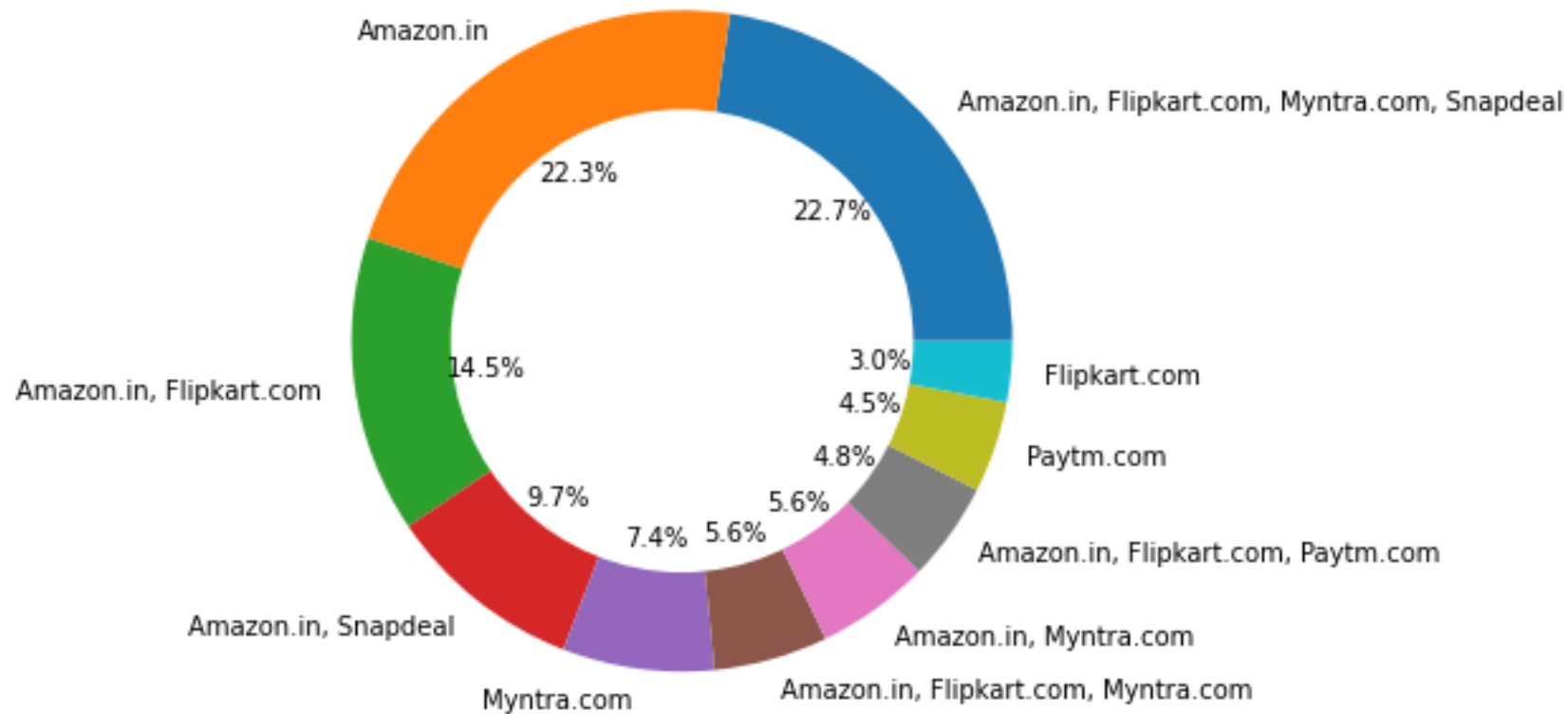


Security of customer financial information

<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



Presence of online assistance through multi-channel

<Figure size 432x288 with 0 Axes>

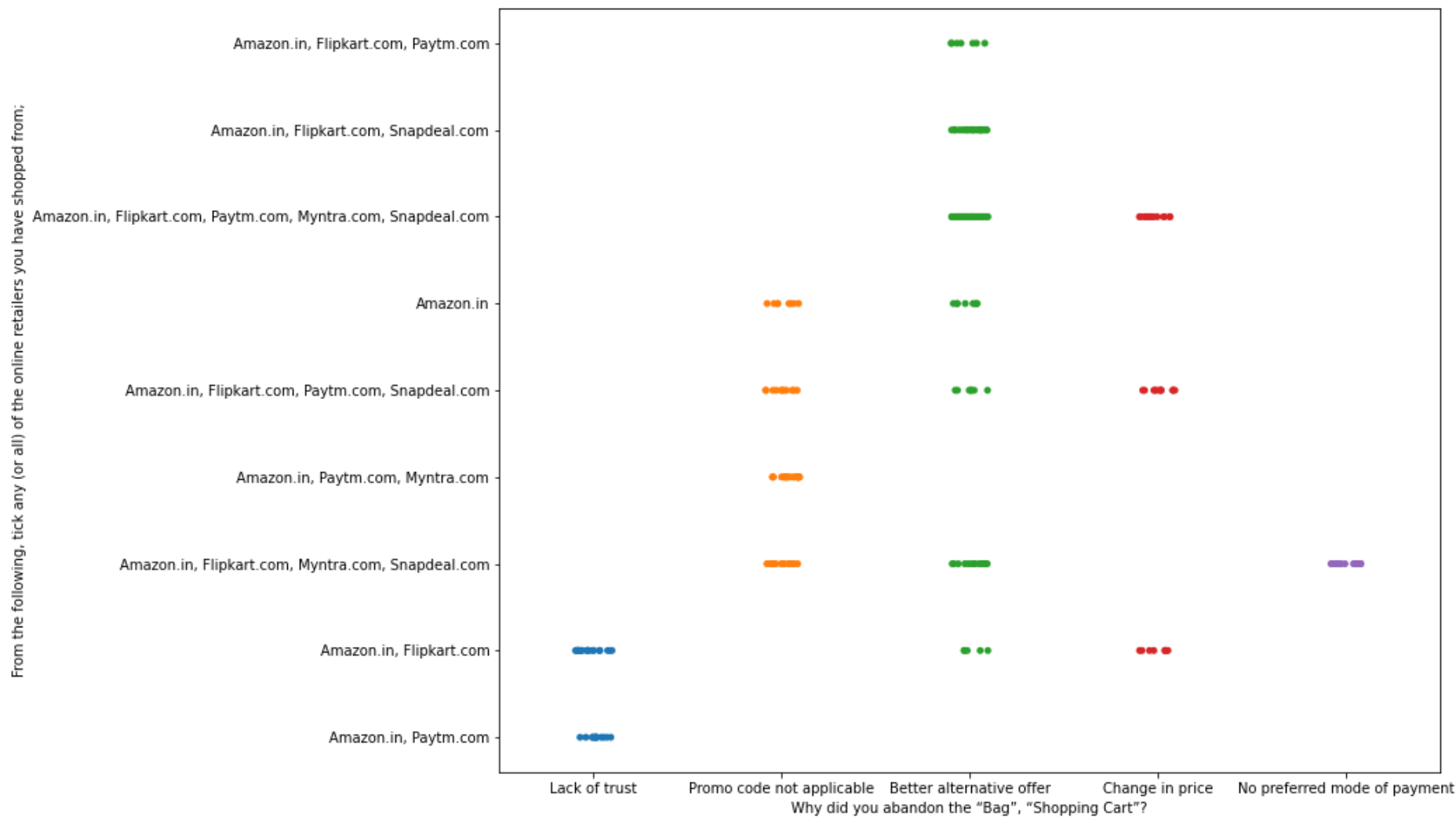
Amazon, Flipkart have been had the highest votes for having all the positive points and have maintained a very good brand image followed by paytm and the myntra.

In [36]:

```
plt.figure(figsize=(12,10))
sns.stripplot(newdata['Why did you abandon the "Bag", "Shopping Cart"?'],
              newdata['From the following, tick any (or all) of the online retailers you have shopped from;'])
```

Out[36]:

```
<AxesSubplot:xlabel='Why did you abandon the "Bag", "Shopping Cart"?', ylabel='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 abandon the bag is because they get a better alternative offer or promo code not applicable. There is also lack of trust seen in amazon, flipkart and paytm by some people.

# Loyalty

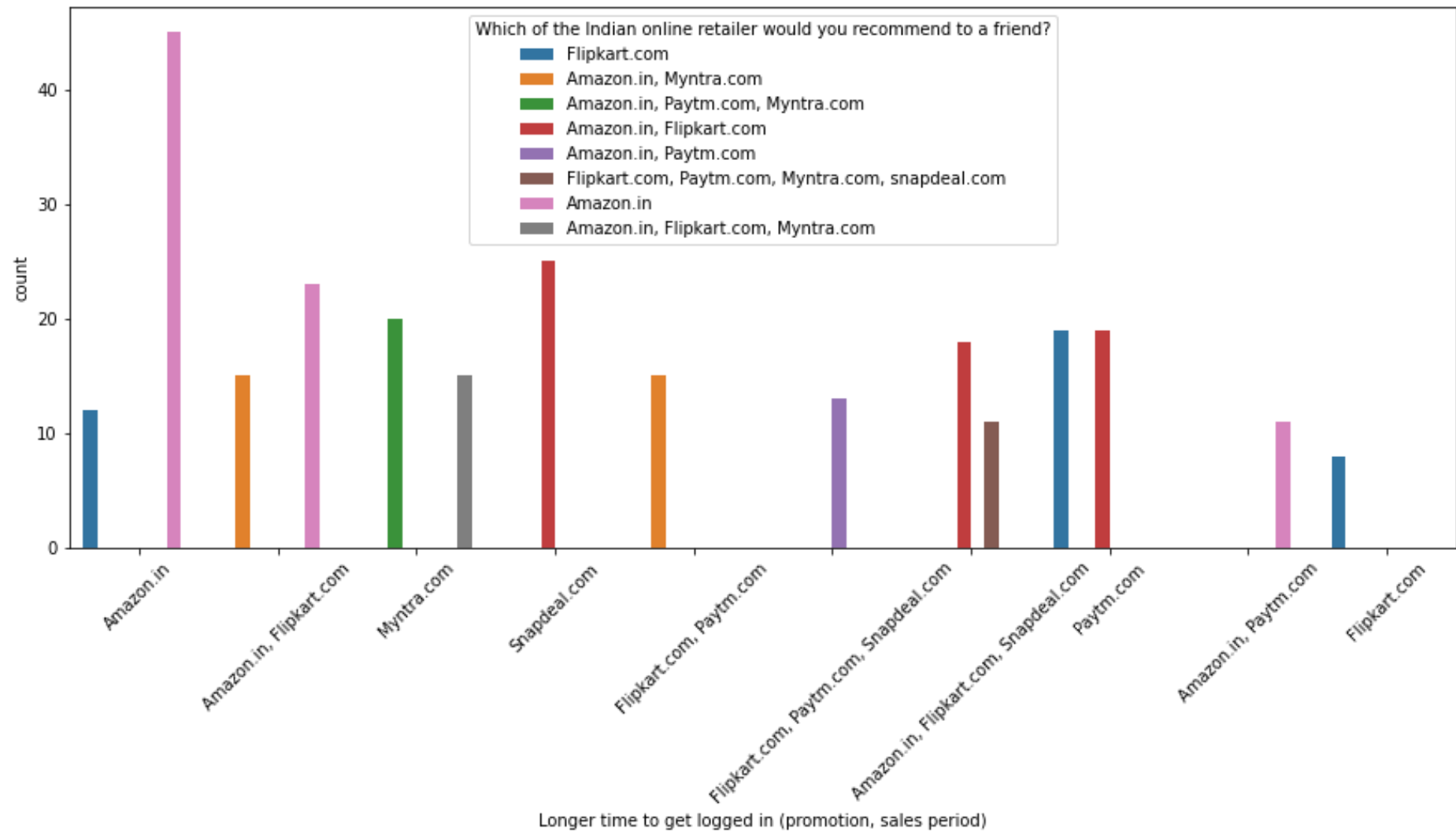
Loyal customers are those who keep using the same brand even if it is not good as other brands

In [37]:

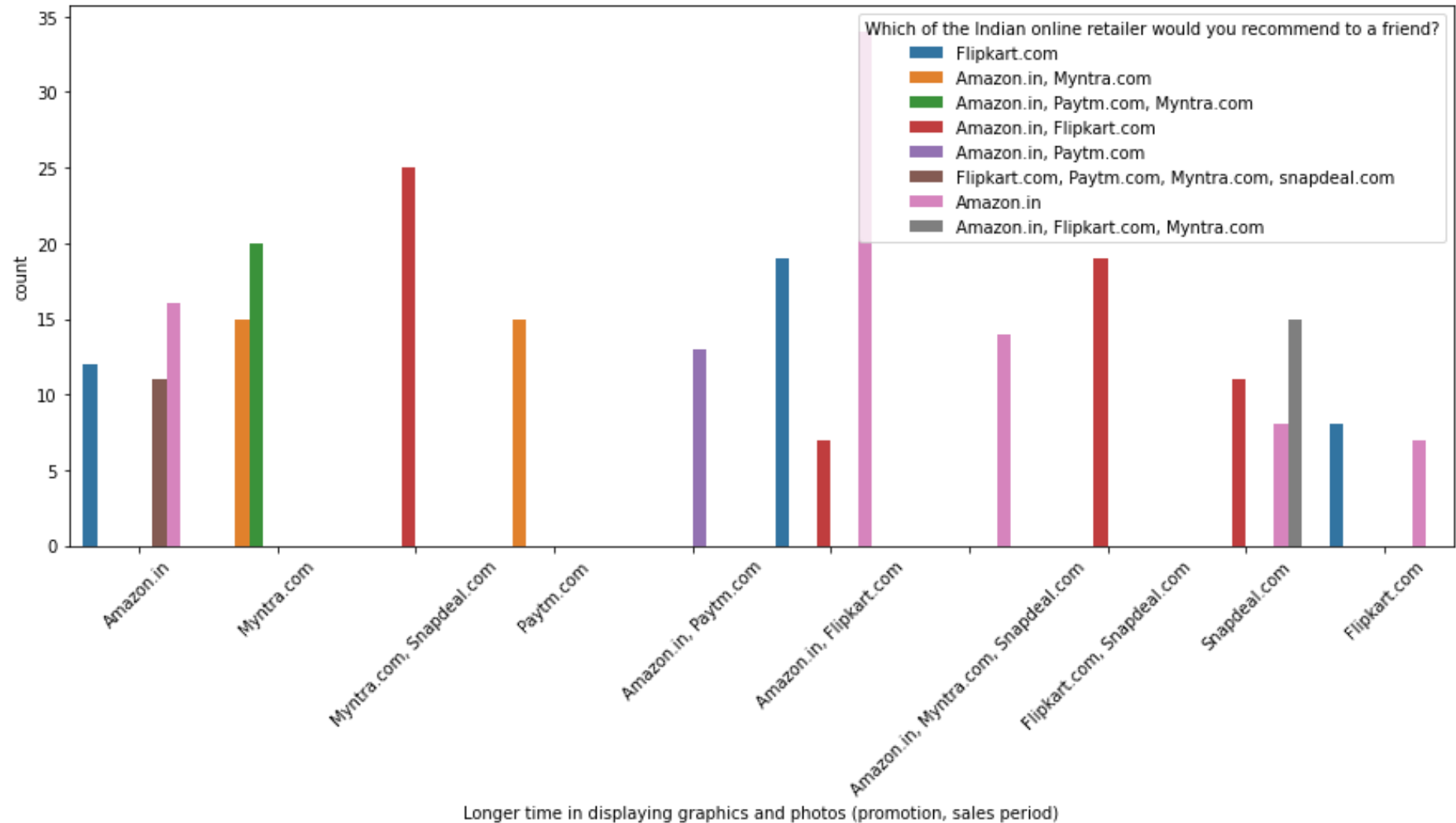
```
#Collecting all the negative remarks about a brand
bad=['Longer time to get logged in (promotion, sales period)',
     'Longer time in displaying graphics and photos (promotion, sales period)',
     'Late declaration of price (promotion, sales period)',
     'Longer page loading time (promotion, 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']
```

In [38]:

```
for i in bad:
    plt.figure(figsize=(15,6))
    sns.countplot(newdata[i],hue=newdata['Which of the Indian online retailer would you recommend to a
friend?'])
    plt.xticks(rotation=45)
    plt.figure()
```

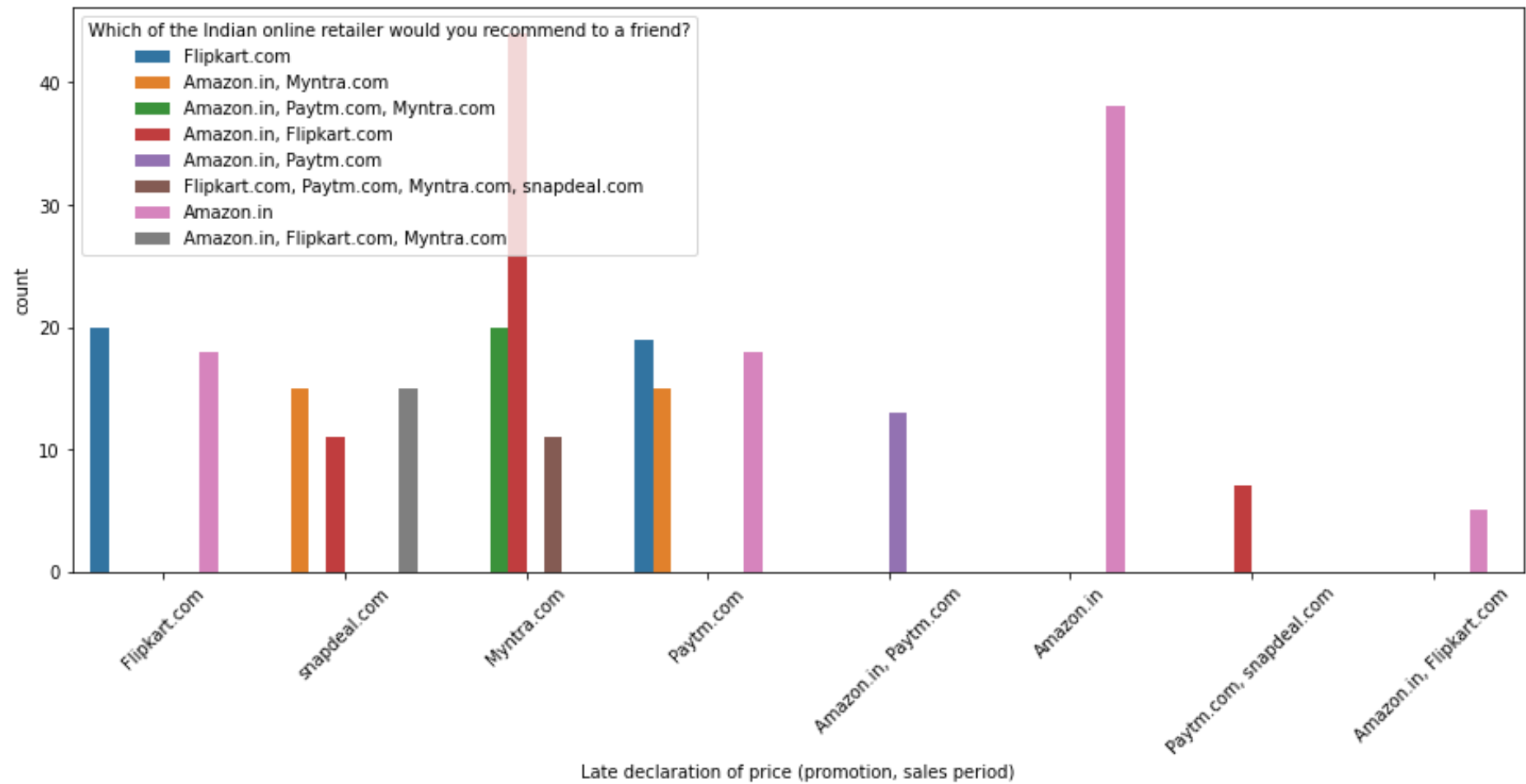


<Figure size 432x288 with 0 Axes>

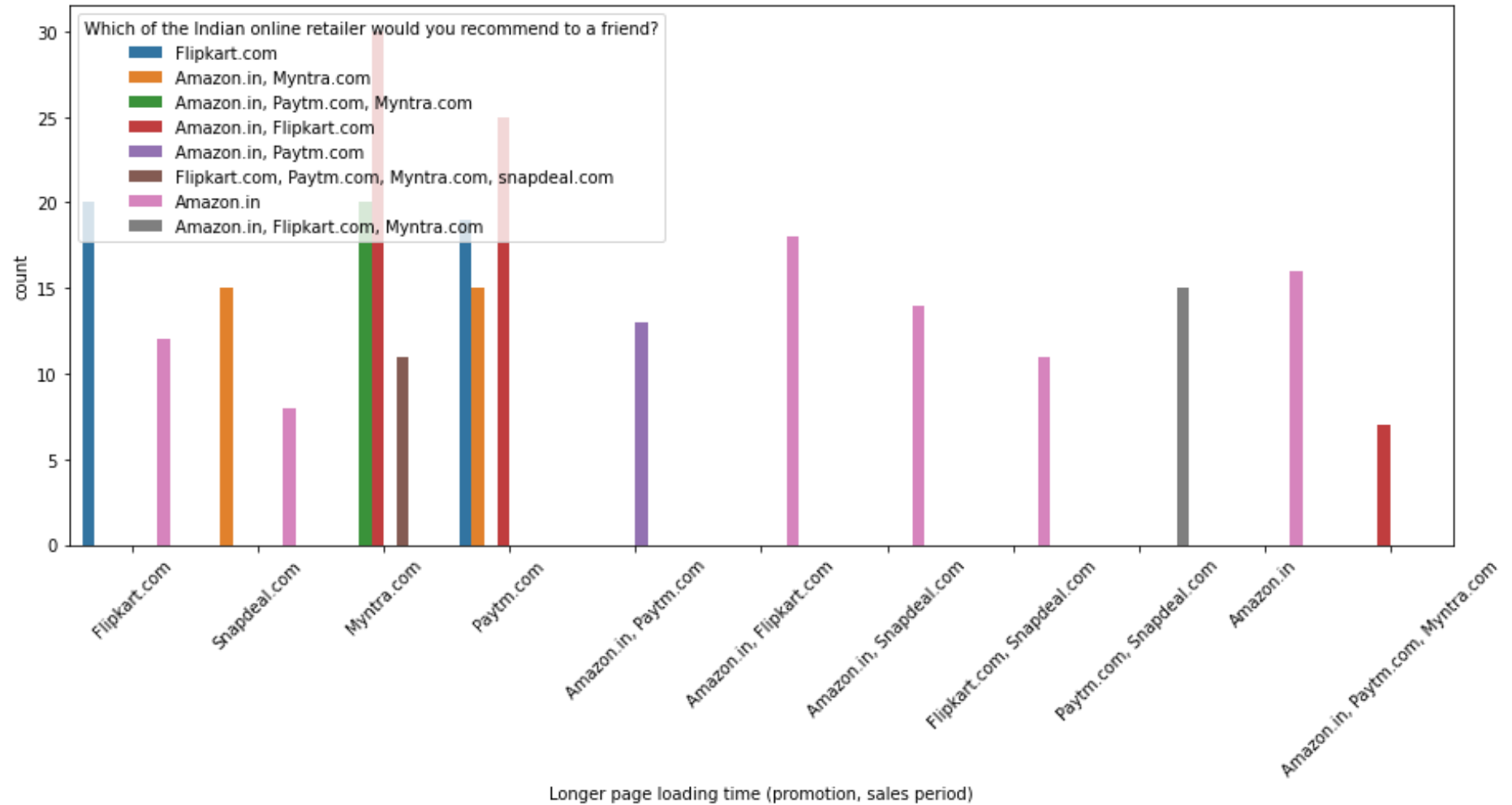


<Figure size 432x288 with 0 Axes>

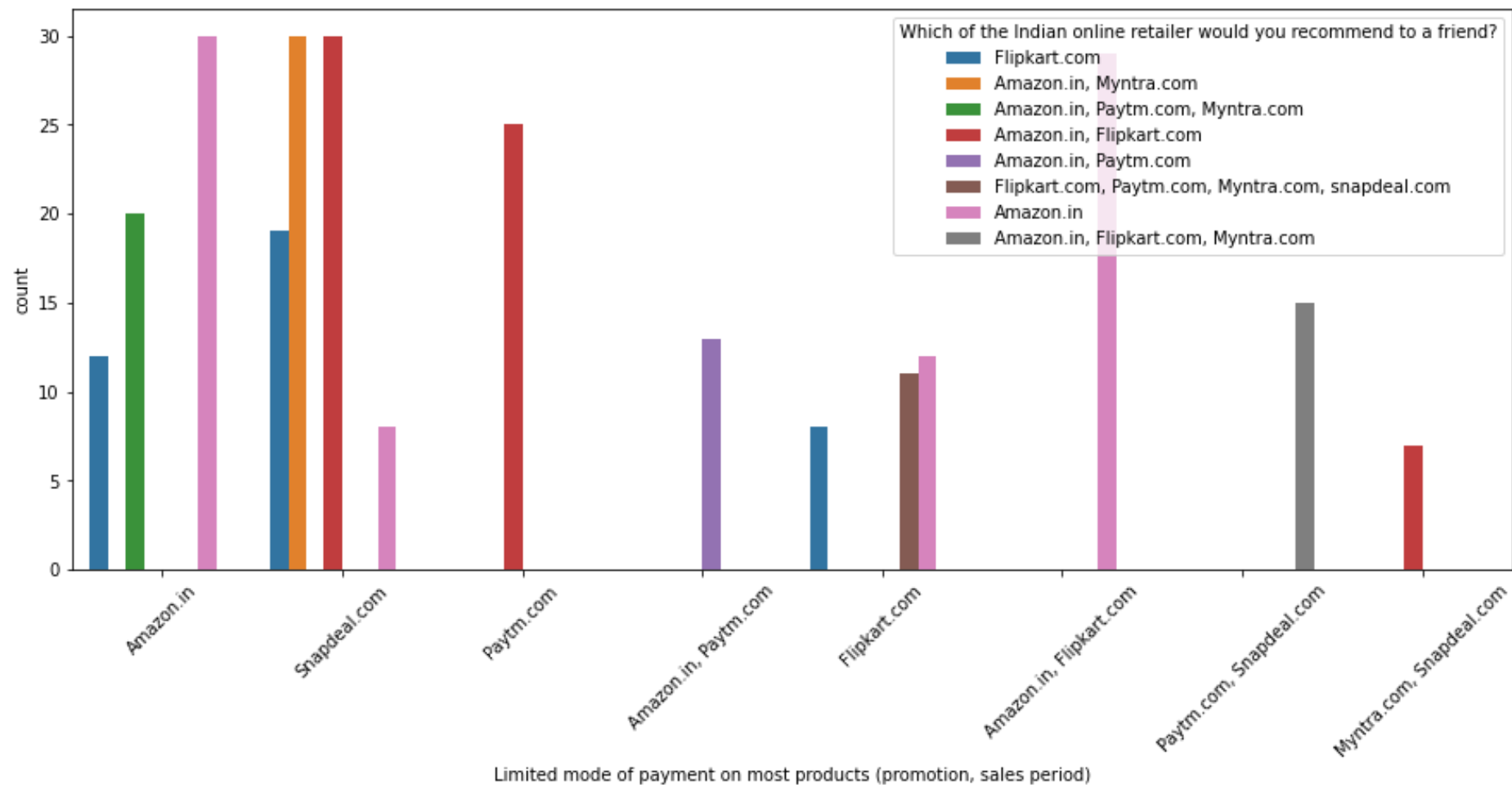




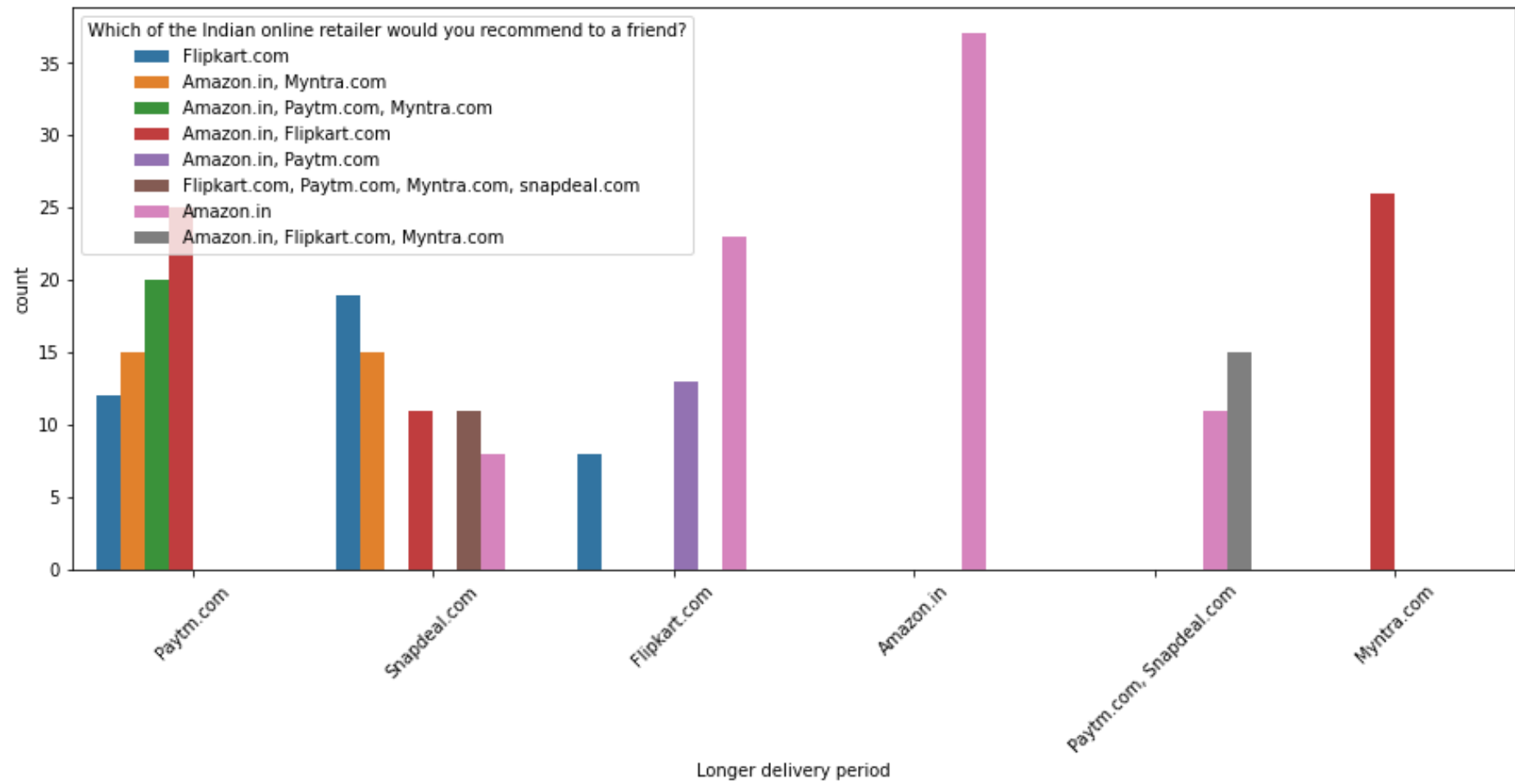
<Figure size 432x288 with 0 Axes>



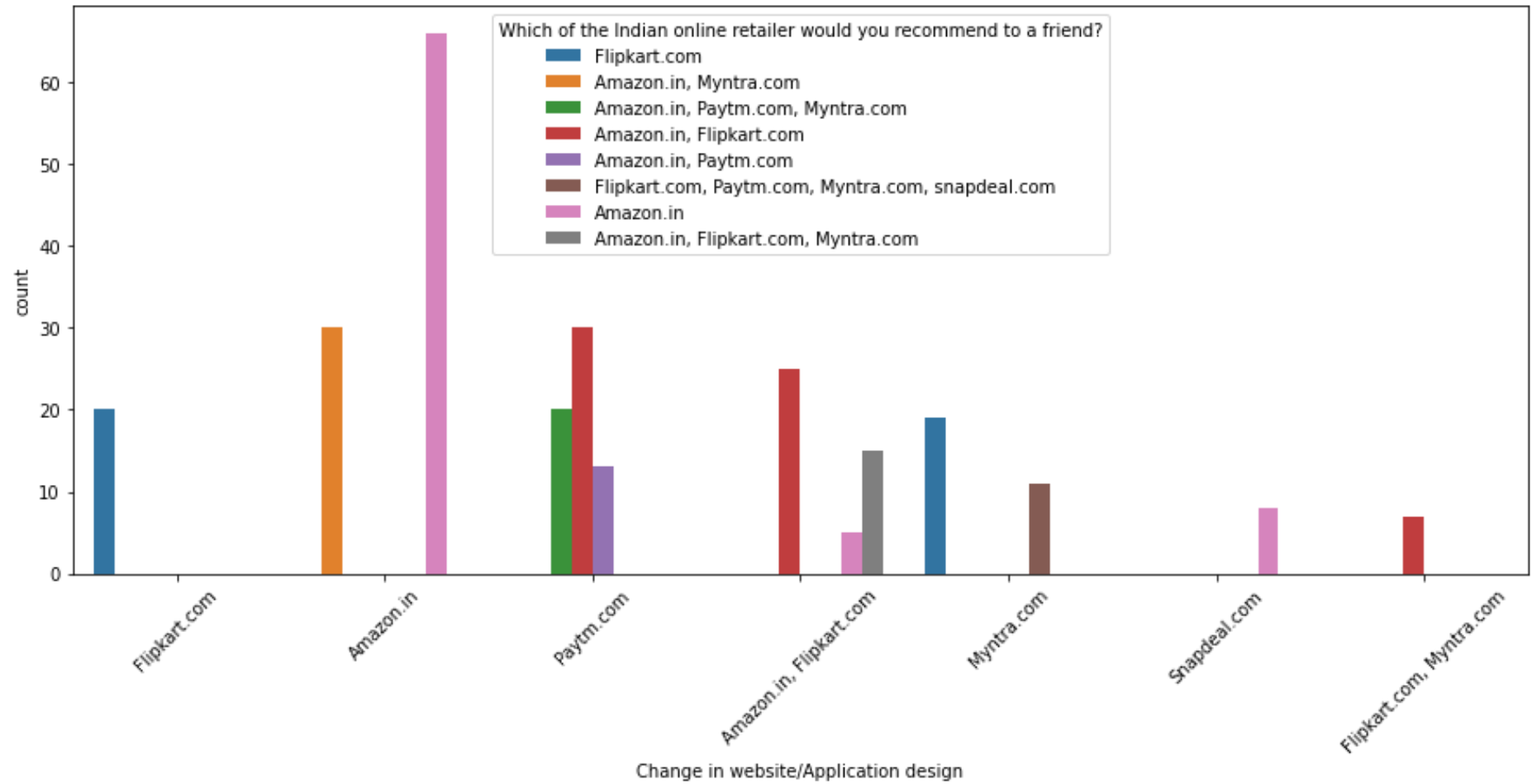
<Figure size 432x288 with 0 Axes>



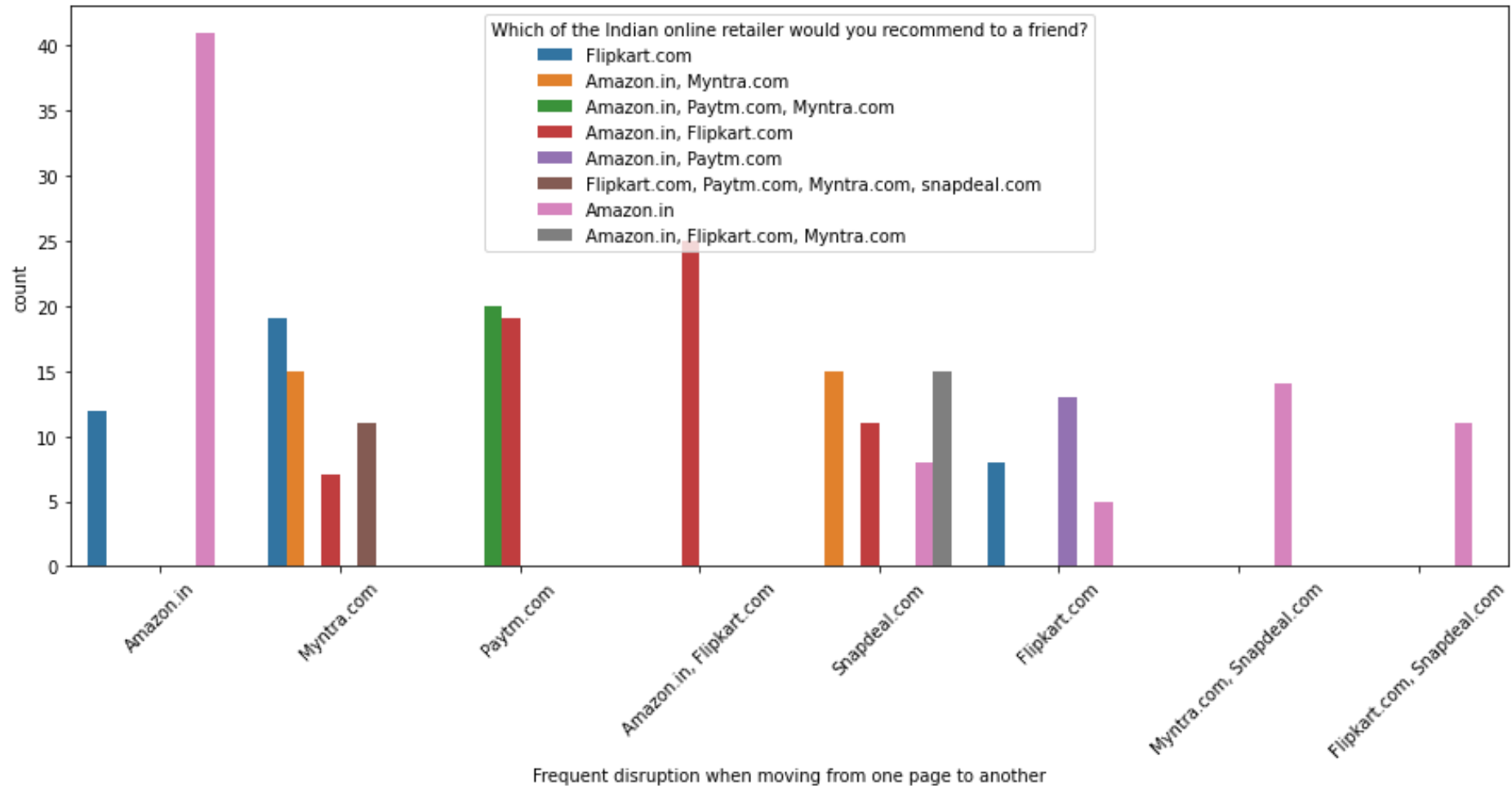
<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>

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 [39]:

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

In [40]:

```
#Encoding Categorical Features
cat=[i for i in x.columns if x[i].dtypes=='O']
```

In [41]:

```
from sklearn.preprocessing import OrdinalEncoder,LabelEncoder
encode=OrdinalEncoder()
labe=LabelEncoder()
```

In [42]:

```
#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)
```

## Scaling

In [43]:

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

In [44]:

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

# Using various feature selection method to see which feature affects the most

Using Feature importance of random forrest

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

In [45]:

```
RandomForestClassifier()
```

Out[45]:

```
RandomForestClassifier()
```

In [46]:

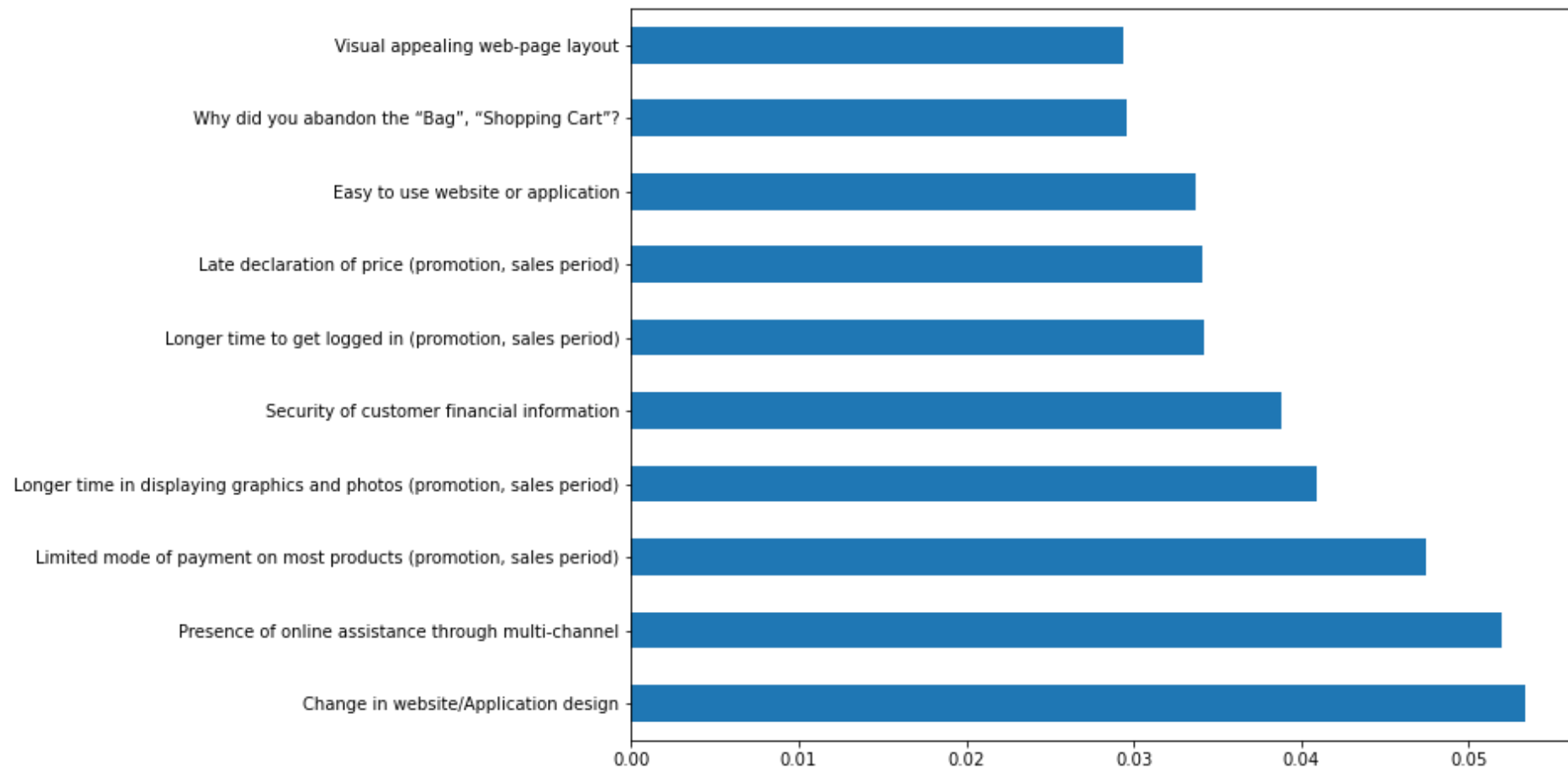
```
RandomForestClassifier()
```

Out[46]:

```
#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()
```

In [47]:





## Using chi2 test

In [48]:

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

In [49]:

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

In [50]:

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

In [51]:

```
print(featureScores.nlargest(10,'Score')) #print 10 best features
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

In [52]:

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

In [53]:

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

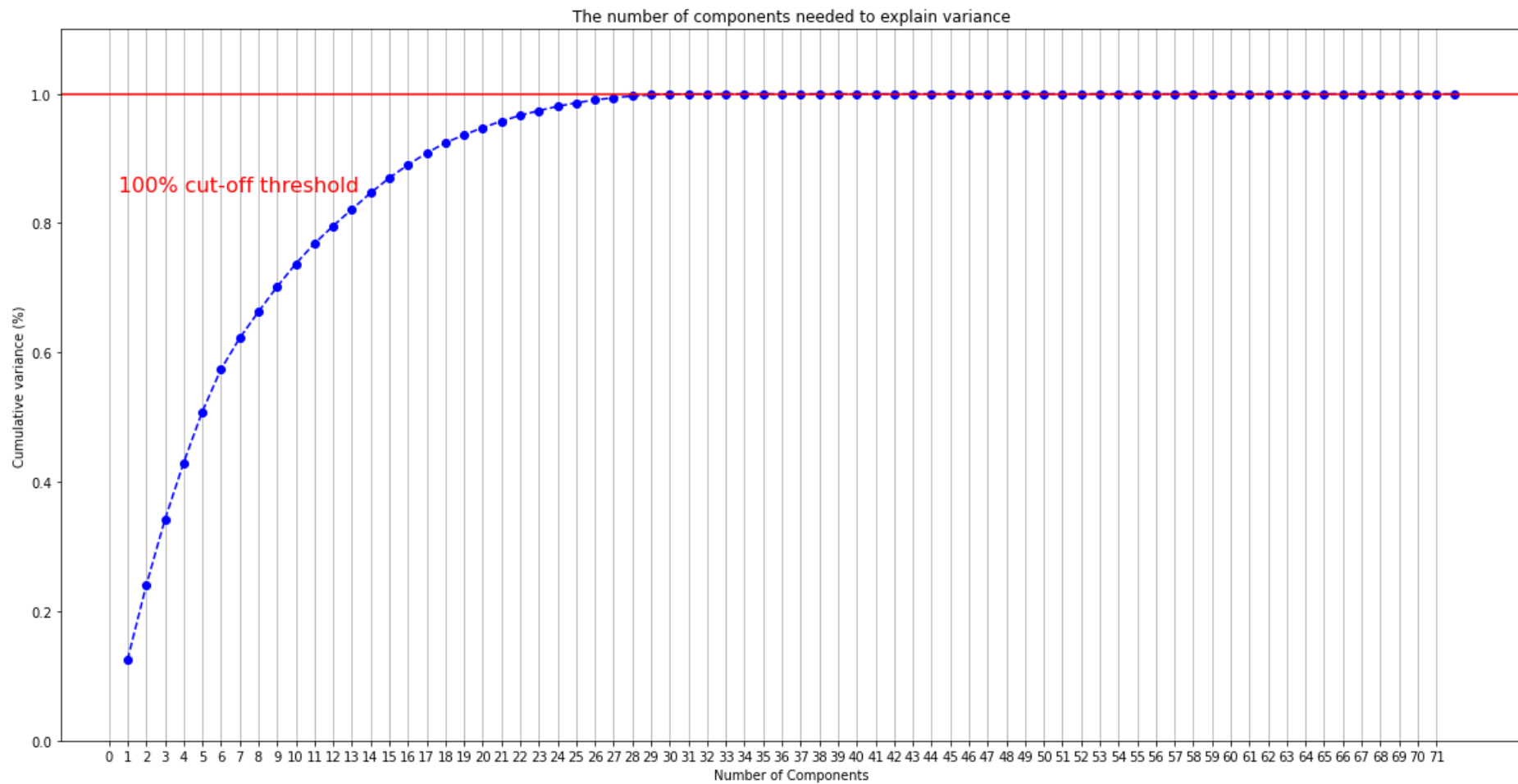
plt.ylim(0.0,1.1)
plt.plot(xi, yi, marker='o', linestyle='--', color='b')

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()
```



We can clearly see that with 29 features all the information can be retained

In [54]:

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

Out[54]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28
0	2.065419	-0.57759	-1.0301	-1.1094	0.652387	-1.137025	0.699876	-0.023177	-0.960103	-0.238855	-0.43650	-0.5391	0.130180	0.178306	-0.10464	-0.339286	0.379243	-0.4315	-0.272189	0.598931	0.068875	-0.266070	-0.0092	-0.12844	-0.02468	-0.22588	-0.10411	-0.20328	-0.20393
1	0.048667	-1.490547	1.081348	0.641617	0.066388	-0.820495	0.072214	-0.644870	0.087754	-0.296247	-0.157354	0.881935	0.648067	0.3459	0.32984	0.3725	-0.486708	-0.456116	-0.403685	-0.176390	-0.008384	0.155024	0.313679	0.079454	-0.162517	-0.101240	0.295586	-0.1357	0.122856
2	1.671684	-0.120022	0.7750	-1.481374	0.1287	0.83615	-0.79360	0.102789	0.448813	-0.51594	-0.033307	-0.086125	0.3685	-0.4477	0.281074	0.230154	-0.136122	0.074572	0.14000	0.038239	-0.068419	0.008284	0.2156	-0.037138	0.09495	-0.174314	0.156931	-0.06150	-0.166877
3	-0.009522	2.146296	0.753236	-0.363176	-1.348954	-0.176575	0.567430	-0.548924	-0.142604	-0.084665	-0.341339	0.095133	0.08917	0.086230	-0.201624	-0.132961	0.167764	0.160252	0.075425	0.025910	0.229481	-0.091051	0.190278	-0.069483	-0.059019	-0.140161	0.103730	0.035920	-0.11666
4	0.051352	-0.187387	2.3865	0.914150	0.273219	-0.92250	-0.511792	0.701105	-0.225943	0.735107	0.138216	-0.81487	-0.204856	0.29430	-0.127501	0.336204	0.21469	-0.030964	0.205835	-0.032298	0.130742	-0.195750	-0.163709	-0.071655	-0.186014	0.047217	0.185140	-0.35241	0.134780

# Modelling Phase

In [55]:

```
from sklearn.model_selection import train_test_split, cross_val_score

from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier

from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, roc_auc_score, roc_curve

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

In [56]:

## Random Forest

In [57]:

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

In [58]:

```
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 0.9926
```

---

#### 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

## Xgboost

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

In [59]:

In [60]:

```

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 0.9926  
-----

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



# Hyperparameter Tuning

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

Random Forest

```
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]}
```

```
g=RandomizedSearchCV(RandomForestClassifier(),params,cv=10)
```

```
g.fit(xtrain,ytrain)
```

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

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

```
RandomForestClassifier(max_depth=30, min_samples_leaf=2, min_samples_split=4,
                       n_estimators=700)
{'n_estimators': 700, 'min_samples_split': 4, 'min_samples_leaf': 2, 'max_depth': 30}
0.9947368421052631
```

In [61]:

In [62]:

In [63]:

In [64]:

Out[64]:

In [65]:

In [66]:

```
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 [67]:

```
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 0.9926  
-----

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

## Xgboost

In [68]:

```
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 [69]:

```
g=RandomizedSearchCV(XGBClassifier(),params,cv=10)
```

In [70]:

```
g.fit(xtrain, ytrain)
```

Out[70]:

[illegible]

```

        n_estimators=100, n_jobs=None,
        num_parallel_tree=None,
        predictor=None, random_state=None,
        reg_alpha=None, reg_lambda=None, ...),
    param_distributions={'learning_rate': [0.001, 0.01, 0.1],
                        'max_depth': [1, 2, 3, 4, 5, 6, 7, 8, 9,
                                      10],
                        'n_estimators': [100, 200, 300, 400,
                                         500],
                        'subsample': [0.5, 1]})

```

In [71]:

```

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

XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
              importance_type=None, interaction_constraints='',
              learning_rate=0.1, max_bin=256, max_cat_to_onehot=4,
              max_delta_step=0, max_depth=7, max_leaves=0, min_child_weight=1,
              missing=nan, monotone_constraints='()', n_estimators=100,
              n_jobs=0, num_parallel_tree=1, objective='multi:softprob',
              predictor='auto', random_state=0, reg_alpha=0, ...)
{'subsample': 0.5, 'n_estimators': 100, 'max_depth': 7, 'learning_rate': 0.1}
0.9894736842105264

```

In [72]:

```

m=XGBClassifier(max_depth=10, learning_rate=0.1, n_estimators=500, subsample=0.5)
m.fit(xtrain, ytrain)
p=m.predict(xtest)
score=cross_val_score(m, x, y, cv=10)

```

In [73]:

```

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 0.9926

-----

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

Conclusion Both the models give accurate and equal results so we choose xgboost as or final model because of its quick speed.

## Finalizing the best Model

In [74]:

```
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)
```

## Evaluation Metrics

In [75]:

```
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 0.9926  
-----

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]]
```

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Classification Report

	precision	recall	f1-score	support
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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

In [ ]: