



Customer Retention

Submitted by:

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ACKNOWLEDGMENT

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INTRODUCTION

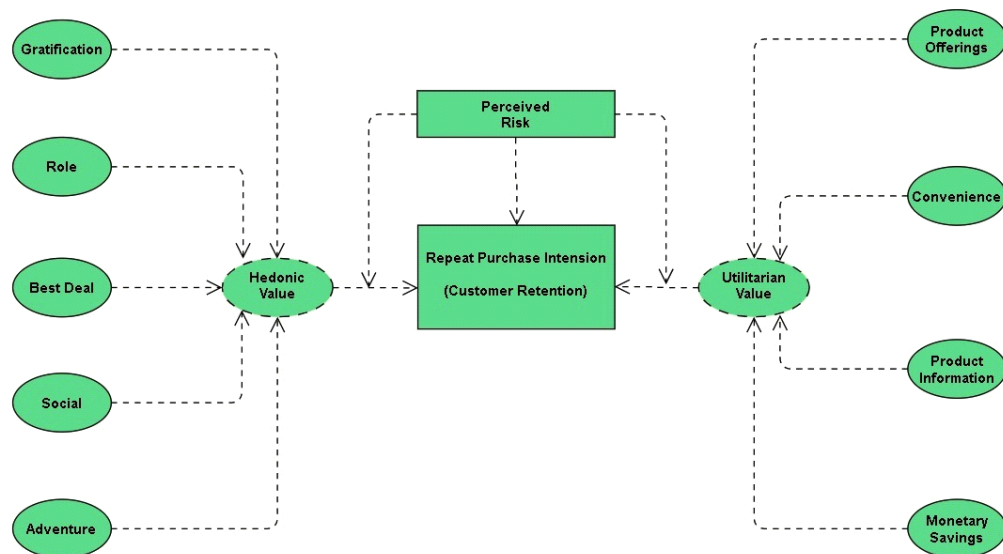
Objective of the study

The objective of the project is to apply analytical skills to give findings and conclusions in detailed data analysis of E-retail factors for customer activation and retention.

Business Model

Customer satisfaction has emerged as one of the most important factors that guarantee the success of online store; it has been posited as a key stimulant of purchase, repurchase intentions and customer loyalty. 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



Literature Survey

Hedonic and utilitarian shopping values

A consumer's behaviour is a result of motives, attitudes and values and may manifest into purchase and consumption behaviour. Westbrook and Black (1985) posit that some shopping motives are utilitarian in nature whereas others are hedonic. The utilitarian and hedonic values have been the focus of much interest and research (Hirschman and Holbrook, 1982; Batra and Ahtola, 1991; Babin et al, 1994; Wang et al, 2000; Millan and Howard, 2007; Teller et al, 2008). Consumer values have been broadly termed as utilitarian (Bloch and Bruce, 1984; Batra and Ahtola, 1991; Engel et al, 1993; Babin et al, 1994) which are more task oriented in nature and hedonic which are related to entertainment and fun-seeking behaviour (Bellenger et al, 1976). Bloch and Richins (1983) postulate that hedonic values are characterized by heightened arousal, excitement, adventure and entertainment. Shopping

behaviour provides excitement whereas the consumer interacts with the store environment and gives cues while they examine products (MacInnis and Price, 1987) that may be perceived as enjoyment.

Consumers with strong hedonic values may not be satisfied with the functional aspects of shopping and may look for pleasurable stimulants (Fischer and Arnold, 1990; Wang et al, 2000). The hedonic values are related to gratification of the senses enhanced through experiences of pleasure, entertainment, fantasy and playfulness (Hirschman and Holbrook, 1982; Babin et al, 1994). The consumer values have been defined in terms of being intrinsic and extrinsic; the extrinsic values are related to the functional attributes of shopping, and are mainly 'utilitarian' in nature. The intrinsic values signify the 'enjoyment, fun and leisure' motives (Babin et al, 1994). The utilitarian values are based upon rational and analytical information processing whereas the hedonic values comprise of arousal of the senses (Holbrook and Hirschman, 1982; Hirschman, 1983; Fischer and Arnold, 1990) and self gratification.

The traditional shopping behaviours of product acquisition and consumption may no longer explain the shopping 'experience' the consumers seek when they go to a store or a mall. They look beyond mere assortment of products and functional attributes. Babin et al (1994) state that most consumption activities must combine both utilitarian and hedonic attributes and their absence may not reflect the totality of shopping experience (Bloch and Richins, 1983). Research in the past few years has recognized the pivotal role hedonic values play in shopping and how they add to the emotional value (Langrehr, 1991; Babin et al, 1994; Roy, 1994).

EDA Steps

1. Checking the missing values
2. Checking for numerical columns

3.Checking for the distribution of numerical variables

4.Checking for Categorical variables

5.Types of categorical variables

6.detecting outliers

Analytical Problem Framing

```
In [6]: data.head()
```

Out[6]:

	Gender	Age	City	Pincode	YearsOfOnlineShopping	PurchaseInPast1Year	InternetAccess	DeviceUsed	MobileScreenSize
0	Male	31-40 years	Delhi	110009	Above 4 years	31-40 times	Dial-up	Desktop	
1	Female	21-30 years	Delhi	110030	Above 4 years	41 times and above	Wi-Fi	Smartphone	4.7
2	Female	21-30 years	Greater Noida	201308	3-4 years	41 times and above	Mobile Internet	Smartphone	5.5
3	Male	21-30 years	Karnal	132001	3-4 years	Less than 10 times	Mobile Internet	Smartphone	5.5

```
In [7]: # Checking shape in our dataset
data.shape
```

Out[7]: (269, 10)

Data Preprocessing

Replacing columns

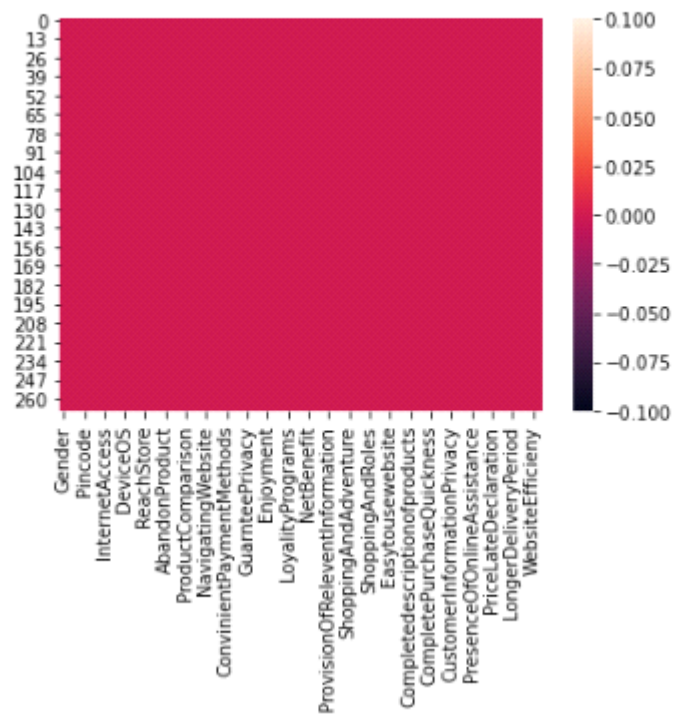
```
data.columns

Index(['Gender', 'Age', 'City', 'Pincode', 'YearsOfOnlineShopping',
      'PurchaseInPast1Year', 'InternetAccess', 'DeviceUsed',
      'MobileScreenSize', 'DeviceOS', 'DeviceBrowser', 'Channel',
      'ReachStore', 'ExploreTime', 'PaymentOption', 'AbandonProduct',
      'WhyAbandon', 'WebsiteContent', 'ProductComparison', 'PurchaseDecision',
      'RelevantInfoOnListedProducts', 'NavigatingWebsite', 'Speed',
      'UserFriendlyInterface', 'ConvinientPaymentMethods', 'Trust', 'Empathy',
      'GuarnteePrivacy', 'CommunicationChannelsAvailability',
      'BenifitsAndDiscounts', 'Enjoyment', 'Flexibility',
      'ReturnAndReplacementPolicy', 'LoyaltyPrograms',
      'DisplayQualityInformation', 'goodqualitywebsitesatisfaction',
      'NetBenefit', 'UserSatisfactionAndTrust', 'WideVarietyOfProducts',
      'ProvisionOfRelevantInformation', 'MonetarySavings',
      'Convenienceofpatronizingonlineretailer', 'ShoppingAndAdventure',
      'ShoppingAndSocialStatus', 'ShoppingAndGratification',
      'ShoppingAndRoles', 'ValueForMoneySpent', 'OnlineRetailersShoppedFrom',
      'Easytousewebsite', 'Visualappealingwebpagelayout',
      'Varietyofproductonoffer', 'Completedescriptionofproducts',
      'FastLoadingWebsiteSpeed', 'WebSiteReliability',
      'CompletePurchaseQuickness', 'PaymentsOptionsAvailability',
      'Speedyorderdelivery', 'CustomerInformationPrivacy',
      'CustomerFinancialInformationSecurity', 'PerceivedTrustworthiness',
      'PresenceOfOnlineAssistance', 'LogInTime', 'DisplayGraphicsTime',
      'PriceLateDeclaration', 'PageLoadingTime', 'LimitedModeOfPayment',
      'LongerDeliveryPeriod', 'WebsiteDesignChange',
      'FrequentDisruptionInMovingFromPageToPage', 'WebsiteEfficiency',
      'IndianOnlineRetailerToRecommend'],
      dtype='object')
```

Dealing with null values

```
In [16]: sns.heatmap(data.isnull())
```

```
Out[16]: <AxesSubplot:>
```



No null values present

Data Info And Description

Data columns (total 71 columns):

#	Column	Non-Null Count	Dtype
0	Gender	269 non-null	object
1	Age	269 non-null	object
2	City	269 non-null	object
3	Pincode	269 non-null	int64
4	YearsOfOnlineShopping	269 non-null	object
5	PurchaseInPast1Year	269 non-null	object
6	InternetAccess	269 non-null	object
7	DeviceUsed	269 non-null	object
8	MobileScreenSize	269 non-null	object
9	DeviceOS	269 non-null	object
10	DeviceBrowser	269 non-null	object
11	Channel	269 non-null	object
12	ReachStore	269 non-null	object
13	ExploreTime	269 non-null	object
14	PaymentOption	269 non-null	object
15	AbandonProduct	269 non-null	object
16	WhyAbandon	269 non-null	object
17	WebsiteContent	269 non-null	object
18	ProductComparison	269 non-null	object
19	PurchaseDecision	269 non-null	object
20	RelevantInfoOnListedProducts	269 non-null	object
21	NavigatingWebsite	269 non-null	object
22	Speed	269 non-null	object
23	UserFriendlyInterface	269 non-null	object
24	ConvinientPaymentMethods	269 non-null	object
25	Trust	269 non-null	object
26	Empathy	269 non-null	object
27	GuaranteePrivacy	269 non-null	object
28	CommunicationChannelsAvailability	269 non-null	object
29	BenifitsAndDiscounts	269 non-null	object
30	Enjoyment	269 non-null	object
31	Flexibility	269 non-null	object
32	ReturnAndReplacementPolicy	269 non-null	object
33	LoyaltyPrograms	269 non-null	object
34	DisplayQualityInformation	269 non-null	object
35	goodqualitywebsitesatisfaction	269 non-null	object
36	NetBenefit	269 non-null	object
37	UserSatisfactionAndTrust	269 non-null	object
38	WideVarietyOfProducts	269 non-null	object
39	ProvisionOfRelevantInformation	269 non-null	object
40	MonetarySavings	269 non-null	object


```
In [12]: data.describe()
```

```
Out[12]:
```

	Pincode
count	289.000000
mean	220485.747212
std	140524.341051
min	110008.000000
25%	122018.000000
50%	201303.000000
75%	201310.000000
max	580037.000000

```
In [13]: data.describe(include='object')
```

```
Out[13]:
```

	Gender	Age	City	YearsOfOnlineShopping	PurchaseInPast1Year	InternetAccess	DeviceUsed	MobileScreenSize	DeviceOS	DeviceBrowser	Ch
count	289	289	289	289	289	289	289	289	289	289	289
unique	2	5	11	5	6	4	4	4	3	4	4
top	Female	31-40 years	Delhi	Above 4 years	Less than 10 times	Mobile internet	Smartphone	Others	Window/windows Mobile	Google chrome	SE
freq	181	81	58	98	114	142	141	134	122	216	

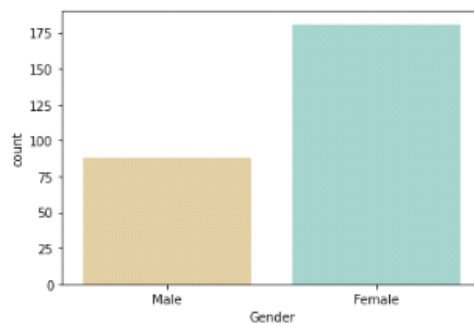
Data Visualization

Univariate Analysis

We will use a single characteristic to assess practically all of its attributes in a univariate analysis.

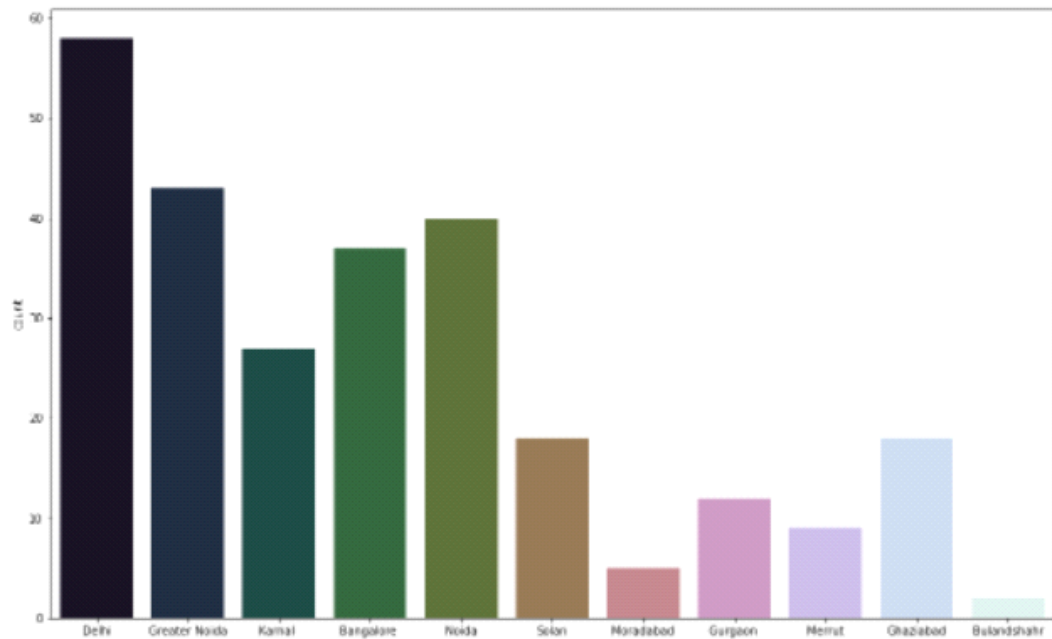
```
[']: # Let's Plot countplot for each columns to check unique values counts.
sns.countplot(data['Gender'],palette='BrBG')
data['Gender'].value_counts()
```

```
[']: Female    181
      Male      88
      Name: Gender, dtype: int64
```



```
8]: # Let's check different cities in our data collection.
plt.figure(figsize=(16,10))
sns.countplot(data['City'],palette='cubehelix')
data['City'].value_counts()
```

```
8]: Delhi          58
Greater Noida     43
Noida             40
Bangalore         37
Karnal            27
Solon             18
Ghaziabad         18
Gurgaon           12
Merrut            9
Moradabad         5
Bulandshahr       2
Name: City, dtype: int64
```



```

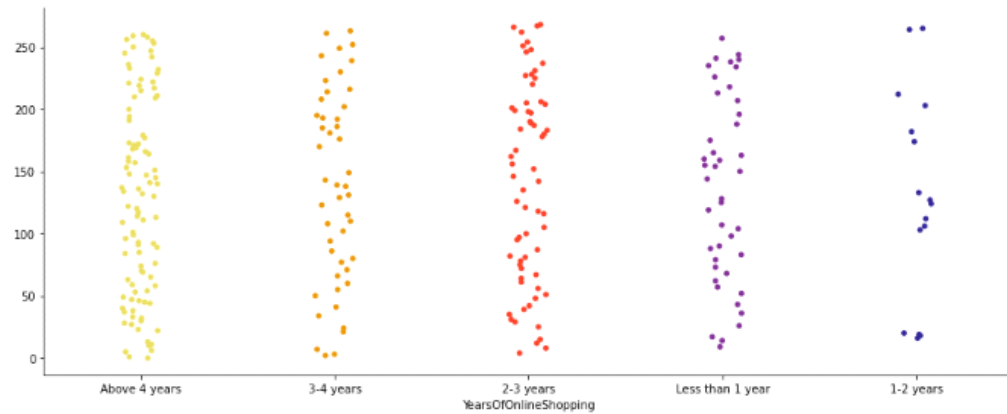
]: # Plotting catplot for column 5 Since How Long You are Shopping Online ?
sns.catplot(x='YearsOfOnlineShopping',y= data.index,data=data, palette='CMRmap_r',aspect=2.5)
data['YearsOfOnlineShopping'].value_counts()

```

```

]: Above 4 years      98
   2-3 years         65
   3-4 years         47
   Less than 1 year  43
   1-2 years         16
Name: YearsOfOnlineShopping, dtype: int64

```



From above catplot we can say that we have some fixed amount of people who do online shop regularly also they are the customers who already shopping from more then 4 years, also very less people who recently doing online shopping.

```

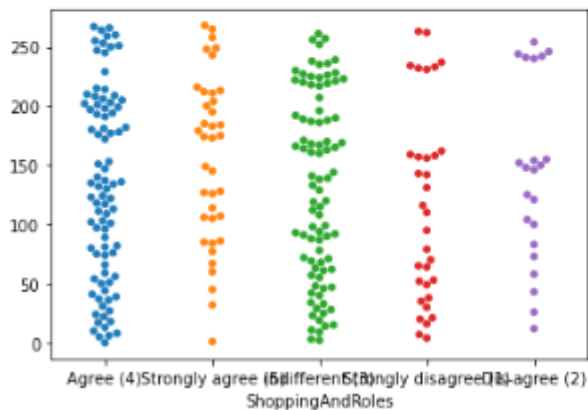
]: sns.swarmplot(x= 'ShoppingAndRoles',
                 y= data.index, data= data)
data['ShoppingAndRoles'].value_counts()

```

```

]: Agree (4)          88
   indifferent (3)     88
   Strongly agree (5)  38
   Strongly disagree (1) 33
   Dis-agree (2)       22
Name: ShoppingAndRoles, dtype: int64

```



```

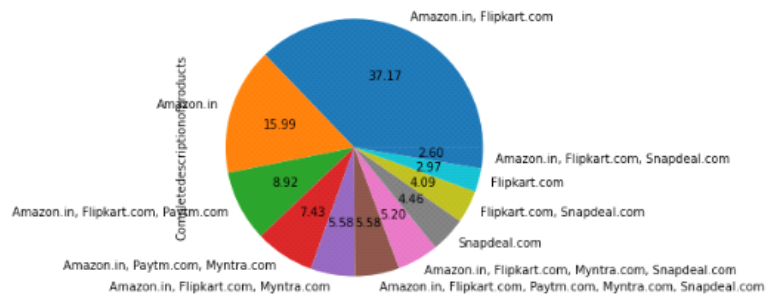
17: x = data['Completeddescriptionofproducts'].value_counts([0])
x.plot(kind = 'pie', figsize = (5,5), fontsize=10, autopct = '%.2f')
data['Completeddescriptionofproducts'].value_counts()

```

```

17: Amazon.in, Flipkart.com      100
Amazon.in                     43
Amazon.in, Flipkart.com, Paytm.com 24
Amazon.in, Paytm.com, Myntra.com 20
Amazon.in, Flipkart.com, Myntra.com 15
Amazon.in, Flipkart.com, Paytm.com, Myntra.com, Snapdeal.com 15
Amazon.in, Flipkart.com, Myntra.com, Snapdeal.com 14
Snapdeal.com                  12
Flipkart.com, Snapdeal.com     11
Flipkart.com                   8
Amazon.in, Flipkart.com, Snapdeal.com 7
Name: Completeddescriptionofproducts, dtype: int64

```



```

17: y = data['FactoringwebsiteSpeed'].value_counts([0])

```

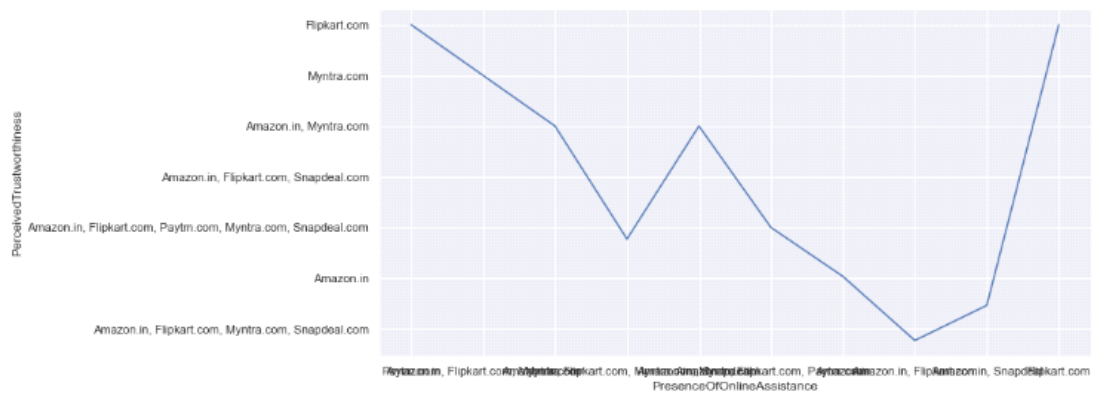
Bivariate Analysis:

Bivariate analysis is when we compare data between two attributes that are precisely the same.

```

17: plt.figure(figsize=(12, 6))
sns.set_theme(style="darkgrid")
sns.lineplot(data=data, x="PresenceOfOnlineAssistance", y="PerceivedTrustworthiness", ci=None)
plt.show()

```



```

In [ ]: plt.figure(figsize=(20,5))
sns.catplot(x= 'PriceLateDeclaration', y= 'PageLoadingTime', hue='City', data=data)
data['PageLoadingTime'].value_counts()

```

```

In [ ]: Myntra.com 61
Paytm.com 59
Flipkart.com 32
Snapdeal.com 23
Amazon.in, Flipkart.com 18
Amazon.in 16
Paytm.com, Snapdeal.com 15
Amazon.in, Snapdeal.com 14
Amazon.in, Paytm.com 13
Flipkart.com, Snapdeal.com 11
Amazon.in, Paytm.com, Myntra.com 7
Name: PageLoadingTime, dtype: int64

```

<Figure size 1440x360 with 0 Axes>

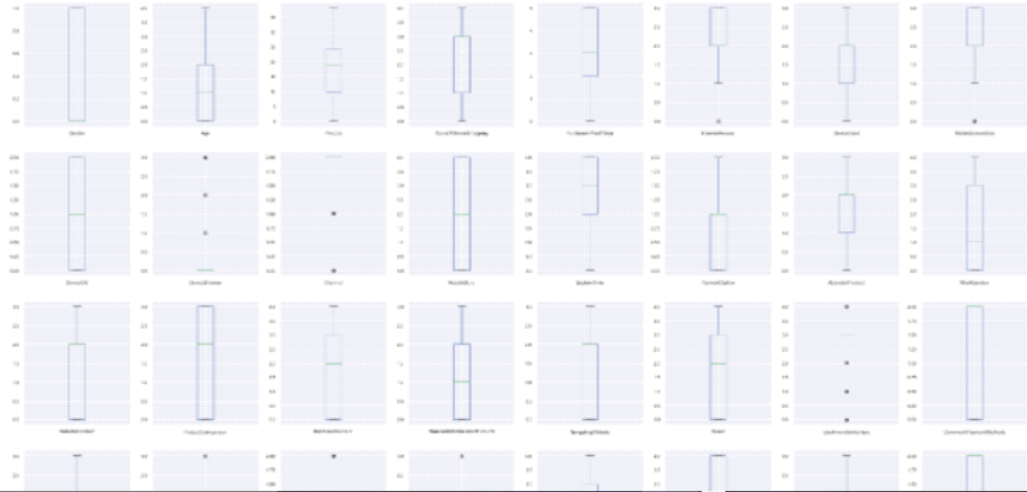


Multivarite Analysis:

We shall compare more than two variables in the multivariate analysis.

```
In [81]: #plotting the boxplot for each column in order to check the outliers
df.plot(kind='box',subplots = True,layout=(10,8),figsize = (40,60))
```

```
Out[81]: Gender AxesSubplot(0.125,0.816017;0.0824468x0.0639831)
Age AxesSubplot(0.223936,0.816017;0.0824468x0.0639...
Pincode AxesSubplot(0.322872,0.816017;0.0824468x0.0639...
YearsOfOnlineShopping AxesSubplot(0.421809,0.816017;0.0824468x0.0639...
PurchaseInPast1Year AxesSubplot(0.520745,0.816017;0.0824468x0.0639...
...
WebsiteDesignChange AxesSubplot(0.322872,0.20178;0.0824468x0.0639831)
FrequentDisruptionInMovingFromPageToPage AxesSubplot(0.421809,0.20178;0.0824468x0.0639831)
WebsiteEfficiency AxesSubplot(0.520745,0.20178;0.0824468x0.0639831)
IndianOnlineRetailerToRecommend AxesSubplot(0.619681,0.20178;0.0824468x0.0639831)
City AxesSubplot(0.718617,0.20178;0.0824468x0.0639831)
Length: 71, dtype: object
```



Using of Label Encoder to encode catagorical data:

It is used to convert

Now Importing Label Encoder to encode catagorical data.

```
] from sklearn.compose import make_column_transformer # Importing colum transformer to apply encoding technique.
from sklearn.preprocessing import LabelEncoder # Importing Lable Encoder to encode catagorical colummns.
```

```
] le = LabelEncoder() # Instantsiating Label encoder for converting our catagorical data.
```

```
] # Applying Label Encoder on selected columns.
df[headers] = df[headers].apply(le.fit_transform)
```

```
] df.head()
```

```
] :
```

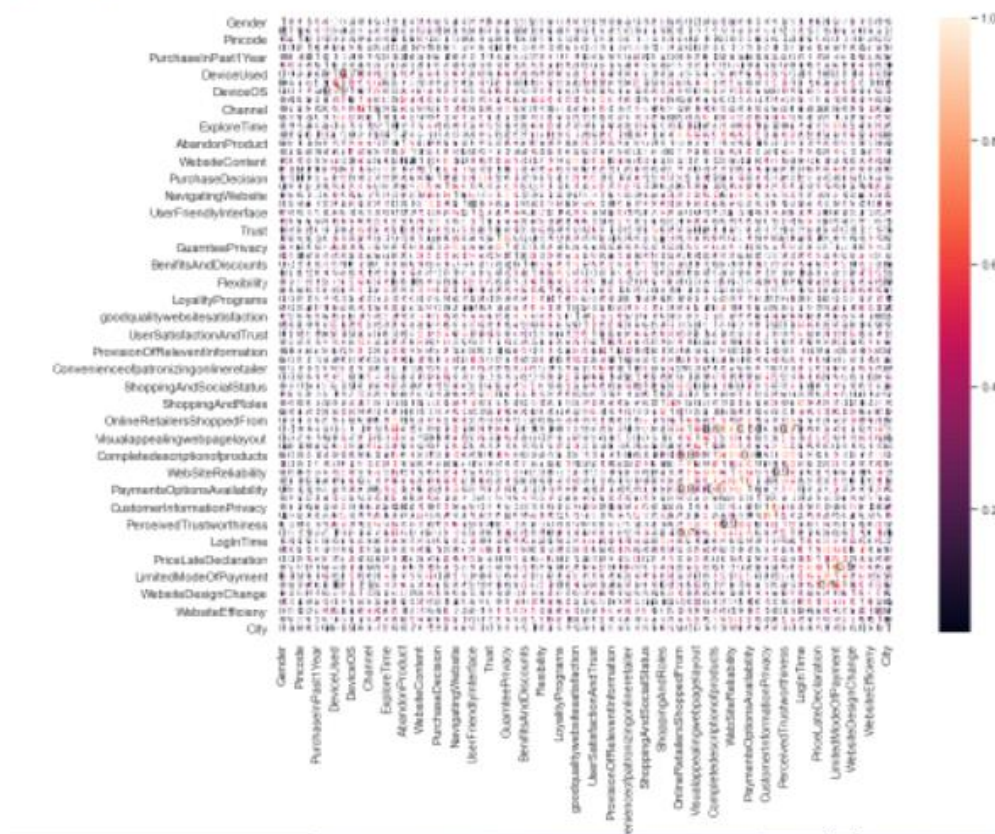
	Gender	Age	Pincode	YearsOfOnlineShopping	PurchaseInPast1Year	InternetAccess	DeviceUsed	MobileScreenSize	DeviceOS	DeviceBrowser	Channel	Re
0	1	1	1	3	2	0	0	3	2	0	2	
1	0	0	5	3	3	3	2	0	1	0	2	
2	0	0	23	2	3	1	2	2	0	0	2	
3	1	0	11	2	5	1	2	2	1	3	2	
4	0	0	31	1	0	3	2	0	1	3	0	

Now we can see all the catagorical columns in our dataset are conveted into Numeric value.

Correlation:

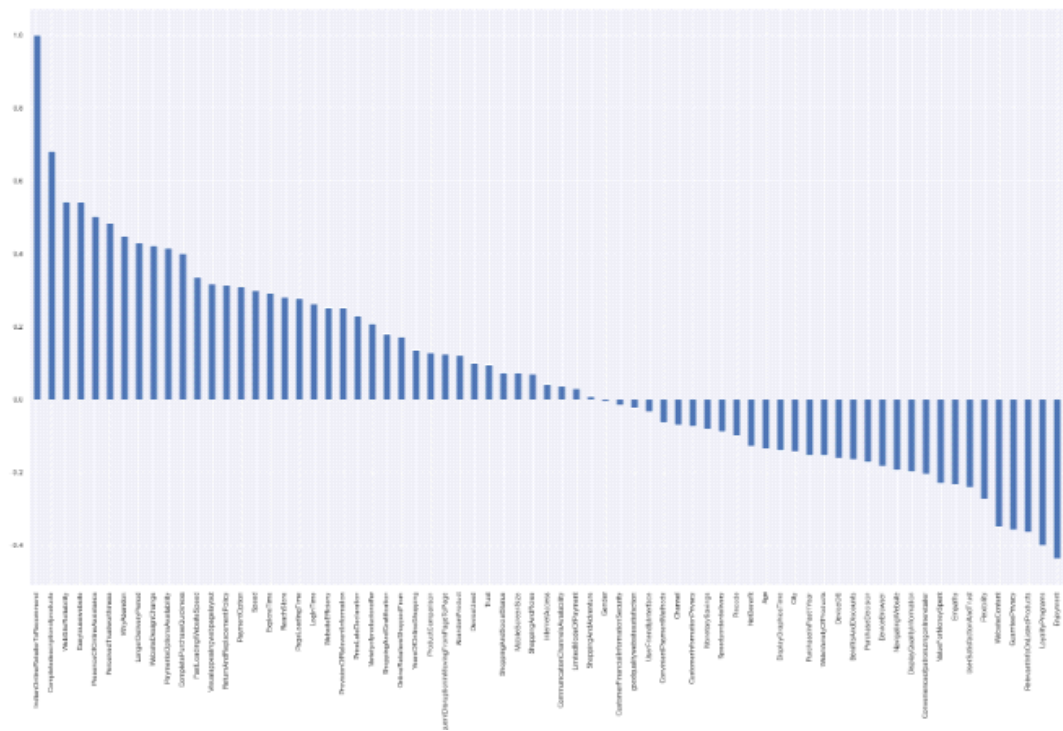
- Correlation: correlation between the available features and customer retention will be evaluated using the Pearson Coefficient Correlation (default correlation method) to identify whether the features have a negative, positive or zero correlation with regards the customer repurchase chances.

```
1): # Let's check correlation between target variable and features variable.  
data_corr = df.corr().abs()  
plt.figure(figsize=(15,10))  
sns.heatmap(data=data_corr,linewidths=1,annot=True, square=True,)  
1): <AxesSubplot:>
```



```
[84]: #correlation of independent features with regards the target "Price"
plt.figure(figsize=(28, 16))
correlations = df.corr()['IndianOnlineRetailerToRecommend'].sort_values(ascending=False)
correlations.plot(kind='bar')
```

[84]: <AxesSubplot:>



unique values and their corresponding counts of each column:


```
-----
1    100
0     43
4     24
7     20
2     15
5     15
3     14
10    12
9     11
8      8
6      7
Name: Completedescriptionofproducts, dtype: int64
```

```
-----
0     51
7     44
1     30
2     30
5     30
4     25
6     25
3     14
9     12
8      8
Name: FastLoadingWebsiteSpeed, dtype: int64
```

```
-----
0     61
1     50
3     36
6     35
5     18
7     15
8     15
2     14
4     13
9     12
Name: WebSiteReliability, dtype: int64
```

```
-----
0     66
3     47
1     37
2     30
8     25
5     20
4     15
6     15
7     14
Name: CompletePurchaseQuickness, dtype: int64
-----
1     65
2     40
```

```

3      33
1      22
Name: ShoppingAndRoles, dtype: int64
-----
0      149
1       82
2       38
Name: ValueForMoneySpent, dtype: int64
-----
4       82
2       44
1       32
5       29
6       27
8       20
0       16
7       12
3        7
Name: OnlineRetailersShoppedFrom, dtype: int64
-----
4       64
1       44
3       44
0       29
5       22
7       20
2       19
9       12
8        8
6        7
Name: Easytousewebsite, dtype: int64
-----
1       87
0       44
3       36
6       20
5       15
8       15
9       15
2       14
7       12
4       11
Name: Visualappealingwebpagelayout, dtype: int64
-----
1      130
0       43
4       20
6       15
7       15
2       14
3       13
5        7

```

```

1      5
Name: ProvisionOfRelevantInformation, dtype: int64
-----
2     148
0      75
1      31
3      15
Name: MonetarySavings, dtype: int64
-----
0     138
2      77
1      54
Name: Convenienceofpatronizingonlineretailer, dtype: int64
-----
0     101
4      59
2      54
1      50
3       5
Name: ShoppingAndAdventure, dtype: int64
-----
4     100
0      59
2      48
3      33
1      29
Name: ShoppingAndSocialStatus, dtype: int64
-----
4     101
2      65
0      63
1      22
3      18
Name: ShoppingAndGratification, dtype: int64
-----
0      88
4      88
2      38
3      33
1      22
Name: ShoppingAndRoles, dtype: int64
-----
0     149
1      82
2      38
Name: ValueForMoneySpent, dtype: int64
-----
4      82
2      44
1      32
5      29

```

```

1      20
Name: ReturnAndReplacementPolicy, dtype: int64
-----
2      115
0       64
4       64
1       15
3       11
Name: LoyaltyPrograms, dtype: int64
-----
1      133
0      80
2       56
Name: DisplayQualityInformation, dtype: int64
-----
2      175
0      86
1        8
Name: goodqualitywebsitesatisfaction, dtype: int64
-----
2      164
0       54
3       40
1       11
Name: NetBenefit, dtype: int64
-----
2      122
0      117
3       18
1        7
4        5
Name: UserSatisfactionAndTrust, dtype: int64
-----
2      111
0       94
3       57
1        7
Name: WideVarietyOfProducts, dtype: int64
-----
2      135
0       98
3       31
1        5
Name: ProvisionOfRelevantInformation, dtype: int64
-----
2      148
0       75

```

```

1      30
3      12
Name: Trust, dtype: int64
-----
1      194
0      42
2      18
3      15
Name: Empathy, dtype: int64
-----
1      185
0      58
2      26
Name: GuaranteePrivacy, dtype: int64
-----
1      149
0      94
3      15
2      11
Name: CommunicationChannelsAvailability, dtype: int64
-----
2      105
0      85
4      50
3      18
1      11
Name: BenifitsAndDiscounts, dtype: int64
-----
2      86
4      75
0      59
3      30
1      19
Name: Enjoyment, dtype: int64
-----
2      146
0      78
3      33
1      12
Name: Flexibility, dtype: int64
-----
2      198
0      51
1      20
Name: ReturnAndReplacementPolicy, dtype: int64
-----
2      115
0      64
4      64
1      15
3      11
Name: Loss11, dtype: int64

```

```

3      116
0      92
2      43
1      18
Name: ProductComparison, dtype: int64
-----
0      101
3      87
2      52
1      18
4      11
Name: PurchaseDecision, dtype: int64
-----
0      132
2      107
3      18
1      12
Name: RelevantInfoOnListedProducts, dtype: int64
-----
2      141
0      105
3      18
1      5
Name: NavigatingWebsite, dtype: int64
-----
3      115
0      112
1      18
2      12
4      12
Name: Speed, dtype: int64
-----
3      109
0      45
4      18
1      12
2      5
Name: UserFriendlyInterface, dtype: int64
-----
2      159
0      80
1      30
Name: ConvinientPaymentMethods, dtype: int64
-----
2      141
0      86
1      30
3      12
Name: Trust, dtype: int64
-----
1      194

```

```

1      5
Name: DeviceBrowser, dtype: int64
-----
2      230
0      20
1      19
Name: Channel, dtype: int64
-----
2      87
4      86
0      70
1      18
3      8
Name: ReachStore, dtype: int64
-----
4      123
2      71
1      46
3      15
0      14
Name: ExploreTime, dtype: int64
-----
1      148
0      76
2      45
Name: PaymentOption, dtype: int64
-----
2      171
1      48
0      35
3      15
Name: AbandonProduct, dtype: int64
-----
0      133
4      54
1      37
2      31
3      14
Name: WhyAbandon, dtype: int64
-----
2      164
0      80
3      18
1      7
Name: WebsiteContent, dtype: int64
-----
3      116
0      92
2      43
1      18
-----

```

```

26      2
27      1
28      1
32      1
Name: Pincode, dtype: int64
-----
3      98
1      65
2      47
4      43
0      16
Name: YearsOfOnlineShopping, dtype: int64
-----
5     114
2      63
3      47
0      29
1      10
4       6
Name: PurchaseInPast1Year, dtype: int64
-----
2     142
3      76
1      47
0       4
Name: InternetAccess, dtype: int64
-----
2     141
1      86
0      30
3      12
Name: DeviceUsed, dtype: int64
-----
3     134
2      99
0      29
1       7
Name: MobileScreenSize, dtype: int64
-----
2     122
0      85
1      62
Name: DeviceOS, dtype: int64
-----
0     216
3      40
2       8
1       5
Name: DeviceBrowser, dtype: int64
-----
2     230
0     20

```



```
]: #unique values and their corresponding counts of each column:  
for col in df.columns:  
    print(df[col].value_counts())  
    print('-----')
```

```
0    181
```

```
1     88
```

```
Name: Gender, dtype: int64
```

```
-----
```

```
1     81
```

```
0     79
```

```
2     70
```

```
4     20
```

```
3     19
```

```
Name: Age, dtype: int64
```

```
-----
```

```
23    38
```

```
11    19
```

```
24    18
```

```
8     16
```

```
30     9
```

```
14     9
```

```
13     9
```

```
38     8
```

```
12     8
```

```
35     8
```

```
10     8
```

```
22     7
```

```
0      7
```

```
2      7
```

```
3      6
```

```
4      6
```

```
29     5
```

```
17     5
```

```
18     5
```

```
21     5
```

```
31     5
```

```
25     5
```

```
9      4
```

```
37     4
```

```
34     4
```

```
33     4
```

```
19     4
```

```
7      4
```

```
5      4
```

```
6      4
```

```
20     4
```

```
1      4
```

```
16     4
```

```
15     4
```

```

r      1+
Name: CompletePurchaseQuickness, dtype: int64
-----
1      65
2      40
4      39
0      23
10     20
3      19
5      18
8      14
9      12
6      11
7       8
Name: PaymentsOptionsAvailability, dtype: int64
-----
0     107
1      82
3      36
2      15
4      15
5      14
Name: Speedyorderdelivery, dtype: int64
-----
0      71
1      54
2      25
5      24
10     18
7      15
8      15
9      15
3      14
4      11
6       7
Name: CustomerInformationPrivacy, dtype: int64
-----
0      51
4      42
8      33
5      25
1      24
6      20
7      19
9      15
10     15
2      14
3      11
Name: CustomerFinancialInformationSecurity, dtype: int64
-----
0      76
5      36

```

Correlation values with our target variable

Age	0.309575
Channel	0.215928
City	0.173871
ShoppingAndRoles	0.167532
WideVarietyOfProducts	0.144087
GuarnteePrivacy	0.135745
NetBenefit	0.112002

Convenienceofpatronizingonlineretailer	0.105267
Speedyorderdelivery	0.101356
ShoppingAndGratification	0.079476
NavigatingWebsite	0.078981
AbandonProduct	0.078278
Gender	0.077876
Empathy	0.075615
MobileScreenSize	0.062622
LogInTime	0.062336
DisplayQualityInformation	0.056794
Trust	0.049143
Enjoyment	0.043482
LoyaltyPrograms	0.036268
InternetAccess	0.017990
DeviceOS	0.015316
FastLoadingWebsiteSpeed	0.015289
UserFriendlyInterface	0.013640
YearsOfOnlineShopping	0.013315
WebsiteDesignChange	0.007841
Flexibility	0.004376
ShoppingAndSocialStatus	-0.004694
PageLoadingTime	-0.005474
DeviceBrowser	-0.012791
MonetarySavings	-0.021391
WhyAbandon	-0.026906
LimitedModeOfPayment	-0.030008
DeviceUsed	-0.051741
ConvinientPaymentMethods	-0.052107
PresenceOfOnlineAssistance	-0.058209

OnlineRetailersShoppedFrom	-0.068387
ExploreTime	-0.071392
ReachStore	-0.083088
ValueForMoneySpent	-0.087458
DisplayGraphicsTime	-0.096575
PaymentsOptionsAvailability	-0.097651
RelevantInfoOnListedProducts	-0.100875
ProductComparison	-0.107277
CompletePurchaseQuickness	-0.107802
WebsiteEfficiency	-0.124076
FrequentDisruptionInMovingFromPageToPage	-0.127148
LongerDeliveryPeriod	-0.130651
WebsiteContent	-0.139930
ProvisionOfRelevantInformation	-0.144277
WebSiteReliability	-0.146351
PurchaseDecision	-0.147507
IndianOnlineRetailerToRecommend	-0.152028
BenefitsAndDiscounts	-0.159635
Easytousewebsite	-0.160976
CustomerInformationPrivacy	-0.164571
PerceivedTrustworthiness	-0.169235
Varietyofproductonoffer	-0.177938
CommunicationChannelsAvailability	-0.190372
CustomerFinancialInformationSecurity	-0.192403
Completedescriptionofproducts	-0.195169
PaymentOption	-0.199719
UserSatisfactionAndTrust	-0.206904
PriceLateDeclaration	-0.209112
Visualappealingwebpagelayout	-0.223378

goodqualitywebsitesatisfaction	-0.226581
Speed	-0.261066
Pincode	-0.304554
ReturnAndReplacementPolicy	-0.310908
ShoppingAndAdventure	-0.318657

See screenshot below for all correlations:

```
]: # To display all value of rows
pd.set_option("display.max_rows", None)
# Let's calculate the features Correlation values with our target variable.
df.drop('Target',axis=1).corrwith(df.Target ).sort_values(ascending=False)
|
```

Age	0.309575
Channel	0.215928
City	0.173871
ShoppingAndRoles	0.167532
WideVarietyOfProducts	0.144087
GuaranteePrivacy	0.135745
NetBenefit	0.112002
Convenienceofpatronizingonlineretailer	0.105267
Speedyorderdelivery	0.101356
ShoppingAndGratification	0.079476
NavigatingWebsite	0.078981
AbandonProduct	0.078278
Gender	0.077876
Empathy	0.075615
MobileScreenSize	0.062622
LogInTime	0.062336
DisplayQualityInformation	0.056794
Trust	0.049143
Enjoyment	0.043482
LoyaltyPrograms	0.036268
InternetAccess	0.017990
DeviceOS	0.015316
FastLoadingWebsiteSpeed	0.015289
UserFriendlyInterface	0.013640
YearsOfOnlineShopping	0.013315
WebsiteDesignChange	0.007841
Flexibility	0.004376
ShoppingAndSocialStatus	-0.004694
PageLoadingTime	-0.005474
DeviceBrowser	-0.012791
MonetarySavings	-0.021391
WhyAbandon	-0.026906
LimitedModeOfPayment	-0.030008
DeviceUsed	-0.051741
ConvinientPaymentMethods	-0.052107
PresenceOfOnlineAssistance	-0.058209
OnlineRetailersShoppedFrom	-0.068387
FullPageTime	-0.071300

```

DeviceUsed -0.051741
ConvinientPaymentMethods -0.052107
PresenceOfOnlineAssistance -0.058209
OnlineRetailersShoppedFrom -0.068387
ExploreTime -0.071392
ReachStore -0.083088
ValueForMoneySpent -0.087458
DisplayGraphicsTime -0.096575
PaymentsOptionsAvailability -0.097651
RelevantInfoOnListedProducts -0.100875
ProductComparison -0.107277
CompletePurchaseQuickness -0.107802
WebsiteEfficiency -0.124076
FrequentDisruptionInMovingFromPageToPage -0.127148
LongerDeliveryPeriod -0.130651
WebsiteContent -0.139930
ProvisionOfRelevantInformation -0.144277
WebsiteReliability -0.146351
PurchaseDecision -0.147507
IndianOnlineRetailerToRecommend -0.152028
BenefitsAndDiscounts -0.159635
Easytousewebsite -0.160976
CustomerInformationPrivacy -0.164571
PerceivedTrustworthiness -0.169235
Varietyofproductonoffer -0.177938
CommunicationChannelsAvailability -0.190372
CustomerFinancialInformationSecurity -0.192403
Completedescriptionofproducts -0.195169
PaymentOption -0.199719
UserSatisfactionAndTrust -0.206904
PriceLateDeclaration -0.209112
Visualappealingwebpagelayout -0.223378
goodqualitywebsitesatisfaction -0.226581
Speed -0.261066
Pincode -0.304554
ReturnAndReplacementPolicy -0.310908
ShoppingAndAdventure -0.318657
dtype: float64

```

Observations

- Female customer often prefer to purchase more as compared to Male customer
- People between 21 to 50 years of age tends shops more.
- Dataset appears to have approximately 67% of Female respondents & 32 % of Male
- Delhi has maximum count which means in Delhi the online purchase is high.
- Mobile screen size has maximum count for others, and 2nd most count is for 5.5 which is the most used screen size.
- Customers with OS windows/mobile are more in number, as it's the most common OS.
- Most of the customers use chrome browser, which seems to be best in market and easy to use.

- Most of the customers used Search engine to reach there favorite online store for the first time , as search engine shows variety of similar product from n-number of sites.
- After first visit most of the customers are reaching the online store through Search engine, Via application and Direct Url.
- Most of the customers are exploring the e-retail store more than 6 mins before making purchase decision (checking all info and deciding which one to buy usually take time).
- Maximum customers are using credit/debit cards for there payment(most convenient and easy to use).
- Amazon and flipkart is performing best in all given parameter

CONCLUSION

After the detailed analysis of problem I found the following conclusions:

- Frequency of Females shoping is high so making them satisfied will help the sellers to get more business.
- Loyal customers prefer buying and tend to spend more money on shopping in your store. Statistics show that engaged consumers purchase more frequently. It is necessary to hear customer feedback because most of them are valuable feedbacks.
- Sometimes customer feedback is the best marketing strategy. They are frequent customers so they will know which areas of your business may well be improved. If their feedback is approved, they will extremely excite and support your company with their best ability.
- It found that Amazon and Flipkart are standing best out in the market by using ethical, reasonable business strategies
- The repeat purchase intention (loyalty) positively, Structural equation model has been presented on the primary data collected from the Indian online shoppers.
- Here as an conclusion part I found that using dead old strategies for retailers will effect customer retention.