Fraudulent Insurance Claims Detection System

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pylab as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from sklearn.model_selection import train_test_split
```

In [2]:

```
df1 = pd.read_excel("D:/Data Science Course PR/Capstone Projects/1.Fraudulent Insurance claims Analysis - Machine Learning/Data/s
df2 = pd.read_excel("D:/Data Science Course PR/Capstone Projects/1.Fraudulent Insurance claims Analysis - Machine Learning/Data/s
df3 = pd.read_excel("D:/Data Science Course PR/Capstone Projects/1.Fraudulent Insurance claims Analysis - Machine Learning/Data/s
df4 = pd.read_excel("D:/Data Science Course PR/Capstone Projects/1.Fraudulent Insurance claims Analysis - Machine Learning/Data/s
```

In [3]:

```
n = df3[df3.duplicated() == True].reset_index()
dulicate = n.loc[:,'index'].to_list()
```

In [4]:

```
df3.drop(index = dulicate,inplace= True)
df2.drop(index = dulicate,inplace= True)
df1.drop(index = dulicate,inplace= True)
df4.drop(index = dulicate,inplace= True)
```

In [5]:

```
df1['PolicyNumber'] = df3['PolicyNumber']
df2['PolicyNumber'] = df3['PolicyNumber']
df4['PolicyNumber'] = df3['PolicyNumber']
```

In [6]:

```
df = df1.merge(df2,on='PolicyNumber')
df = df.merge(df3 , on = 'PolicyNumber' )
df = df.merge(df4 , on = 'PolicyNumber' )
```

In [7]:

```
df.head()
```

Out[7]:

	Month	WeekOfMonth	DayOfWeek	Make	AccidentArea	DayOfWeekClaimed	MonthClaimed	WeekOfMonthClaimed	PolicyNumber	Sex	...	Ag
0	Dec	5	Wednesday	Honda	Urban	Tuesday	Jan	1	1	Female	...	
1	Jan	3	Wednesday	Honda	Urban	Monday	Jan	4	2	Male	...	
2	Oct	5	Friday	Honda	Urban	Thursday	Nov	2	3	Male	...	
3	Jun	2	Saturday	Toyota	Rural	Friday	Jul	1	4	Male	...	r
4	Jan	5	Monday	Honda	Urban	Tuesday	Feb	2	5	Female	...	

5 rows × 33 columns

In [8]:

```
# Checking Null values
df.isnull().sum()
```

Out[8]:

```
Month                   0
WeekOfMonth             0
DayOfWeek               0
Make                    0
AccidentArea            0
DayOfWeekClaimed        0
MonthClaimed            0
WeekOfMonthClaimed      0
PolicyNumber            0
Sex                     0
MaritalStatus           0
Age                     0
Fault                   0
PolicyType              0
VehicleCategory         0
VehiclePrice            0
FraudFound_P            0
RepNumber               0
Deductible              0
DriverRating            0
Days_Policy_Accident    0
Days_Policy_Claim       0
PastNumberOfClaims      0
AgeOfVehicle            0
AgeOfPolicyHolder       0
PoliceReportFiled       0
WitnessPresent          0
AgentType               0
NumberOfSuppliments     0
AddressChange_Claim     0
NumberOfCars            0
Year                    0
BasePolicy              0
dtype: int64
```

In [9]:

```
# Checking Duplicate values in our data frame
df.duplicated().sum()
```

Out[9]:

```
0
```

In [10]:

```
df.describe()
```

Out[10]:

	WeekOfMonth	WeekOfMonthClaimed	PolicyNumber	Age	FraudFound_P	RepNumber	Deductible	DriverRating	Year
count	15420.000000	15420.000000	15420.000000	15420.000000	15420.000000	15420.000000	15420.000000	15420.000000	15420.000000
mean	2.788586	2.693969	7710.500000	39.855707	0.059857	8.483268	407.704280	2.487808	1994.866472
std	1.287585	1.259115	4451.514911	13.492377	0.237230	4.599948	43.950998	1.119453	0.803313
min	1.000000	1.000000	1.000000	0.000000	0.000000	1.000000	300.000000	1.000000	1994.000000
25%	2.000000	2.000000	3855.750000	31.000000	0.000000	5.000000	400.000000	1.000000	1994.000000
50%	3.000000	3.000000	7710.500000	38.000000	0.000000	8.000000	400.000000	2.000000	1995.000000
75%	4.000000	4.000000	11565.250000	48.000000	0.000000	12.000000	400.000000	3.000000	1996.000000
max	5.000000	5.000000	15420.000000	80.000000	1.000000	16.000000	700.000000	4.000000	1996.000000

In [11]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15420 entries, 0 to 15419
Data columns (total 33 columns):
 #   Column                Non-Null Count  Dtype 
---  ------                --------------  ----- 
 0   Month                 15420 non-null  object
 1   WeekOfMonth           15420 non-null  int64 
 2   DayOfWeek             15420 non-null  object
 3   Make                  15420 non-null  object
 4   AccidentArea          15420 non-null  object
 5   DayOfWeekClaimed      15420 non-null  object
 6   MonthClaimed          15420 non-null  object
 7   WeekOfMonthClaimed    15420 non-null  int64 
 8   PolicyNumber          15420 non-null  int64 
 9   Sex                   15420 non-null  object
 10  MaritalStatus         15420 non-null  object
 11  Age                   15420 non-null  int64 
 12  Fault                 15420 non-null  object
 13  PolicyType            15420 non-null  object
 14  VehicleCategory       15420 non-null  object
 15  VehiclePrice          15420 non-null  object
 16  FraudFound_P          15420 non-null  int64 
 17  RepNumber             15420 non-null  int64 
 18  Deductible            15420 non-null  int64 
 19  DriverRating          15420 non-null  int64 
 20  Days_Policy_Accident  15420 non-null  object
 21  Days_Policy_Claim     15420 non-null  object
 22  PastNumberOfClaims    15420 non-null  object
 23  AgeOfVehicle          15420 non-null  object
 24  AgeOfPolicyHolder     15420 non-null  object
 25  PoliceReportFiled     15420 non-null  object
 26  WitnessPresent        15420 non-null  object
 27  AgentType             15420 non-null  object
 28  NumberOfSuppliments   15420 non-null  object
 29  AddressChange_Claim   15420 non-null  object
 30  NumberOfCars          15420 non-null  object
 31  Year                  15420 non-null  int64 
 32  BasePolicy            15420 non-null  object
dtypes: int64(9), object(24)
memory usage: 4.0+ MB
```

In [12]:

```
# Cheaking Data in Balance or In-Balance
df.FraudFound_P.sum()/df.shape[0]*100
```

Out[12]:

```
5.985732814526589
```

Our data is inbalance as only 6 % of data have 1 in it

In [13]:

```
df.columns
```

Out[13]:

```
Index(['Month', 'WeekOfMonth', 'DayOfWeek', 'Make', 'AccidentArea',
       'DayOfWeekClaimed', 'MonthClaimed', 'WeekOfMonthClaimed',
       'PolicyNumber', 'Sex', 'MaritalStatus', 'Age', 'Fault', 'PolicyType',
       'VehicleCategory', 'VehiclePrice', 'FraudFound_P', 'RepNumber',
       'Deductible', 'DriverRating', 'Days_Policy_Accident',
       'Days_Policy_Claim', 'PastNumberOfClaims', 'AgeOfVehicle',
       'AgeOfPolicyHolder', 'PoliceReportFiled', 'WitnessPresent', 'AgentType',
       'NumberOfSuppliments', 'AddressChange_Claim', 'NumberOfCars', 'Year',
       'BasePolicy'],
      dtype='object')
```

Data Manipulation

In [14]:

```
df['DayOfWeekClaimed'].unique()
```

Out[14]:

```
array(['Tuesday', 'Monday', 'Thursday', 'Friday', 'Wednesday', 'Saturday',
       'Sunday', 0], dtype=object)
```

In [15]:

```
df['DayOfWeekClaimed'].replace([0],[df['DayOfWeekClaimed'].mode()],inplace=True)
```

In [16]:

```
df['DayOfWeekClaimed'].unique()
```

Out[16]:

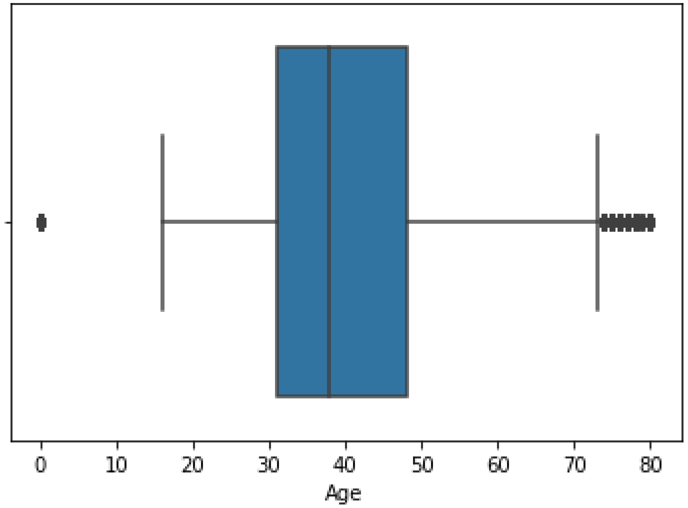
```
array(['Tuesday', 'Monday', 'Thursday', 'Friday', 'Wednesday', 'Saturday',
       'Sunday'], dtype=object)
```

In [17]:

```
# We can see their is some Outliers in our Age section
sns.boxplot(df.Age)
```

Out[17]:

```
<AxesSubplot:xlabel='Age'>
```



In [18]:

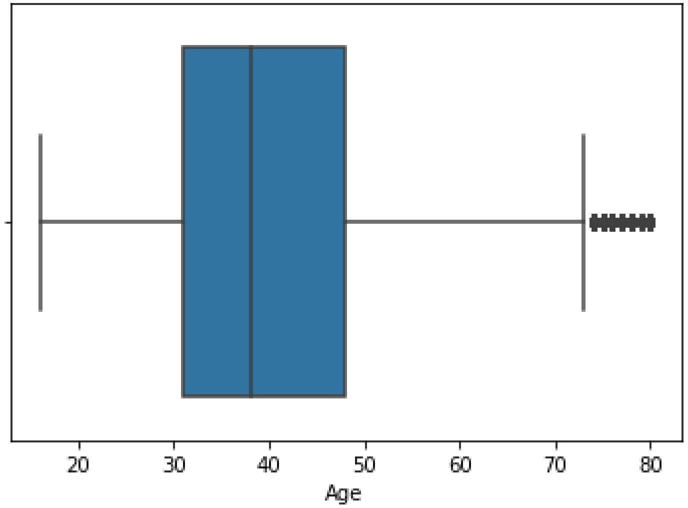
```
# We will replace 0 , with eith 16 or 17
df.Age.replace([0],[17],inplace = True)
```

In [19]:

```
sns.boxplot(df.Age)
```

Out[19]:

```
<AxesSubplot:xlabel='Age'>
```



In [20]:

```
df.Days_Policy_Accident.unique()
```

```
Out[20]: array(['more than 30', '15 to 30', 'none', '1 to 7', '8 to 15'],
               dtype=object)
```

```
In [21]: df.Days_Policy_Accident.replace(['none'], [df.Days_Policy_Accident.mode()],inplace = True)
```

```
In [22]: df.Days_Policy_Accident.unique()
```

```
Out[22]: array(['more than 30', '15 to 30', '1 to 7', '8 to 15'], dtype=object)
```

```
In [23]: df['MonthClaimed'].unique()
```

```
Out[23]: array(['Jan', 'Nov', 'Jul', 'Feb', 'Mar', 'Dec', 'Apr', 'Aug', 'May',
                'Jun', 'Sep', 'Oct', 0], dtype=object)
```

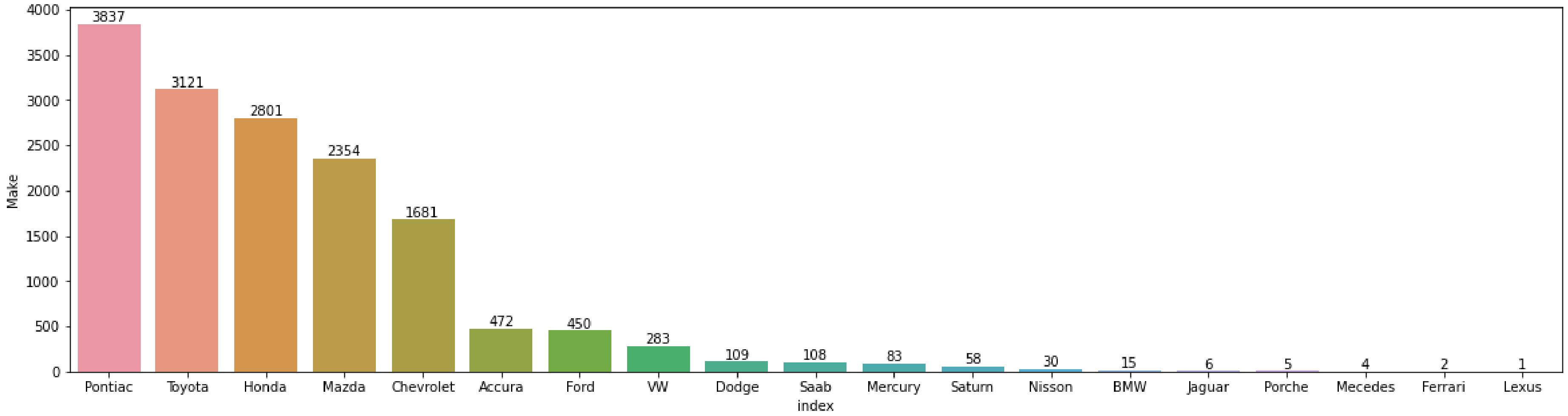
```
In [24]: df.MonthClaimed.replace([0],[df['MonthClaimed'].mode()],inplace=True)
```

EDA

Univariate analysis of each variable

```
In [25]: Make = df['Make'].value_counts().reset_index()
```

```
In [26]: plt.figure(figsize=(20,5))
         ax = sns.barplot(x ='index',y = 'Make' , data = Make )
         ax.bar_label(ax.containers[0])[0]
         plt.show()
```



Observations

Top 5 Car Brands on which Claim has made:

- Pontaiac
- Toyota
- Honda
- Mazda
- Chevrolet

In [27]:

```
AccidentArea = df['AccidentArea'].value_counts().reset_index()
AccidentArea
```

Out[27]:

	index	AccidentArea
0	Urban	13822
1	Rural	1598

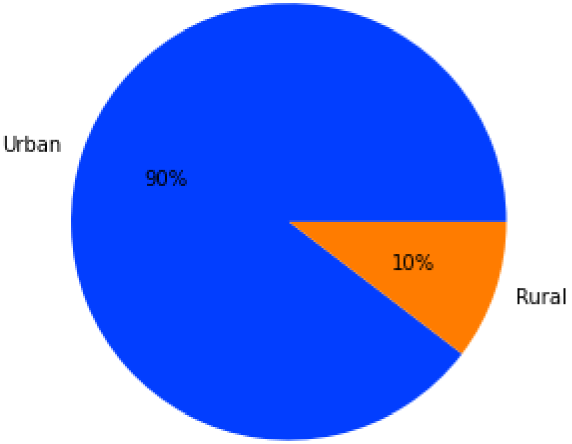
In [28]:

```
x = AccidentArea['AccidentArea'].tolist()
y = AccidentArea['index'].tolist()
plt.figure(figsize=(5,5))
palette_color = sns.color_palette('bright')
```

```
plt.pie(x, labels=y,colors=palette_color, autopct='%.0f%%')[0]
plt.plot()
```

Out[28]:

```
[]
```



In [29]:

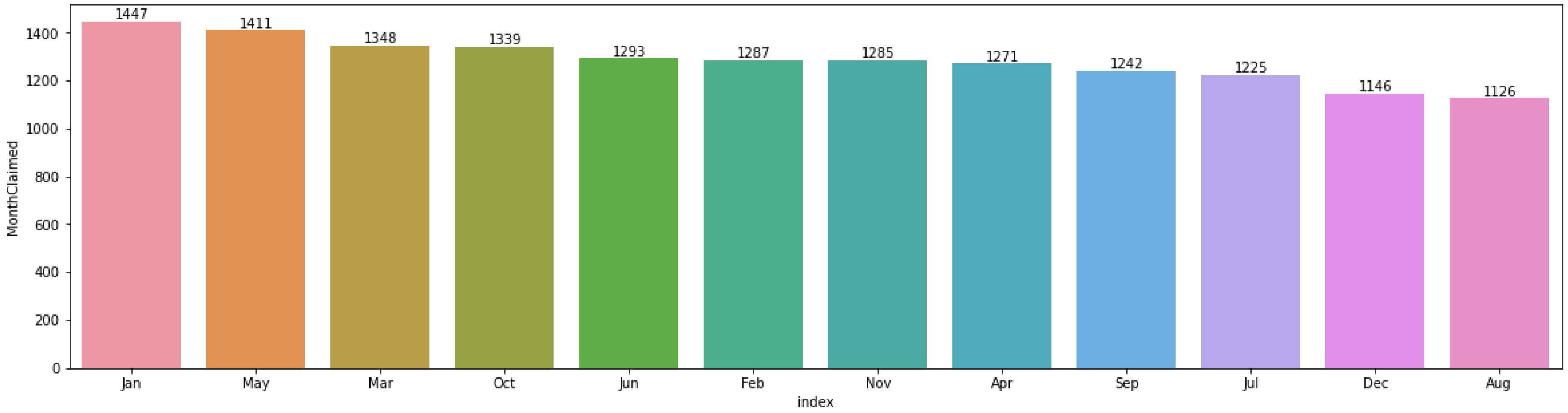
```
MonthClaimed = df['MonthClaimed'].value_counts().reset_index()
MonthClaimed
```

Out[29]:

	index	MonthClaimed
0	Jan	1447
1	May	1411
2	Mar	1348
3	Oct	1339
4	Jun	1293
5	Feb	1287
6	Nov	1285
7	Apr	1271
8	Sep	1242
9	Jul	1225
10	Dec	1146
11	Aug	1126

In [30]:

```
plt.figure(figsize=(20,5))
ax = sns.barplot(x ='index',y = 'MonthClaimed' , data = MonthClaimed )
ax.bar_label(ax.containers[0])[0]
plt.show()
```



- In this we dont find any pattern

In [31]:

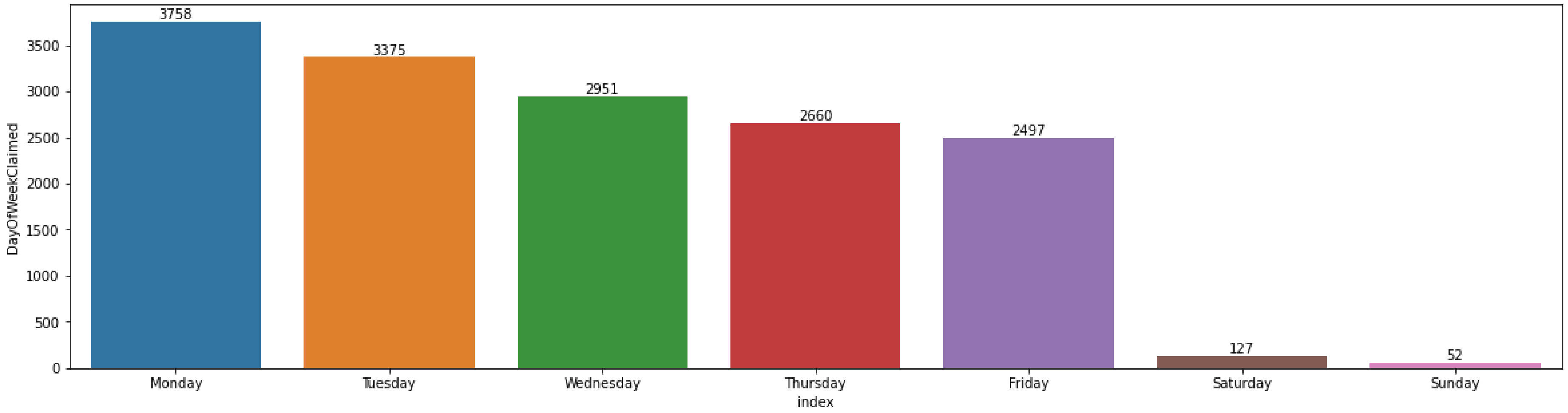
```
# DayOfWeekClaimed = Day of the week the accident was claimed, "control zeros"
DayOfWeekClaimed = df['DayOfWeekClaimed'].value_counts().reset_index()
DayOfWeekClaimed
```

Out[31]:

	index	DayOfWeekClaimed
0	Monday	3758
1	Tuesday	3375
2	Wednesday	2951
3	Thursday	2660
4	Friday	2497
5	Saturday	127
6	Sunday	52

In [32]:

```
plt.figure(figsize=(20,5))
ax = sns.barplot(x ='index',y = 'DayOfWeekClaimed' , data = DayOfWeekClaimed )
ax.bar_label(ax.containers[0])[0]
plt.show()
```



Observations

- Most of accidents is happens on staring of week and than we can see drop in the accidents.
- Approx 99 % of accidents happened on workingdays as we can see less than 1 % accidents is happend on weekends
- This is maybe because of morring office rush or evening rush we dont have data for that we cant say for sure but looking the weekend accident rate we can safely assues this conditions.

In [33]:

```
# Sex =  Gender of the person involved in the accident
Gender = df['Sex'].value_counts().reset_index()
Gender
```

Out[33]:

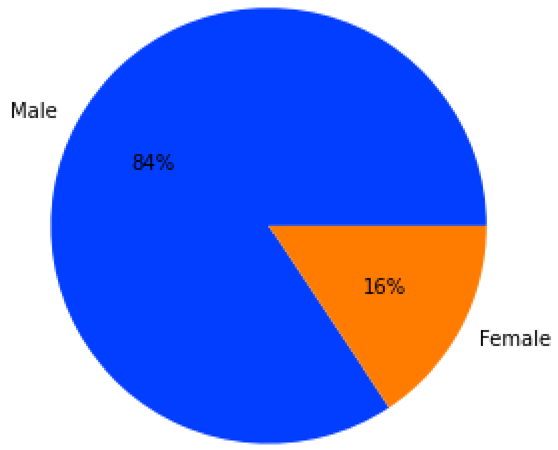
	index	Sex
0	Male	13000
1	Female	2420

In [34]:

```
x = Gender['index'].tolist()
y = Gender['Sex'].tolist()
plt.figure(figsize=(5,5))
palette_color = sns.color_palette('bright')
plt.pie(y, labels=x,colors=palette_color, autopct='%.0f%%')[0]
plt.plot()
```

Out[34]:

```
[]
```



- 84% of male involved in accident and 16% of female involved in accident

In [35]:

```python
# MaritalStatus = Marital status of the person involved in the accident
MaritalStatus = df['MaritalStatus'].value_counts().reset_index()
MaritalStatus
```

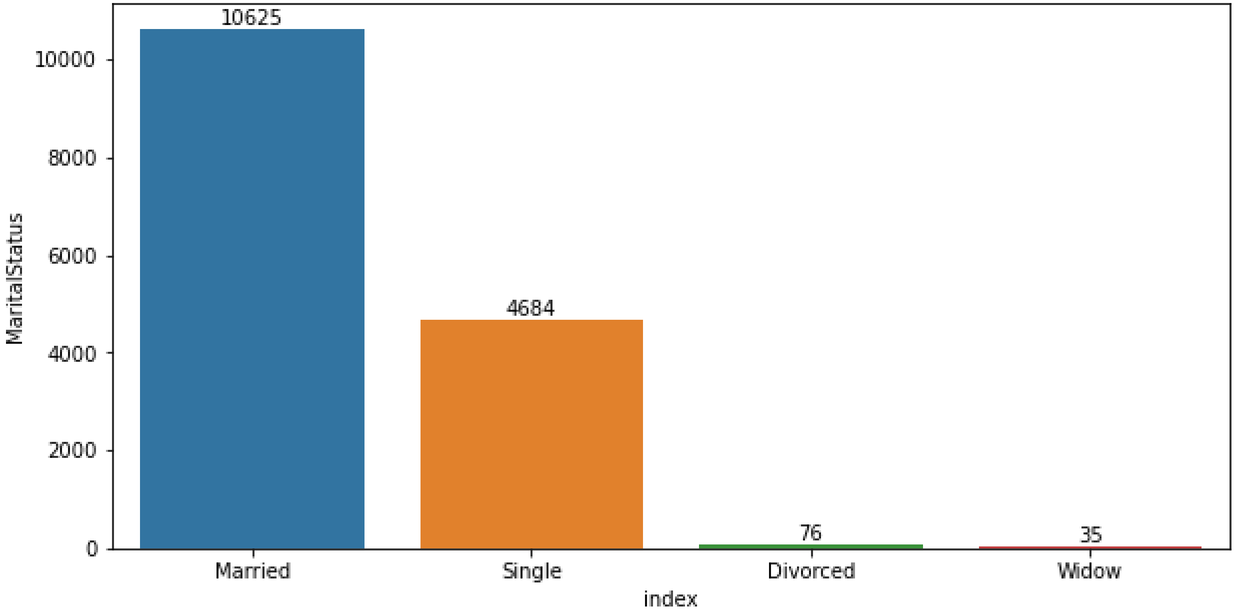
Out[35]:

	index	MaritalStatus
0	Married	10625
1	Single	4684
2	Divorced	76
3	Widow	35

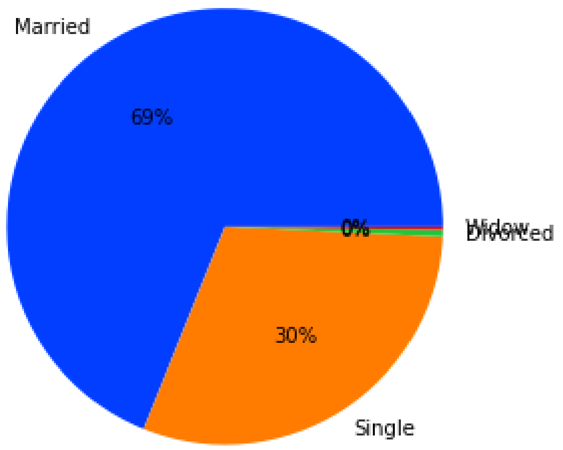
In [36]:

```python
plt.figure(figsize=(10,5))
ax = sns.barplot(x ='index',y = 'MaritalStatus' , data = MaritalStatus )
ax.bar_label(ax.containers[0])[0]
plt.show()
```

```
x = MaritalStatus['index'].tolist()
y = MaritalStatus['MaritalStatus'].tolist()
plt.figure(figsize=(5,5))
palette_color = sns.color_palette('bright')
plt.pie(y, labels=x,colors=palette_color, autopct='%.0f%%')[0]
plt.plot()
```



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



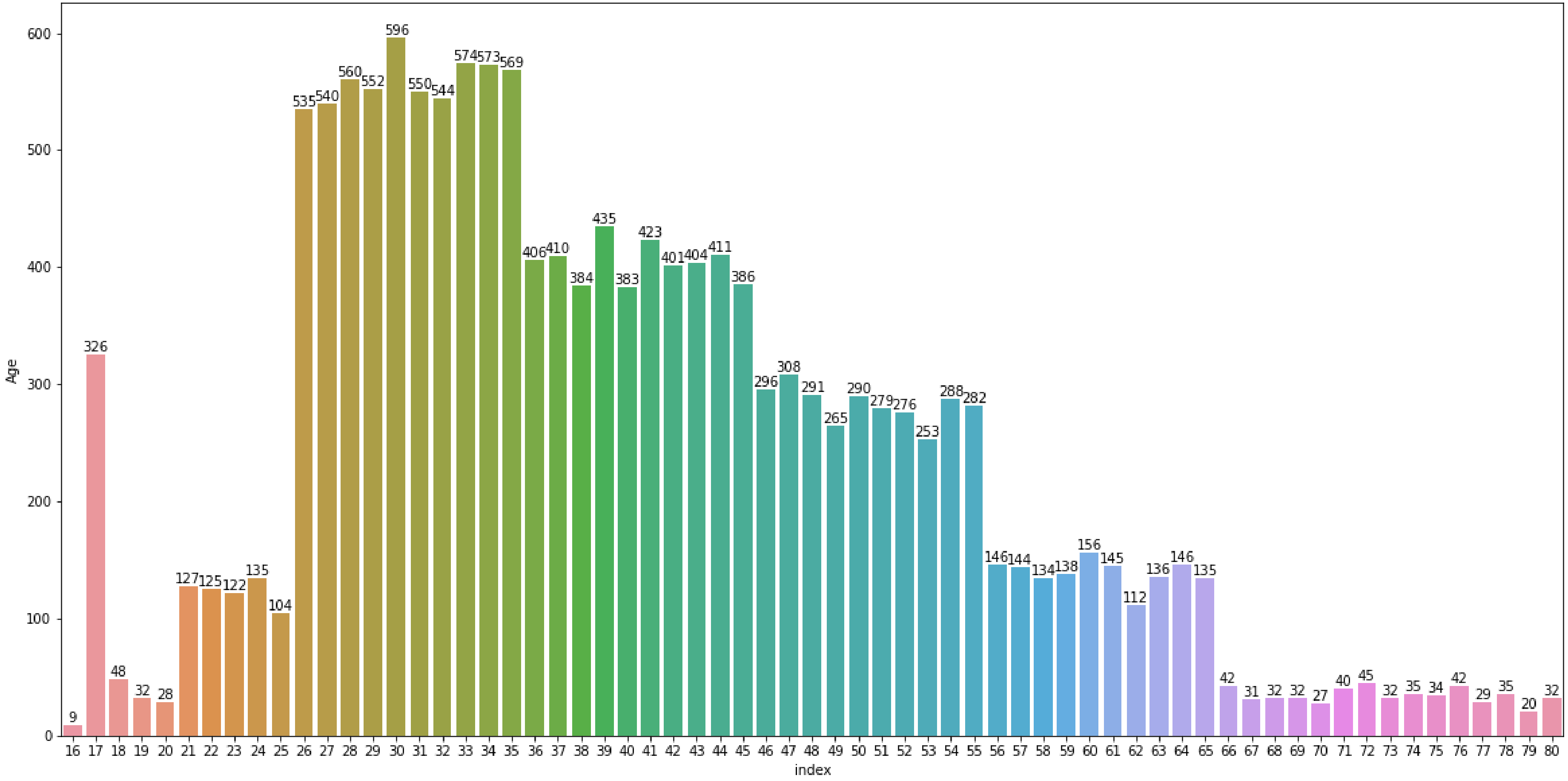
- 69% of Married person involved in the accident
- 30% of Single person involved in the accident

In [37]:

```python
Age = df.Age.value_counts().reset_index()
```

In [38]:

```python
plt.figure(figsize=(20,10))
ax = sns.barplot(x ='index',y = 'Age' , data = Age )
ax.bar_label(ax.containers[0])[0]
plt.show()
```



- In this graph we can not say much but we can see after certain age group no of accident is decreases.

In [39]:

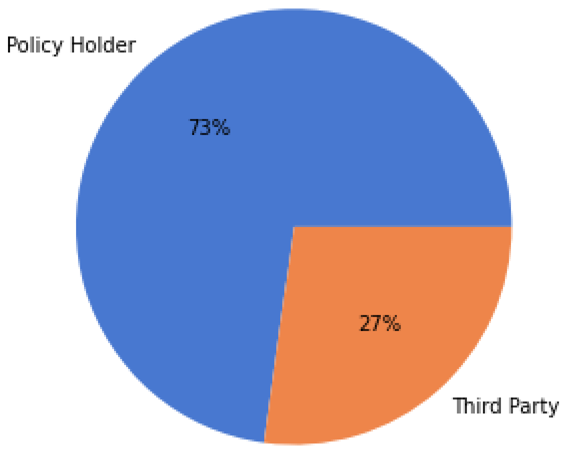
```
# Fault = If the insurance owner was responsible of the accident
Fault = df['Fault'].value_counts().reset_index()
Fault
```

Out[39]:

	index	Fault
0	Policy Holder	11230
1	Third Party	4190

```
In [40]: x = Fault['index'].tolist()
         y = Fault['Fault'].tolist()
         plt.figure(figsize=(5,5))
         palette_color = sns.color_palette('muted')
         plt.pie(y, labels=x,colors=palette_color, autopct='%.0f%%')[0]
         plt.plot()
```

```
Out[40]: []
```



- In this chart we can clearly see the that 73% of time Fault is of Policy Holder.

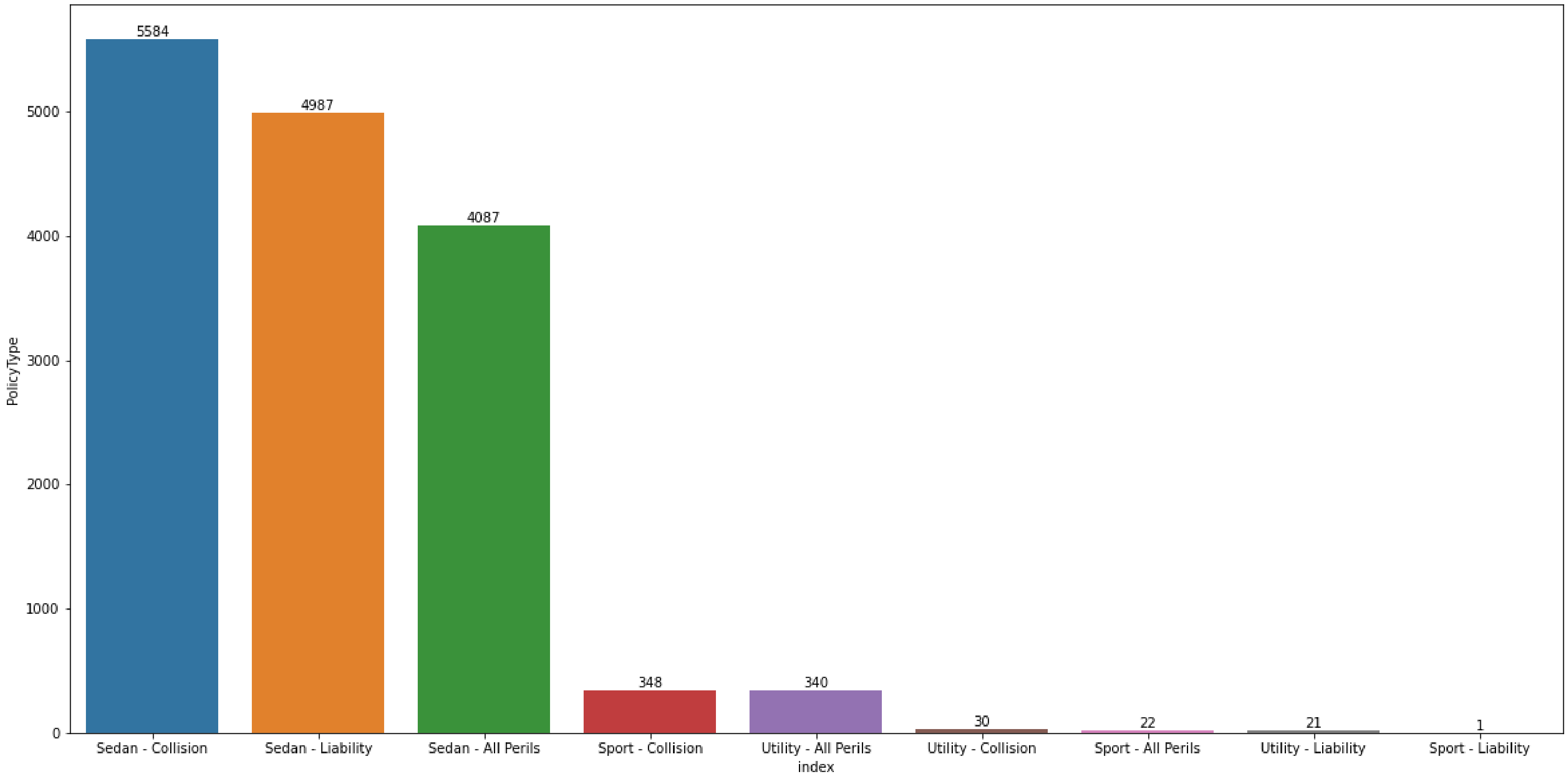
```
In [41]: PolicyType = df['PolicyType'].value_counts().reset_index()
         PolicyType
```

Out[41]:

	index	PolicyType
0	Sedan - Collision	5584
1	Sedan - Liability	4987
2	Sedan - All Perils	4087
3	Sport - Collision	348
4	Utility - All Perils	340
5	Utility - Collision	30
6	Sport - All Perils	22
7	Utility - Liability	21
8	Sport - Liability	1

In [42]:

```
plt.figure(figsize=(20,10))
ax = sns.barplot(x ='index',y = 'PolicyType' , data = PolicyType )
ax.bar_label(ax.containers[0])[0]
plt.show()
```



In [43]:

```
# VehicleCategory = Vehicle categorization
VehicleCategory = df['VehicleCategory'].value_counts().reset_index()
VehicleCategory
```

Out[43]:

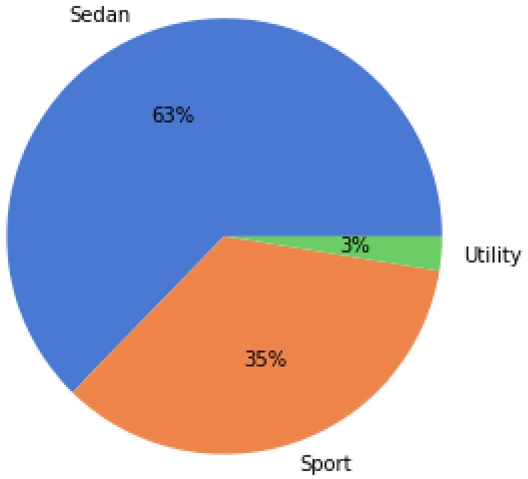
	index	VehicleCategory
0	Sedan	9671
1	Sport	5358
2	Utility	391

In [44]:

```
x = VehicleCategory['index'].tolist()
y = VehicleCategory['VehicleCategory'].tolist()
plt.figure(figsize=(5,5))
palette_color = sns.color_palette('muted')
plt.pie(y, labels=x,colors=palette_color, autopct='%.0f%%')[0]
plt.plot()
```

Out[44]:

```
[]
```



Observation

- More than 50 % of car type is Sedan
- This is the main reason why most of the insurance type/take by Sedan type vehicle

In [45]:

```
# VehiclePrice = Price of the vehicle
VehiclePrice = df['VehiclePrice'].value_counts().reset_index()
```

In [46]:

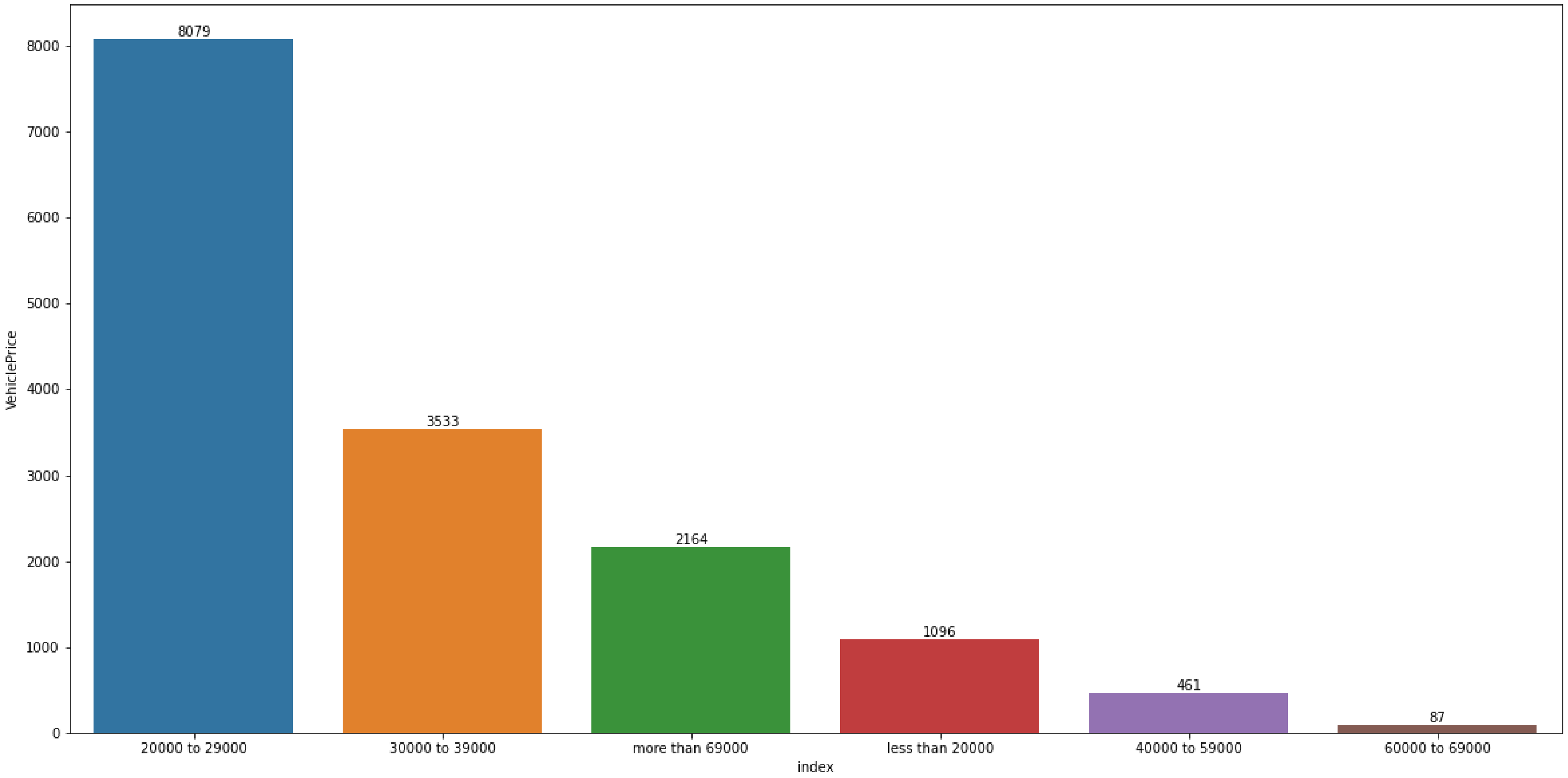
```
VehiclePrice
```

Out[46]:

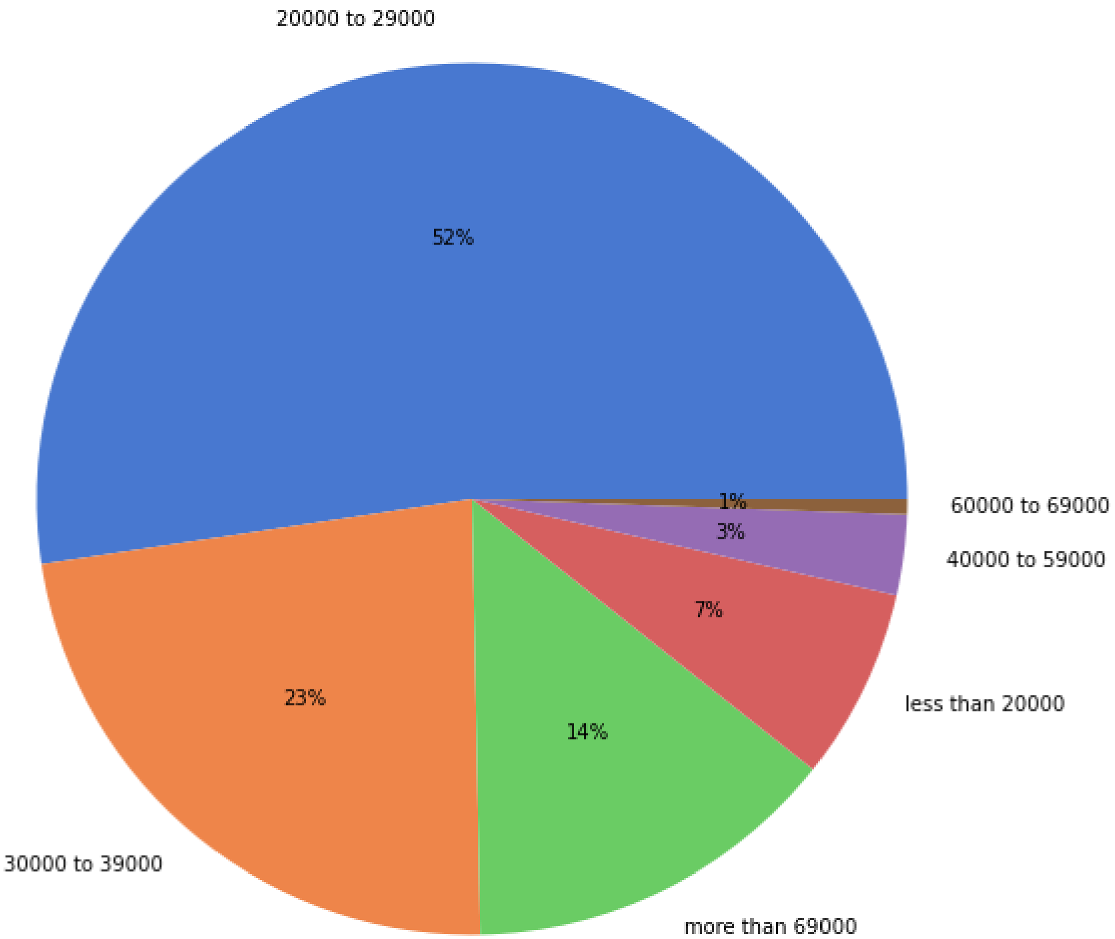
	index	VehiclePrice
0	20000 to 29000	8079
1	30000 to 39000	3533
2	more than 69000	2164
3	less than 20000	1096
4	40000 to 59000	461
5	60000 to 69000	87

In [47]:

```
plt.figure(figsize=(20,10))
ax = sns.barplot(x ='index',y = 'VehiclePrice' , data = VehiclePrice )
ax.bar_label(ax.containers[0])[0]
plt.show()


x = VehiclePrice['index'].tolist()
y = VehiclePrice['VehiclePrice'].tolist()
plt.figure(figsize=(10,10))
palette_color = sns.color_palette('muted')
plt.pie(y, labels=x,colors=palette_color, autopct='%.0f%%')[0]
plt.plot()
```


8079
3533
2164
1096
461
87
VehiclePrice
0
1000
2000
3000
4000
5000
6000
7000
8000
20000 to 29000
30000 to 39000
more than 69000
less than 20000
40000 to 59000
60000 to 69000
index

```
Out[47]: []
```



- More than 50% of cars price range in between 20000 to 29000

In [48]:

```
# RepNumber = Enumeration between 1 and 16

RepNumber = df['RepNumber'].value_counts().reset_index()
RepNumber
```

```
Out[48]:     index  RepNumber
          0      7       1069
          1      9        999
          2      1        987
          3      5        987
          4     10        986
          5     12        977
          6     15        977
          7     16        967
          8      2        956
          9      3        949
         10     11        948
         11      6        942
         12     14        941
         13      8        931
         14      4        912
         15     13        892
```

```
In [49]: #Deductible = Insurance cost

         Deductible = df['Deductible'].value_counts().reset_index()
```

```
In [50]: Deductible
```

Out[50]:

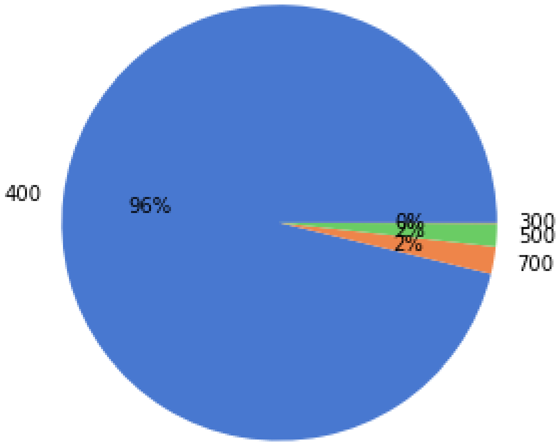
	index	Deductible
0	400	14838
1	700	311
2	500	263
3	300	8

In [51]:

```python
x = Deductible['index'].tolist()
y = Deductible['Deductible'].tolist()
plt.figure(figsize=(5,5))
palette_color = sns.color_palette('muted')
plt.pie(y, labels=x,colors=palette_color, autopct='%.0f%%')[0]
plt.plot()
```

Out[51]:

```
[]
```



- 96% of Insurance cost fee is 400.

In [52]:

```python
# DriverRating = This driver rating might be ordinal
DriverRating = df.DriverRating.value_counts().reset_index()
DriverRating
```

Out[52]:

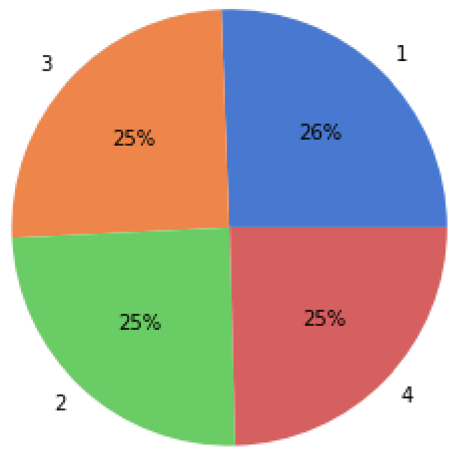
	index	DriverRating
0	1	3944
1	3	3884
2	2	3801
3	4	3791

In [53]:

```
x = DriverRating['index'].tolist()
y = DriverRating['DriverRating'].tolist()
plt.figure(figsize=(5,5))
palette_color = sns.color_palette('muted')
plt.pie(y, labels=x,colors=palette_color, autopct='%.0f%%')[0]
plt.plot()
```

Out[53]:

```
[]
```



- Driver Rating doesnt effect the accident rate

In [54]:

```
# Days_Policy_Accident = Days between Insurance is acquired and the accident occurred
```

```
Days_Policy_Accident = df.Days_Policy_Accident.value_counts().reset_index()
Days_Policy_Accident
```

Out[54]:

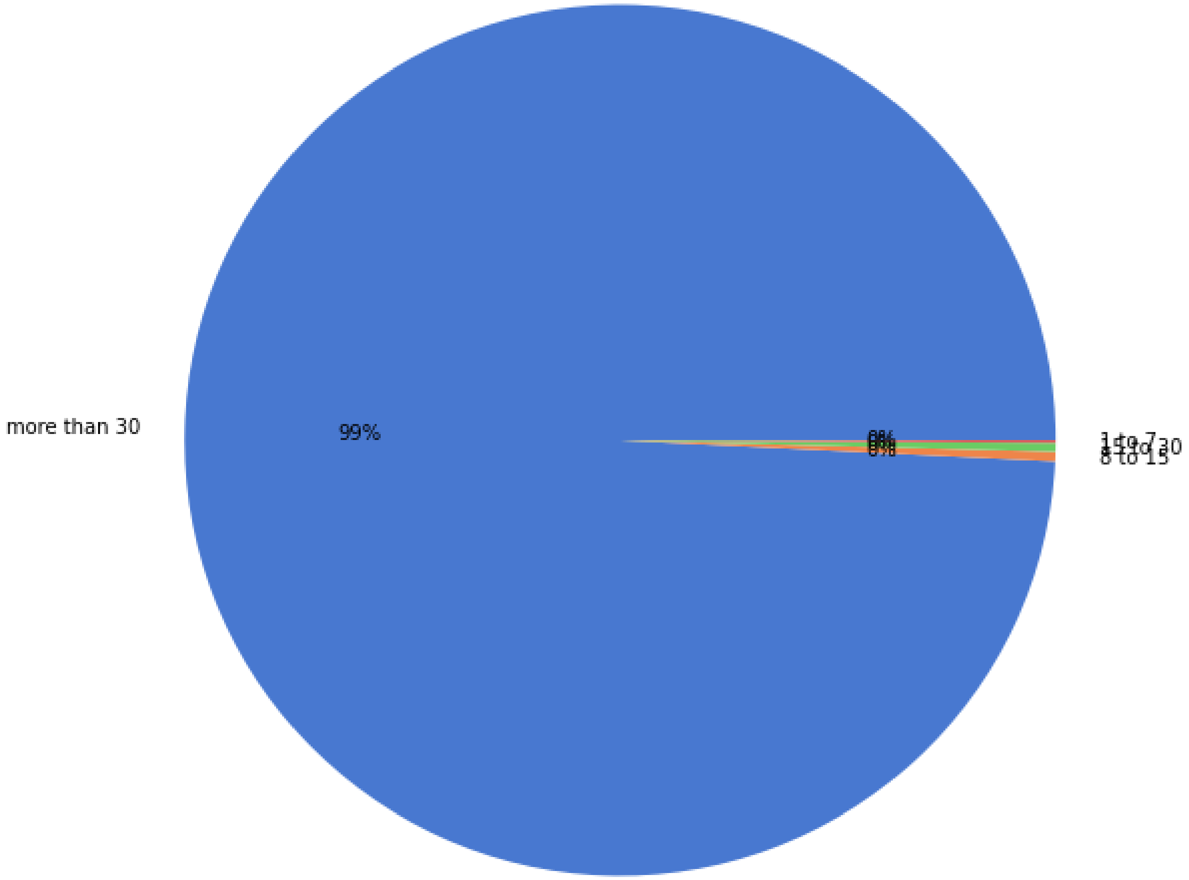
	index	Days_Policy_Accident
0	more than 30	15302
1	8 to 15	55
2	15 to 30	49
3	1 to 7	14

In [55]:

```
x = Days_Policy_Accident['index'].tolist()
y = Days_Policy_Accident['Days_Policy_Accident'].tolist()
plt.figure(figsize=(10,10))
palette_color = sns.color_palette('muted')
plt.pie(y, labels=x,colors=palette_color, autopct='%.0f%%')[0]
plt.plot()
```

Out[55]:

```
[]
```



- We are not using this variable in over ML modal as it will case 99 % data showing More than 30 this result is bias .

```
In [56]: PastNumberOfClaims = df.PastNumberOfClaims.value_counts().reset_index()
         PastNumberOfClaims
```

Out[56]:

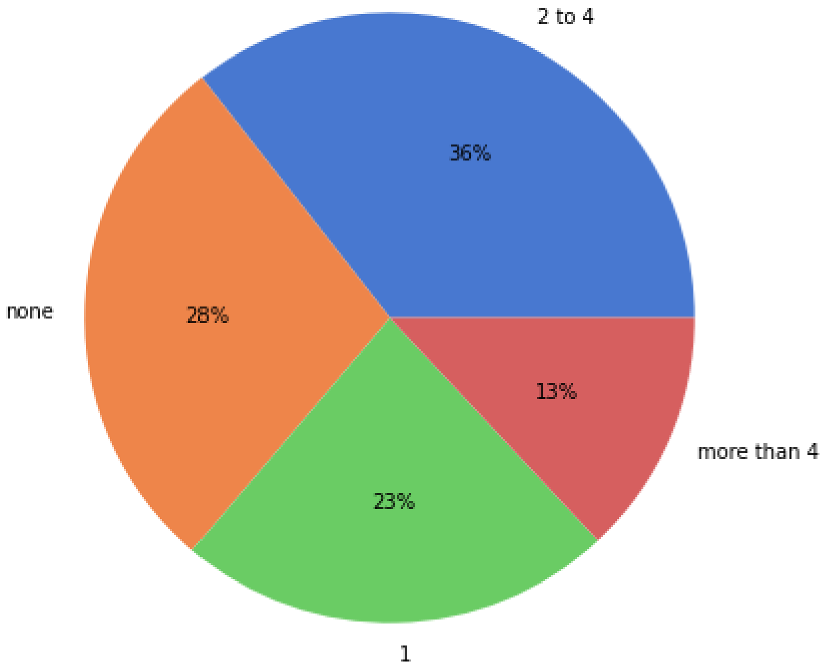
	index	PastNumberOfClaims
0	2 to 4	5485
1	none	4352
2	1	3573
3	more than 4	2010

In [57]:

```
x = PastNumberOfClaims['index'].tolist()
y = PastNumberOfClaims['PastNumberOfClaims'].tolist()
plt.figure(figsize=(7,7))
palette_color = sns.color_palette('muted')
plt.pie(y, labels=x,colors=palette_color, autopct='%.0f%%')[0]
plt.plot()
```

Out[57]:

```
[]
```



In [58]:

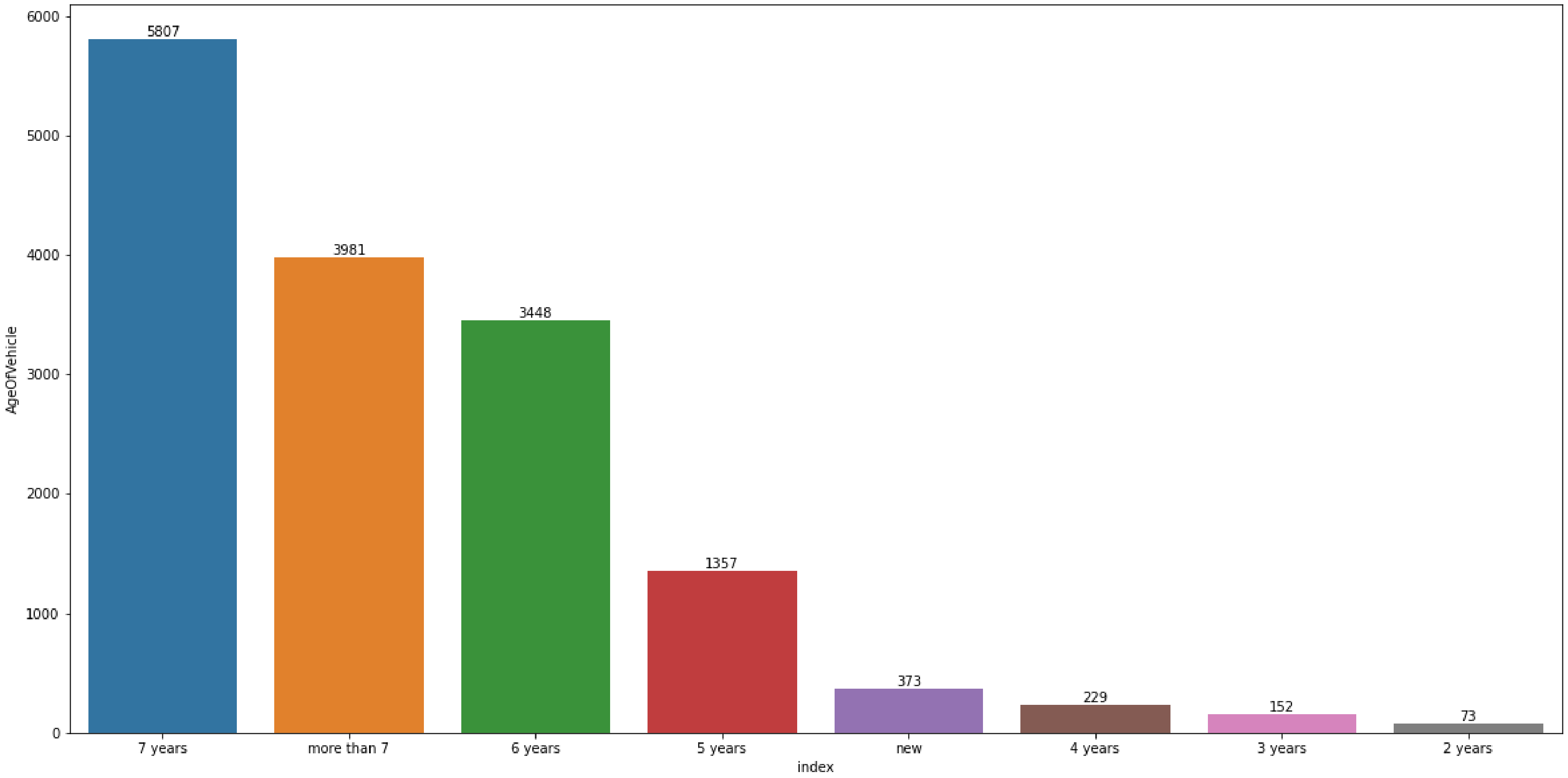
```
AgeOfVehicle = df.AgeOfVehicle.value_counts().reset_index()
AgeOfVehicle
```

Out[58]:

	index	AgeOfVehicle
0	7 years	5807
1	more than 7	3981
2	6 years	3448
3	5 years	1357
4	new	373
5	4 years	229
6	3 years	152
7	2 years	73

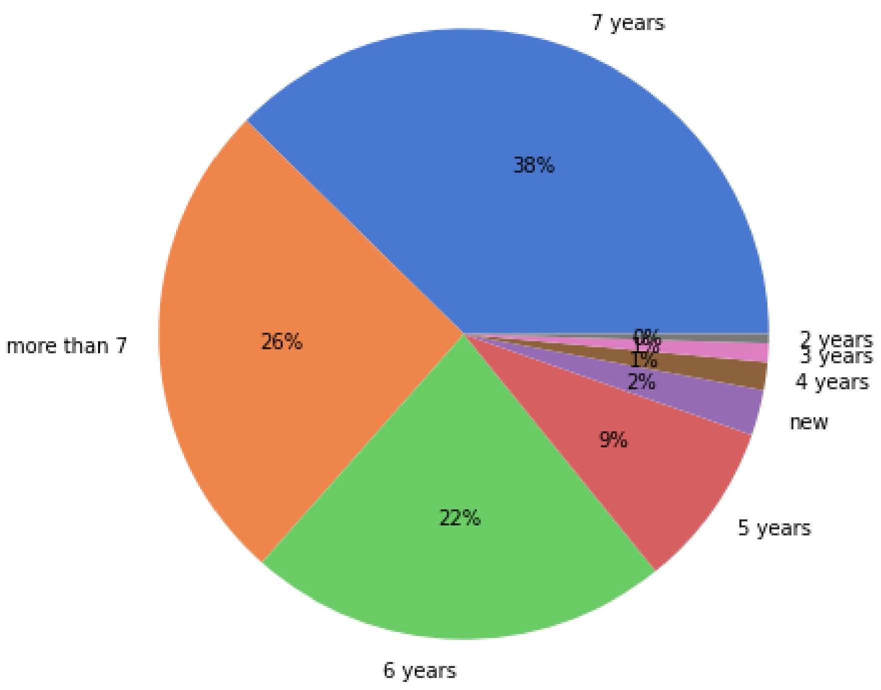
In [59]:

```
plt.figure(figsize=(20,10))
ax = sns.barplot(x ='index',y = 'AgeOfVehicle' , data = AgeOfVehicle )
ax.bar_label(ax.containers[0])[0]
plt.show()

x = AgeOfVehicle['index'].tolist()
y = AgeOfVehicle['AgeOfVehicle'].tolist()
plt.figure(figsize=(7,7))
palette_color = sns.color_palette('muted')
plt.pie(y, labels=x,colors=palette_color, autopct='%.0f%%')[0]
plt.plot()
```



6000
5000
4000
3000
2000
1000
0
AgeOfVehicle
5807
3981
3448
1357
373
229
152
73
7 years
more than 7
6 years
5 years
new
4 years
3 years
2 years
index

```
Out[59]: []
```



Observation

- We can see that cars which are more tha 5 year old are claiming the insurance policy.

In [60]:

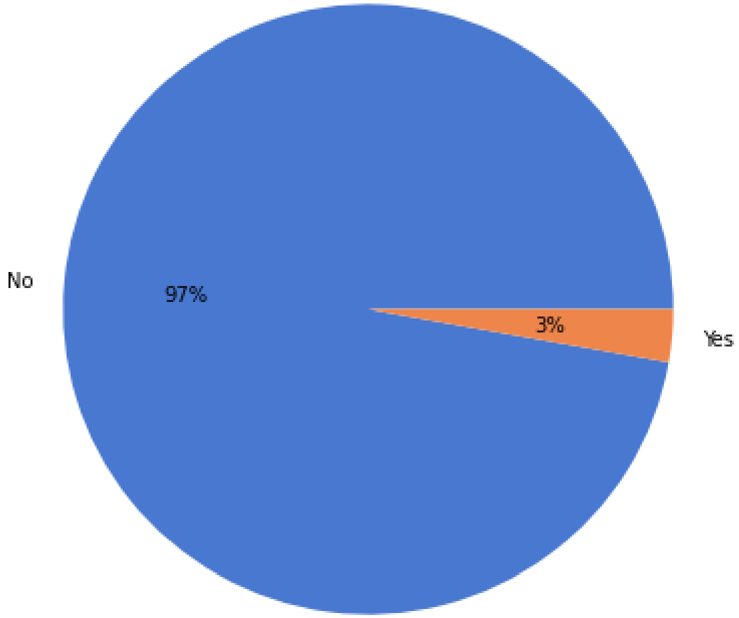
```
PoliceReportFiled = df.PoliceReportFiled.value_counts().reset_index()
```

In [61]:

```
x = PoliceReportFiled['index'].tolist()
y = PoliceReportFiled['PoliceReportFiled'].tolist()
plt.figure(figsize=(7,7))
palette_color = sns.color_palette('muted')
plt.pie(y, labels=x,colors=palette_color, autopct='%.0f%%')[0]
plt.plot()
```

Out[61]:

```
[]
```



- Most of the time after the accident person don't report to police as most of the time person dont want to go throught police process

In [62]:
```
AgentType = df.AgentType.value_counts().reset_index()
AgentType
```

Out[62]:

	index	AgentType
0	External	15179
1	Internal	241

In [63]:
```
df.WitnessPresent.value_counts().reset_index()
```

Out[63]:

	index	WitnessPresent
0	No	15333
1	Yes	87

In [64]:

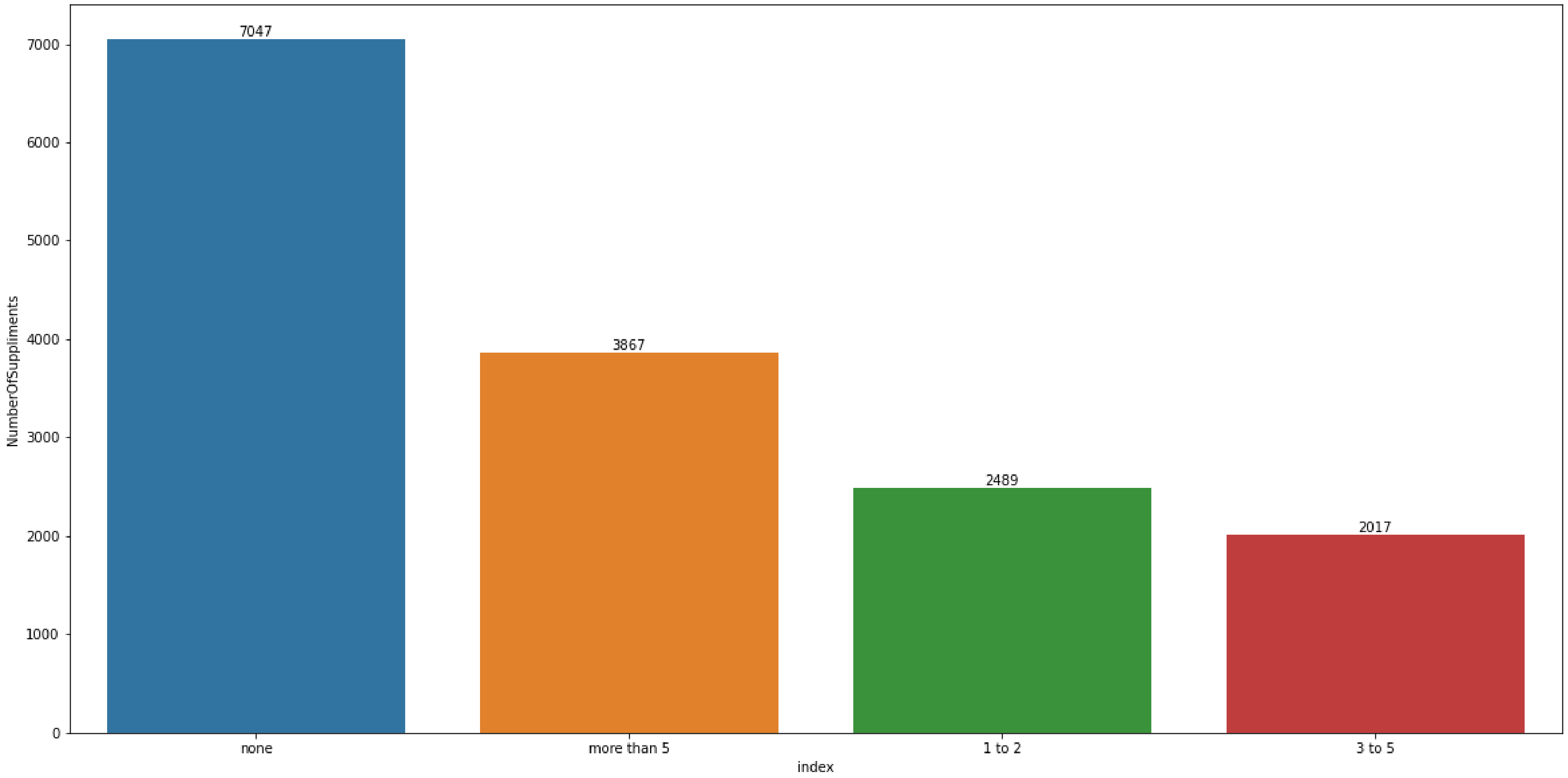
```
#NumberOfSuppliments =Supplements are non-registered damages in the car,
#                     because they are not easily visible, usually internal components like suspension, chassis, etc.

NumberOfSuppliments = df.NumberOfSuppliments.value_counts().reset_index()
NumberOfSuppliments
```

Out[64]:

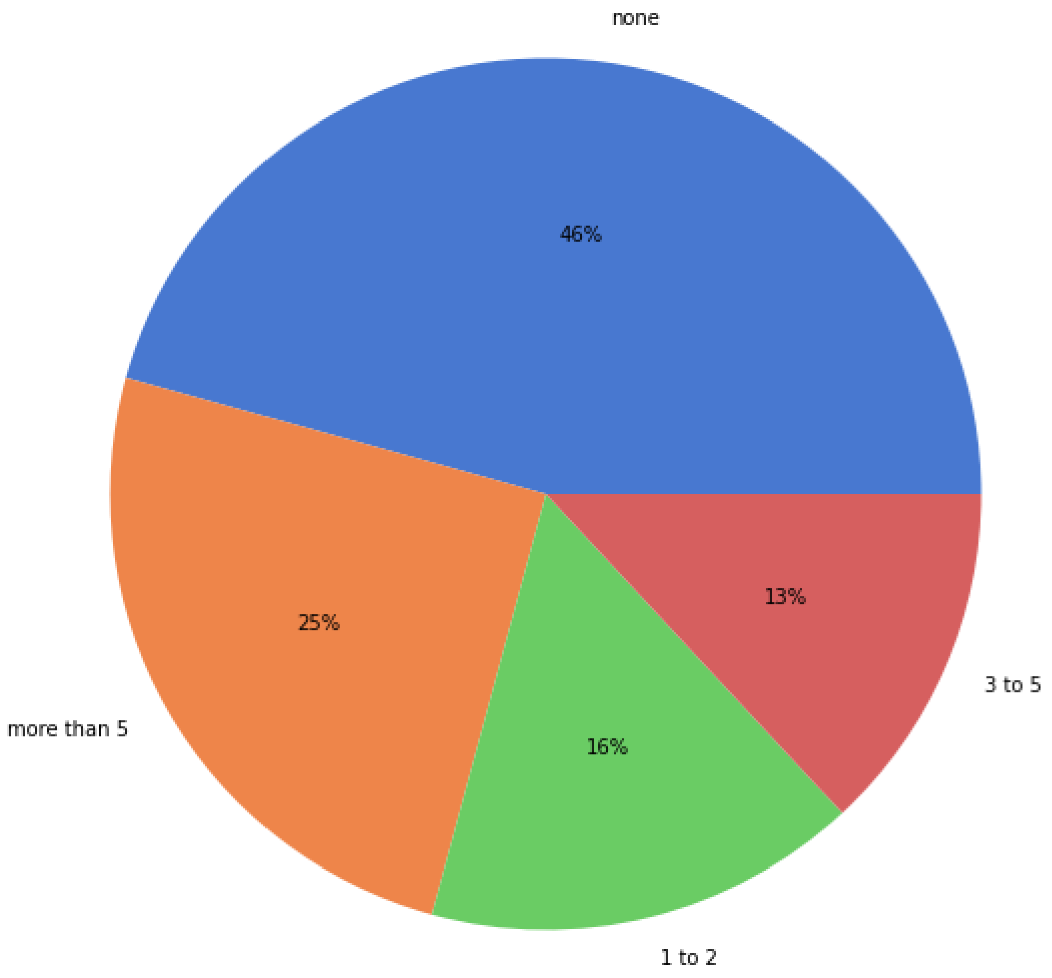
	index	NumberOfSuppliments
0	none	7047
1	more than 5	3867
2	1 to 2	2489
3	3 to 5	2017

In [65]:

```
plt.figure(figsize=(20,10))
ax = sns.barplot(x ='index',y = 'NumberOfSuppliments' , data = NumberOfSuppliments )
ax.bar_label(ax.containers[0])[0]
plt.show()


x = NumberOfSuppliments['index'].tolist()
y = NumberOfSuppliments['NumberOfSuppliments'].tolist()
plt.figure(figsize=(10,10))
palette_color = sns.color_palette('muted')
plt.pie(y, labels=x,colors=palette_color, autopct='%.0f%%')[0]
plt.plot()
```


7047
3867
2489
2017
7000
6000
5000
4000
3000
2000
1000
0
NumberOfSuppliments
none
more than 5
1 to 2
3 to 5
index

```
Out[65]: []
```



- Most of the time over 54% times their is some sort internal damge which cant see visually.

In [66]:
```
AddressChange_Claim = df.AddressChange_Claim.value_counts().reset_index()
AddressChange_Claim
```

Out[66]:

	index	AddressChange_Claim
0	no change	14324
1	4 to 8 years	631
2	2 to 3 years	291
3	1 year	170
4	under 6 months	4

In [67]:

```
NumberOfCars =df.NumberOfCars.value_counts().reset_index()
NumberOfCars
```

Out[67]:

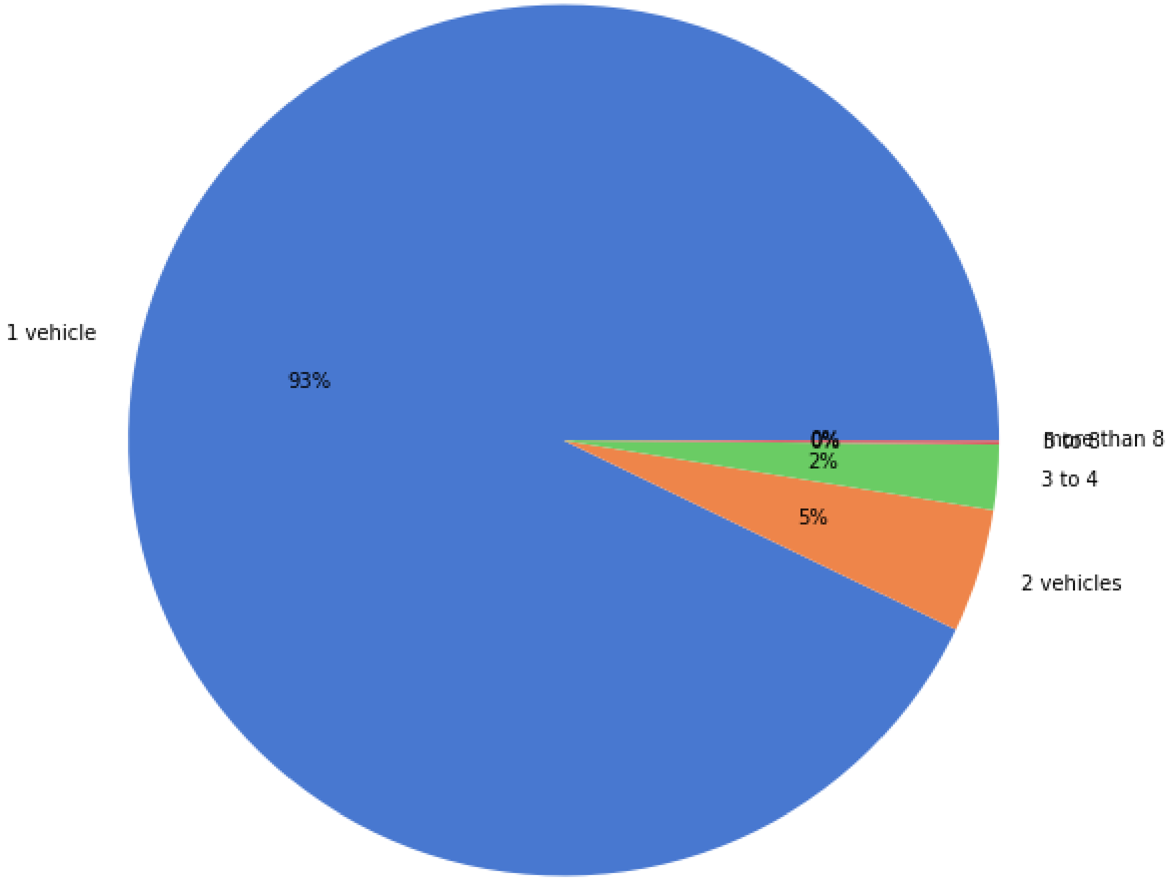
	index	NumberOfCars
0	1 vehicle	14316
1	2 vehicles	709
2	3 to 4	372
3	5 to 8	21
4	more than 8	2

In [68]:

```
x = NumberOfCars['index'].tolist()
y = NumberOfCars['NumberOfCars'].tolist()
plt.figure(figsize=(10,10))
palette_color = sns.color_palette('muted')
plt.pie(y, labels=x,colors=palette_color, autopct='%.0f%%')[0]
plt.plot()
```

Out[68]:

```
[]
```



- Most of the time only one car is involved in accident

```
In [69]: df.Year.value_counts()
```

Out[69]:

```
1994    6142
1995    5195
1996    4083
Name: Year, dtype: int64
```

In [70]:

```
BasePolicy = df.BasePolicy.value_counts().reset_index()
BasePolicy
```

Out[70]:

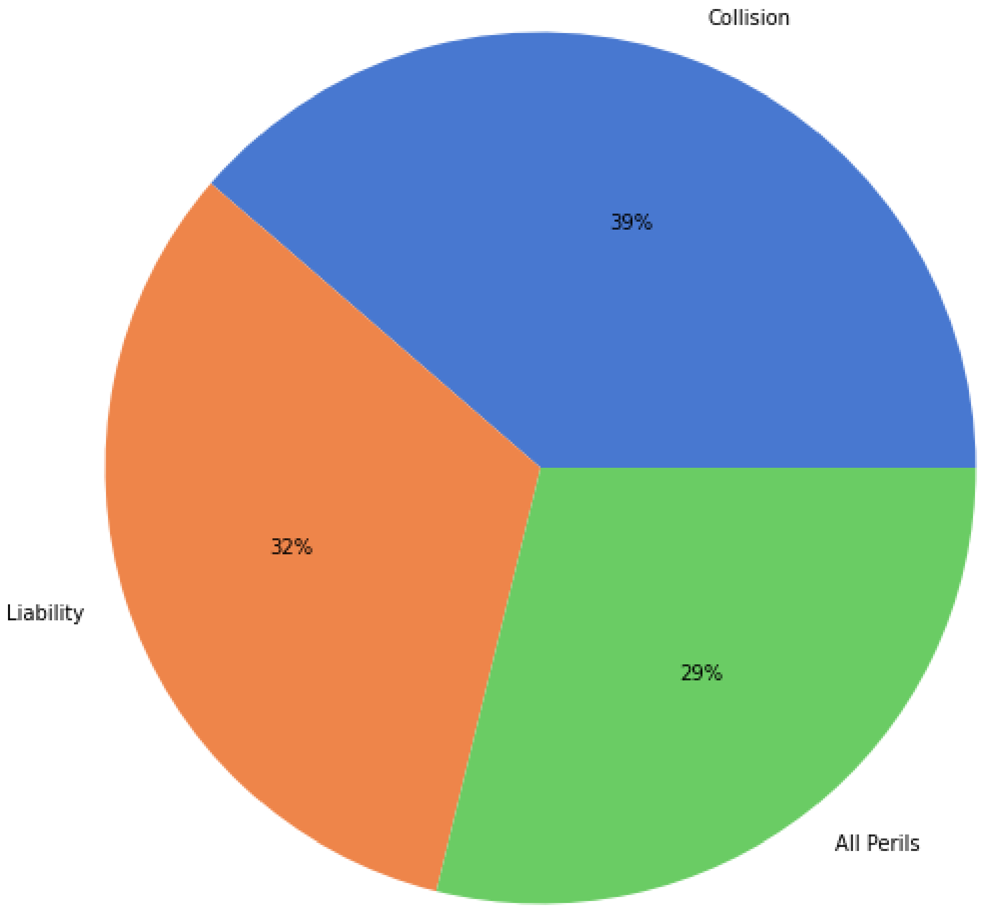
	index	BasePolicy
0	Collision	5962
1	Liability	5009
2	All Perils	4449

In [71]:

```
x = BasePolicy['index'].tolist()
y = BasePolicy['BasePolicy'].tolist()
plt.figure(figsize=(10,10))
palette_color = sns.color_palette('muted')
plt.pie(y, labels=x,colors=palette_color, autopct='%.0f%%')[0]
plt.plot()
```

Out[71]:

```
[]
```

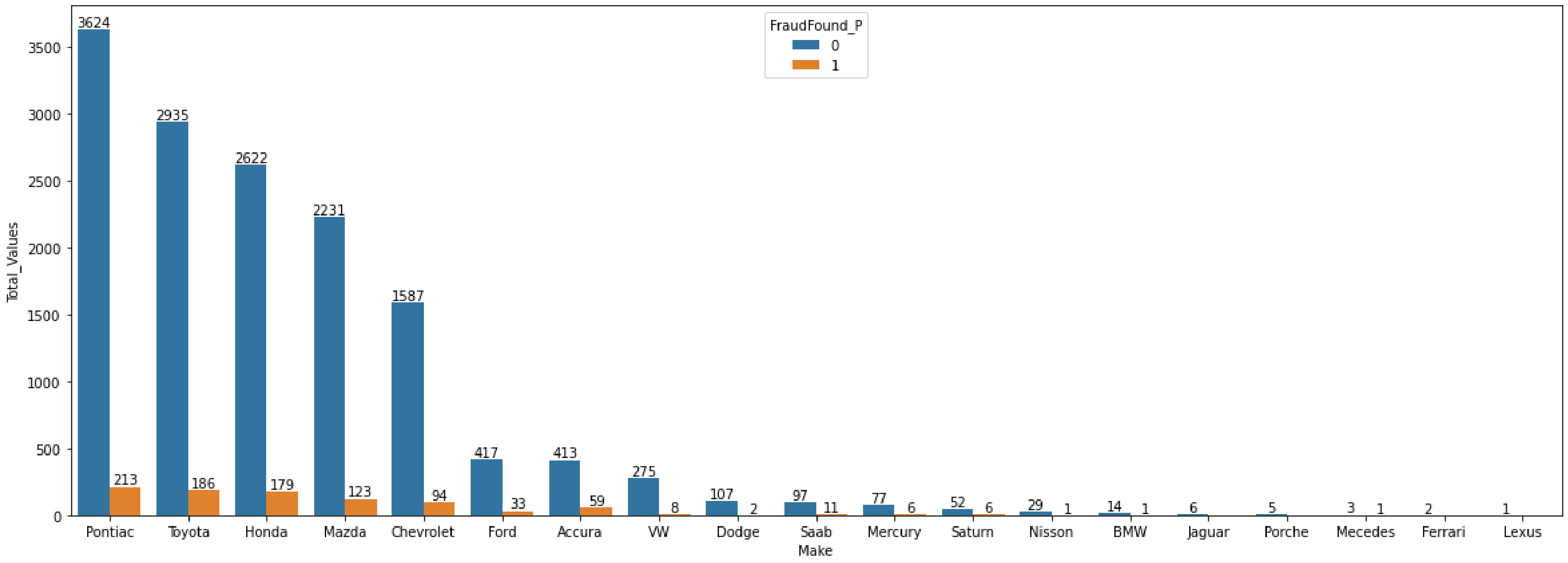


Bivariate Analysis of categorical vs numerical variables (Taking target variable as fixed variable here)

In [72]:

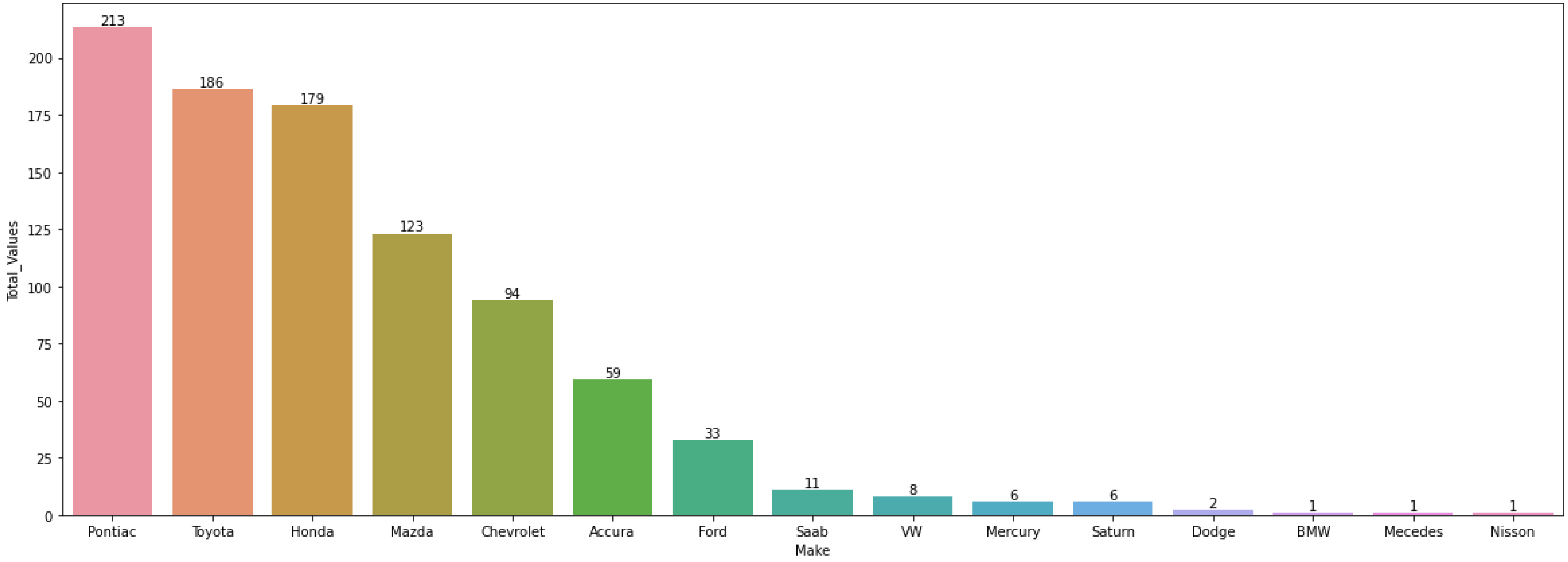
```
Make =df.groupby('FraudFound_P').agg(Total_Values=('Make', 'value_counts')).reset_index()

plt.figure(figsize=(20,7))
ax =sns.barplot(data=Make, x="Make", y="Total_Values" ,hue = "FraudFound_P")
```

```
ax.bar_label(ax.containers[1])[0]
ax.bar_label(ax.containers[0])[0]
plt.show()
```



In [73]:

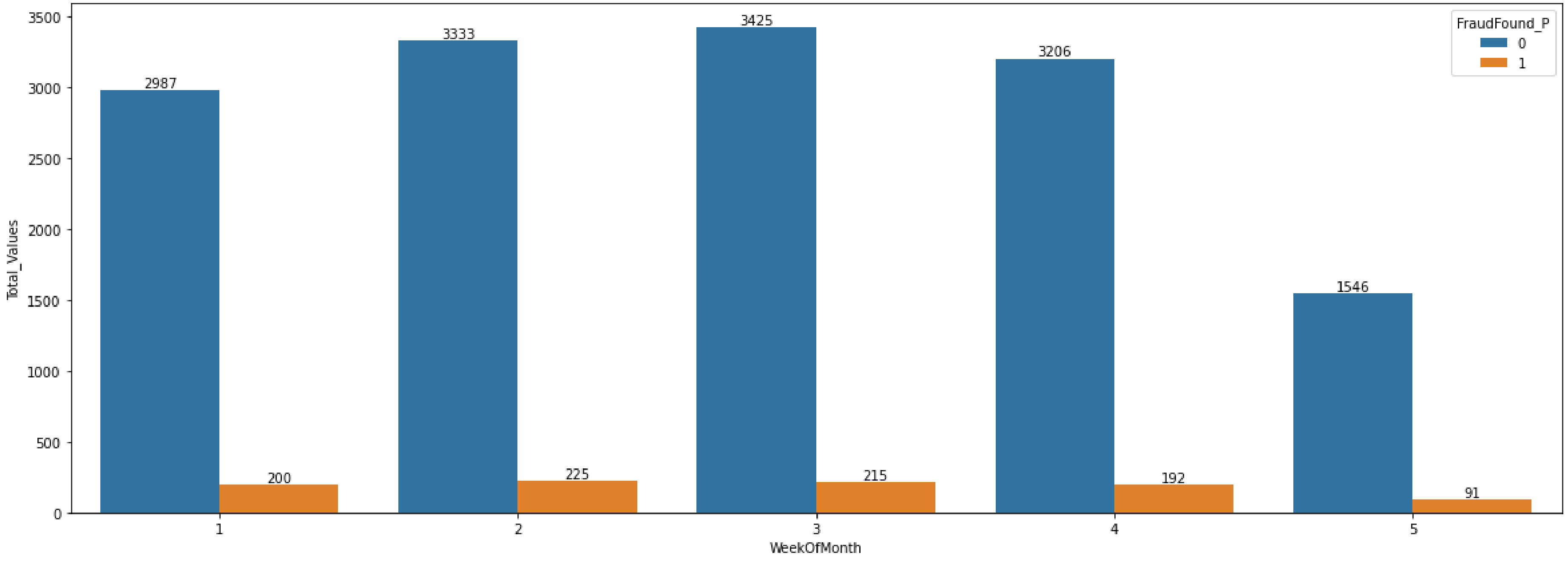
```
Fur_Make = Make[Make.FraudFound_P == 1]

plt.figure(figsize=(20,7))
ax =sns.barplot(data=Fur_Make, x="Make", y="Total_Values" )
ax.bar_label(ax.containers[0])[0]
plt.show()
```



In [ ]:

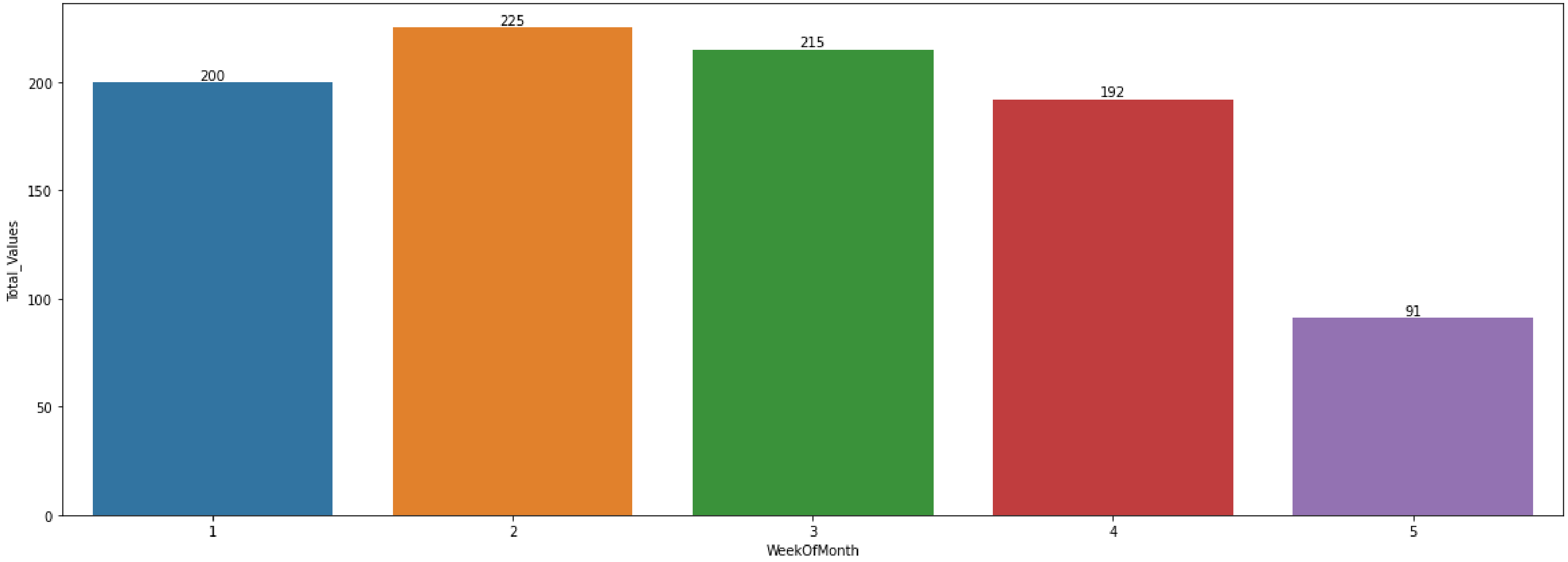
In [74]:

```
WeekOfMonth =df.groupby('FraudFound_P').agg(Total_Values=('WeekOfMonth', 'value_counts')).reset_index()

plt.figure(figsize=(20,7))
ax =sns.barplot(data= WeekOfMonth, x="WeekOfMonth", y="Total_Values" ,hue = "FraudFound_P")
ax.bar_label(ax.containers[1])[0]
ax.bar_label(ax.containers[0])[0]
plt.show()
```



In [75]:

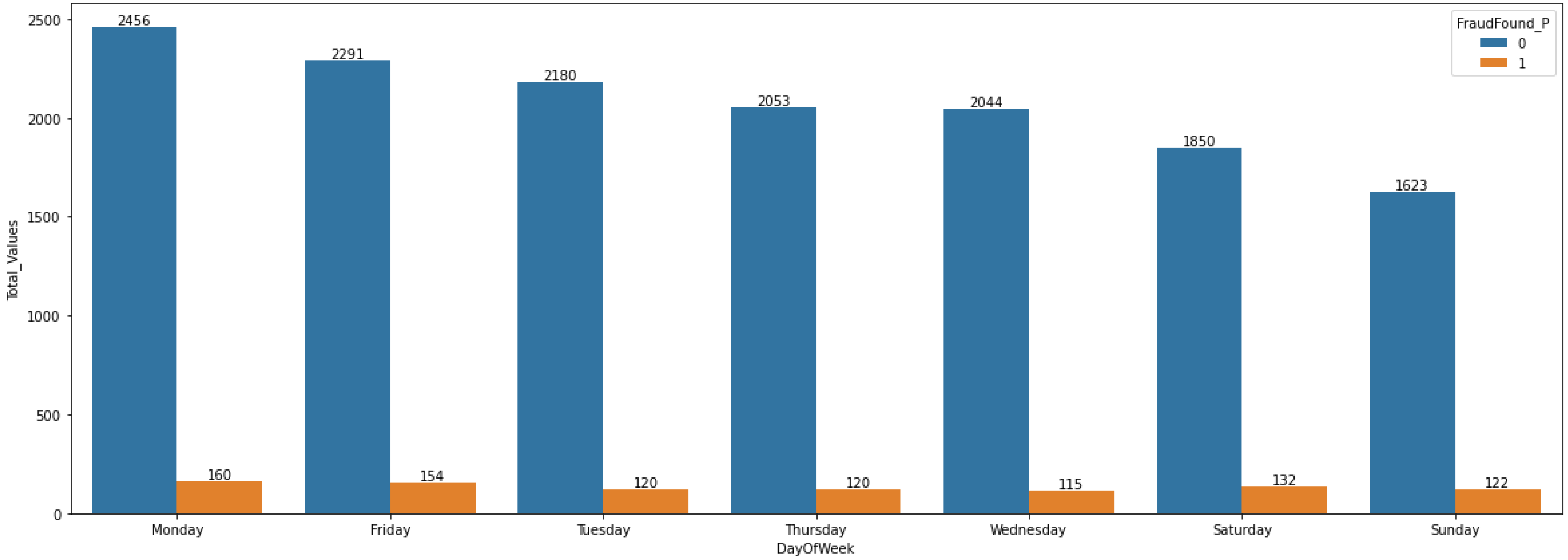
```
Fur_WeekOfMonth = WeekOfMonth[WeekOfMonth.FraudFound_P == 1]

plt.figure(figsize=(20,7))
ax =sns.barplot(data=Fur_WeekOfMonth, x="WeekOfMonth", y="Total_Values" )
ax.bar_label(ax.containers[0])[0]
plt.show()
```



In [ ]:

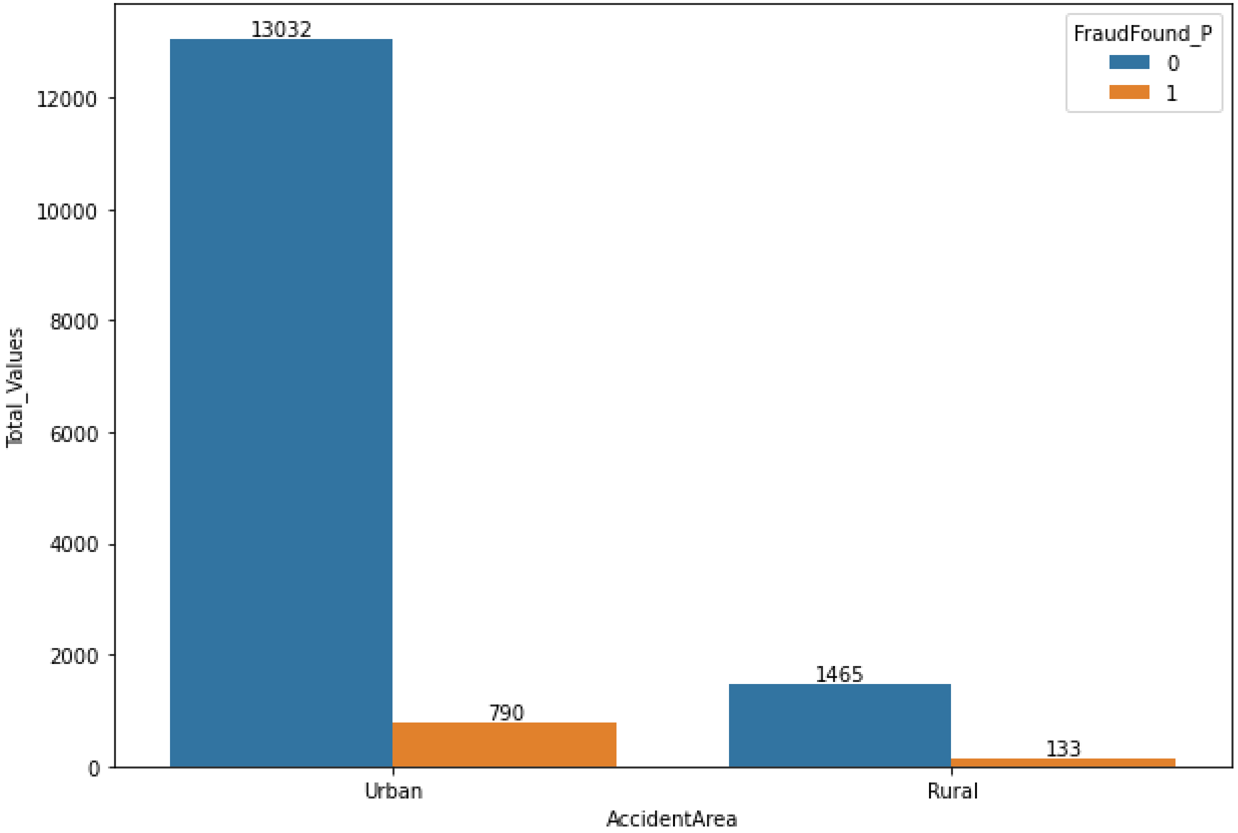
In [76]:

```
DayOfWeek =df.groupby('FraudFound_P').agg(Total_Values=('DayOfWeek', 'value_counts')).reset_index()

plt.figure(figsize=(20,7))
ax =sns.barplot(data= DayOfWeek, x="DayOfWeek", y="Total_Values" ,hue = "FraudFound_P")
ax.bar_label(ax.containers[1])[0]
ax.bar_label(ax.containers[0])[0]
plt.show()
```



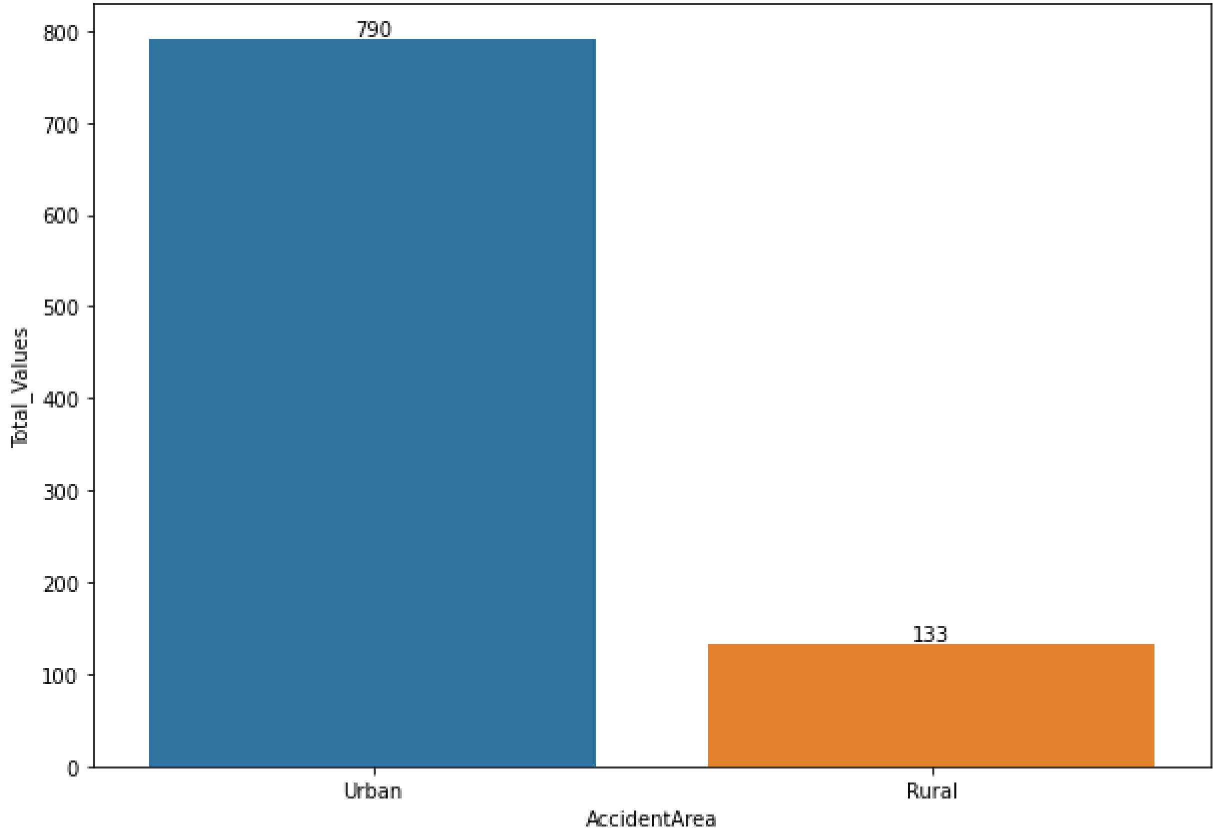
In [77]:

```
AccidentArea =df.groupby('FraudFound_P').agg(Total_Values=('AccidentArea', 'value_counts')).reset_index()

plt.figure(figsize=(10,7))
ax =sns.barplot(data= AccidentArea, x="AccidentArea", y="Total_Values" ,hue = "FraudFound_P")
ax.bar_label(ax.containers[1])[0]
ax.bar_label(ax.containers[0])[0]
plt.show()
```



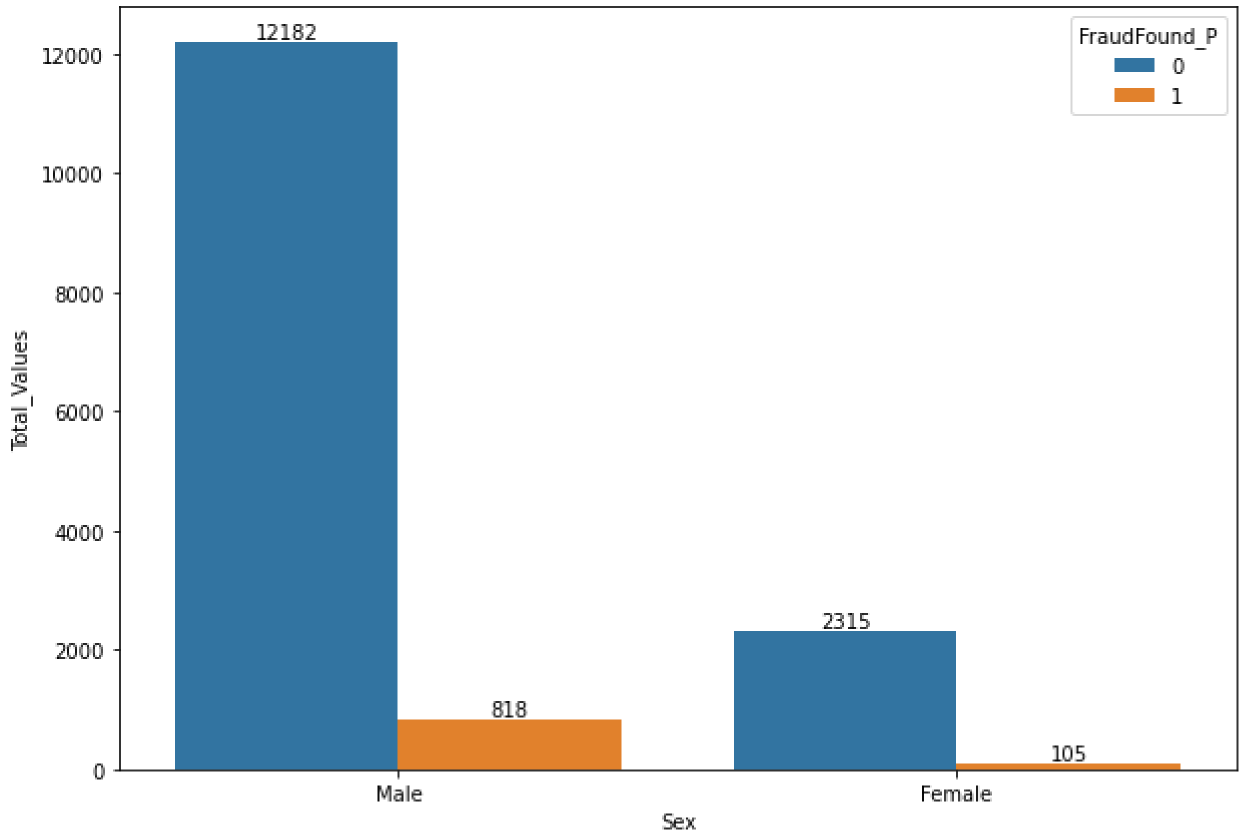
In [78]:

```
Fur_AccidentArea = AccidentArea[AccidentArea.FraudFound_P == 1]

plt.figure(figsize=(10,7))
ax =sns.barplot(data=Fur_AccidentArea, x="AccidentArea", y="Total_Values" )
ax.bar_label(ax.containers[0])[0]
plt.show()
```



In [79]:

```
Sex =df.groupby('FraudFound_P').agg(Total_Values=('Sex', 'value_counts')).reset_index()

plt.figure(figsize=(10,7))
ax =sns.barplot(data= Sex, x="Sex", y="Total_Values" ,hue = "FraudFound_P")
ax.bar_label(ax.containers[1])[0]
ax.bar_label(ax.containers[0])[0]
plt.show()
```

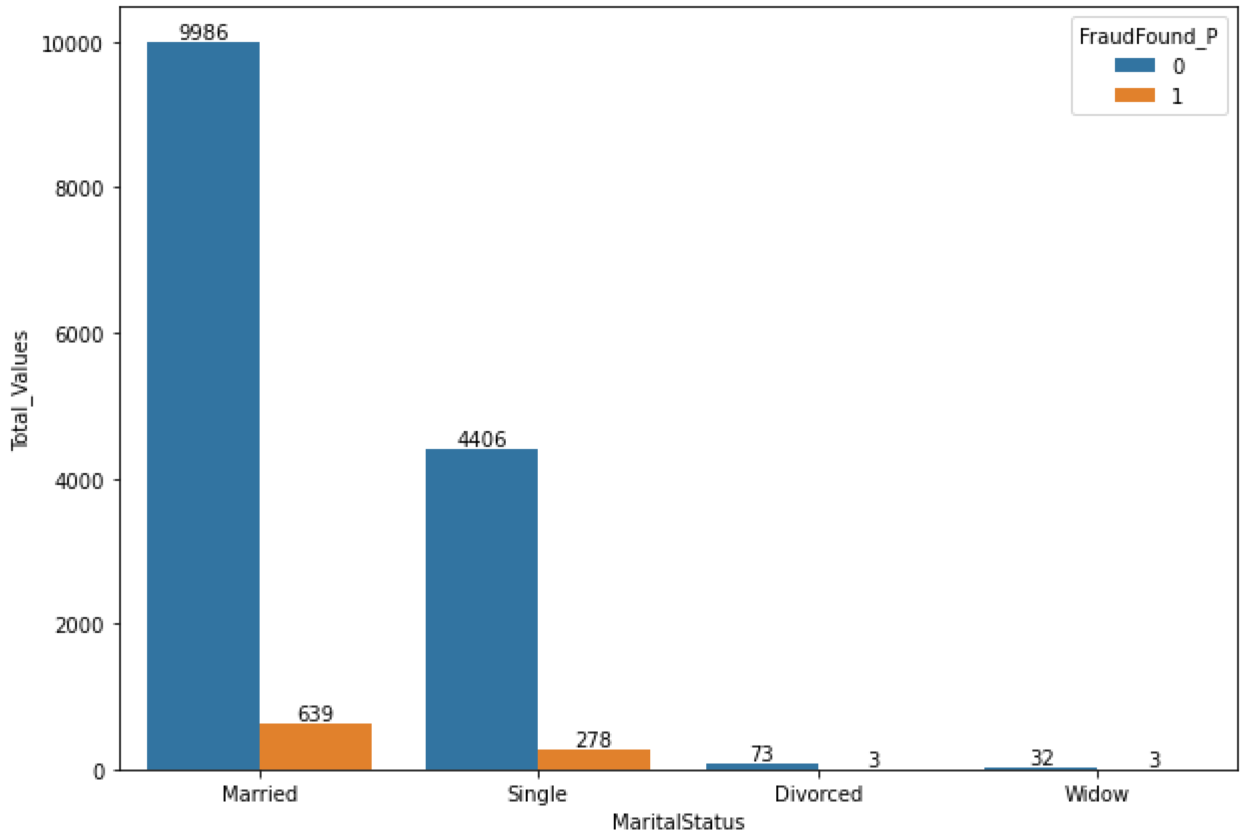


In [ ]:

```
```

In [80]:

```
MaritalStatus =df.groupby('FraudFound_P').agg(Total_Values=('MaritalStatus', 'value_counts')).reset_index()

plt.figure(figsize=(10,7))
ax =sns.barplot(data= MaritalStatus, x="MaritalStatus", y="Total_Values" ,hue = "FraudFound_P")
ax.bar_label(ax.containers[1])[0]
ax.bar_label(ax.containers[0])[0]
plt.show()
```

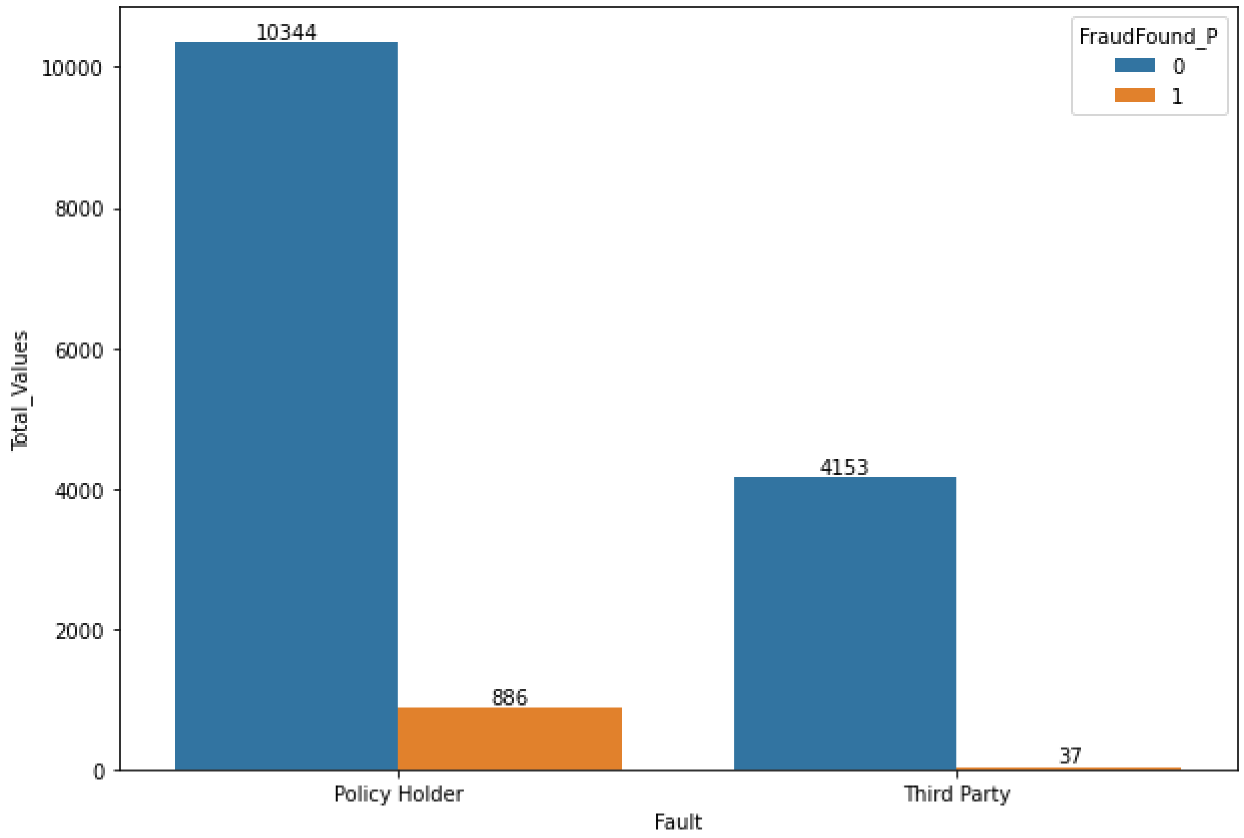


In [ ]:

```
```

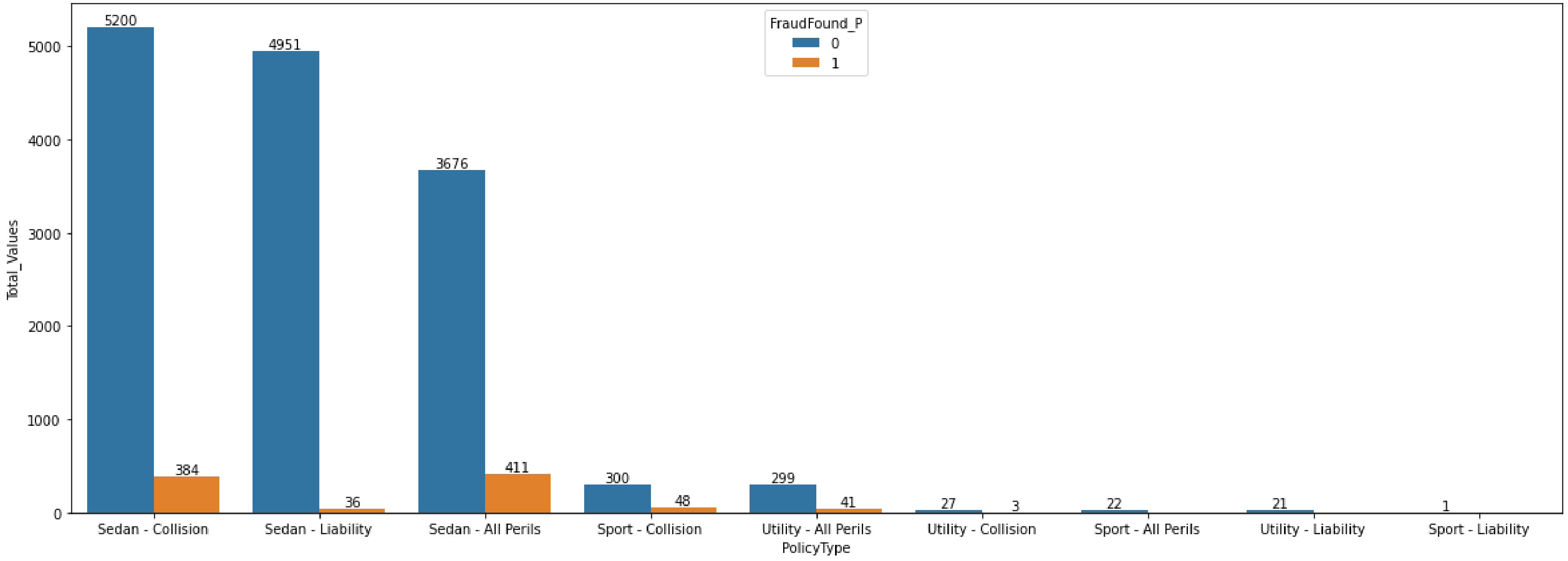
In [81]:

```
Fault =df.groupby('FraudFound_P').agg(Total_Values=('Fault', 'value_counts')).reset_index()

plt.figure(figsize=(10,7))
ax =sns.barplot(data= Fault, x="Fault", y="Total_Values" ,hue = "FraudFound_P")
ax.bar_label(ax.containers[1])[0]
ax.bar_label(ax.containers[0])[0]
plt.show()
```



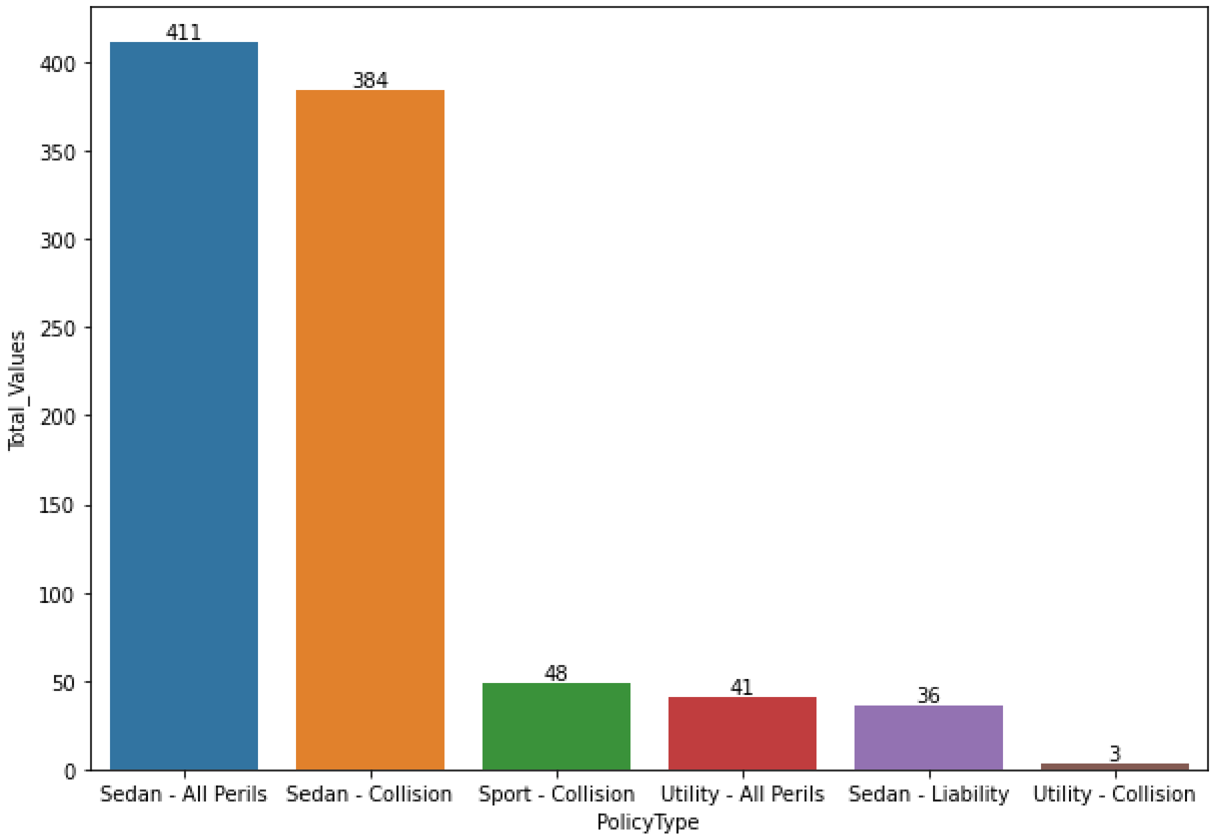
In [82]:

```
PolicyType =df.groupby('FraudFound_P').agg(Total_Values=('PolicyType', 'value_counts')).reset_index()

plt.figure(figsize=(20,7))
ax =sns.barplot(data= PolicyType, x="PolicyType", y="Total_Values" ,hue = "FraudFound_P")
ax.bar_label(ax.containers[1])[0]
ax.bar_label(ax.containers[0])[0]
plt.show()
```



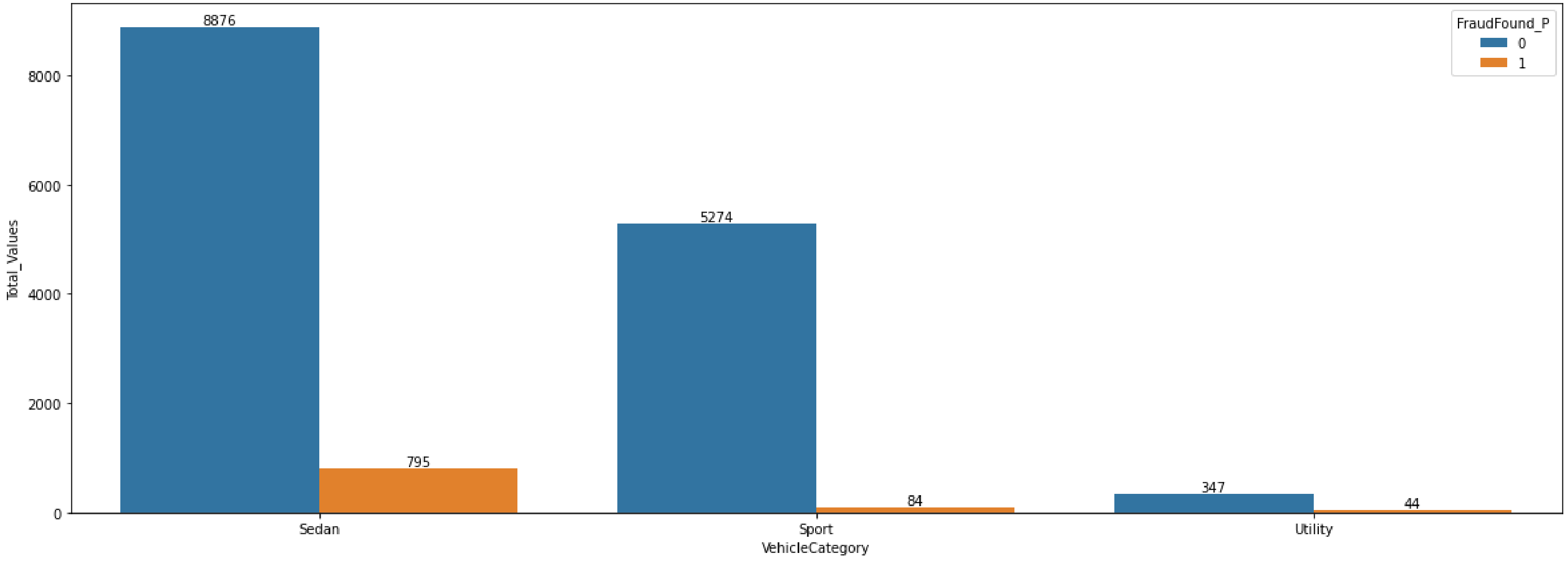
In [83]:

```
Fur_PolicyType = PolicyType[PolicyType.FraudFound_P == 1]

plt.figure(figsize=(10,7))
ax =sns.barplot(data=Fur_PolicyType, x="PolicyType", y="Total_Values" )
ax.bar_label(ax.containers[0])[0]
plt.show()
```



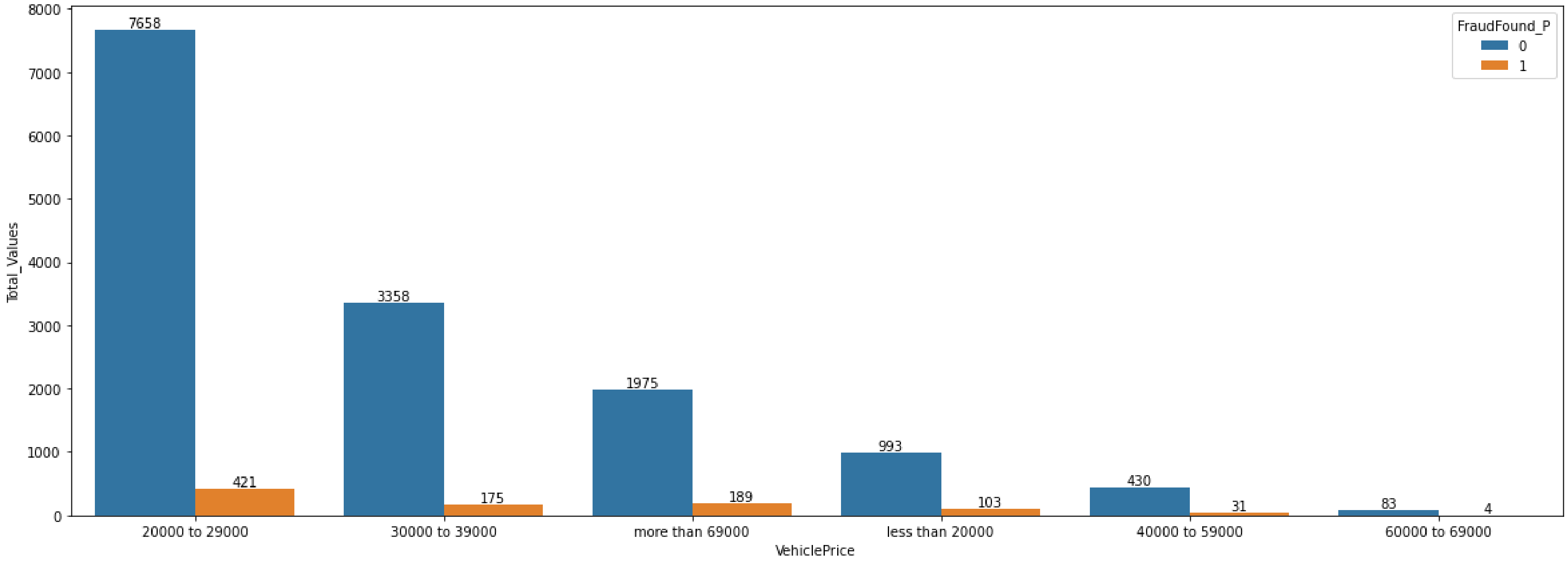
In [84]:

```
VehicleCategory =df.groupby('FraudFound_P').agg(Total_Values=('VehicleCategory', 'value_counts')).reset_index()

plt.figure(figsize=(20,7))
ax =sns.barplot(data= VehicleCategory, x="VehicleCategory", y="Total_Values" ,hue = "FraudFound_P")
ax.bar_label(ax.containers[1])[0]
ax.bar_label(ax.containers[0])[0]
plt.show()
```



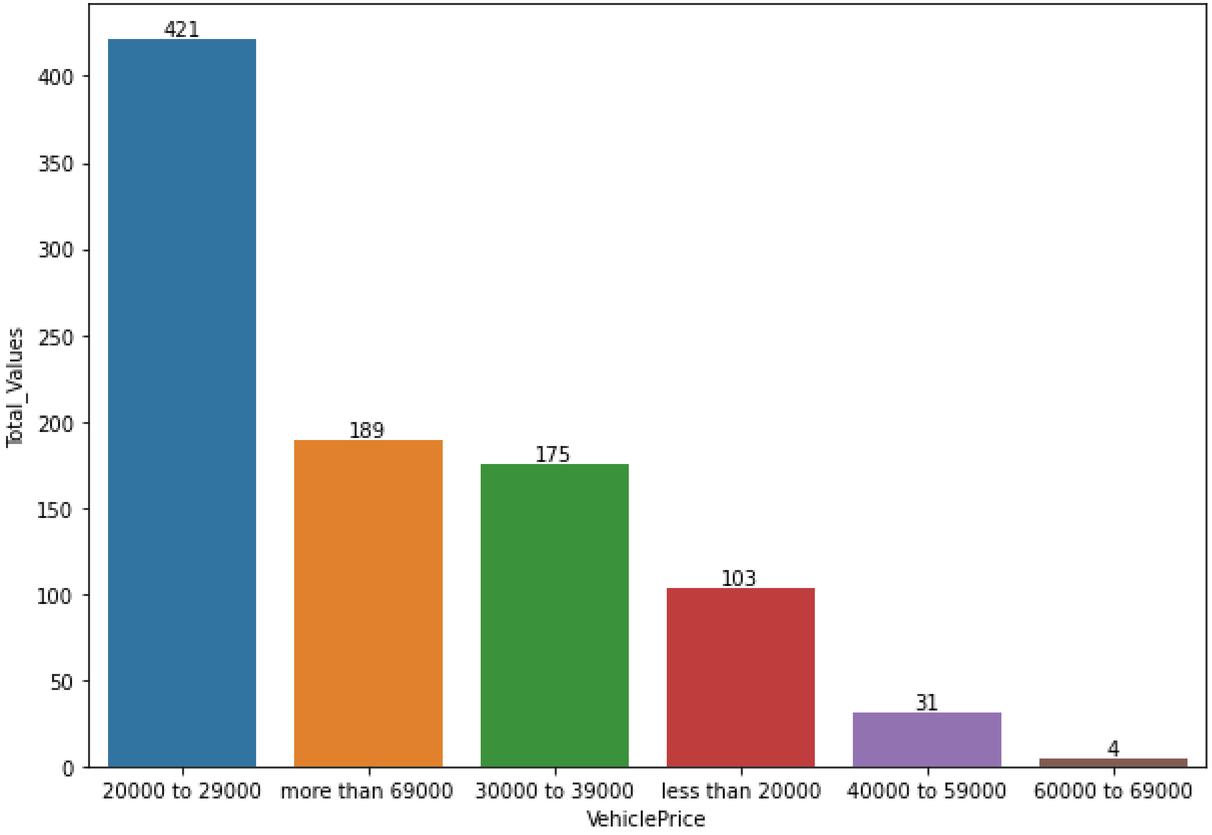
In [85]:

```
VehiclePrice =df.groupby('FraudFound_P').agg(Total_Values=('VehiclePrice', 'value_counts')).reset_index()

plt.figure(figsize=(20,7))
ax =sns.barplot(data= VehiclePrice, x="VehiclePrice", y="Total_Values" ,hue = "FraudFound_P")
ax.bar_label(ax.containers[1])[0]
ax.bar_label(ax.containers[0])[0]
plt.show()
```



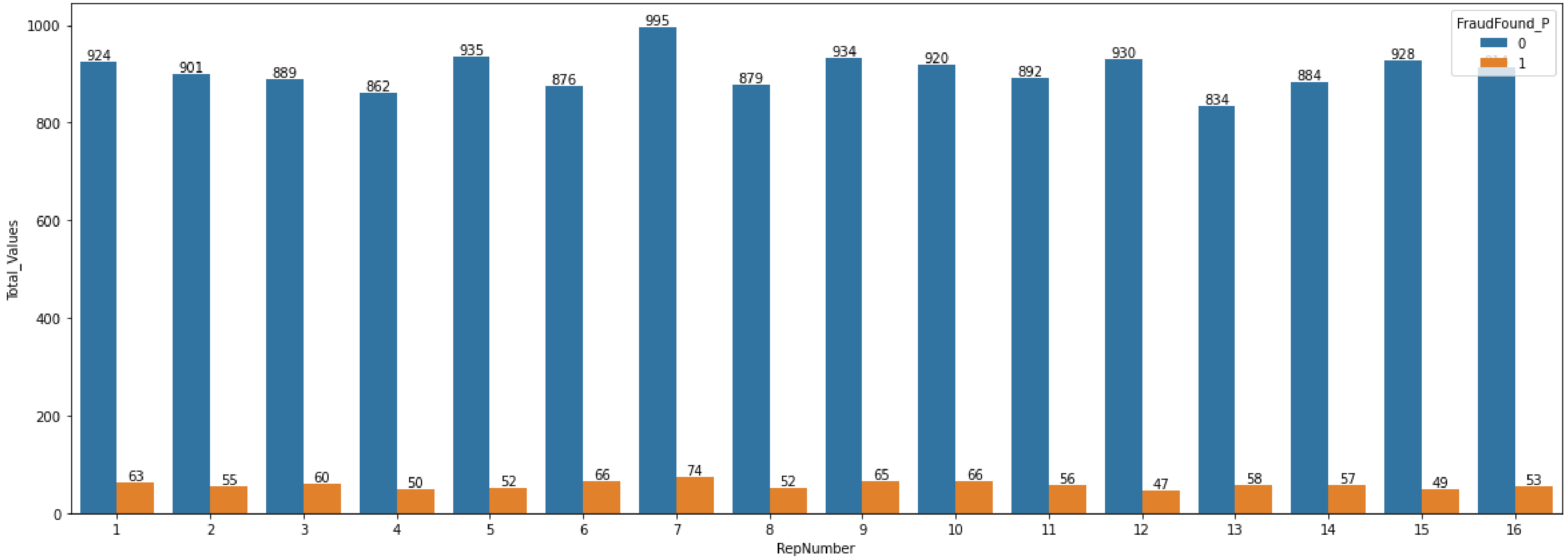
In [86]:

```
Fur_VehiclePrice = VehiclePrice[VehiclePrice.FraudFound_P == 1]

plt.figure(figsize=(10,7))
ax =sns.barplot(data=Fur_VehiclePrice, x="VehiclePrice", y="Total_Values" )
ax.bar_label(ax.containers[0])[0]
plt.show()
```



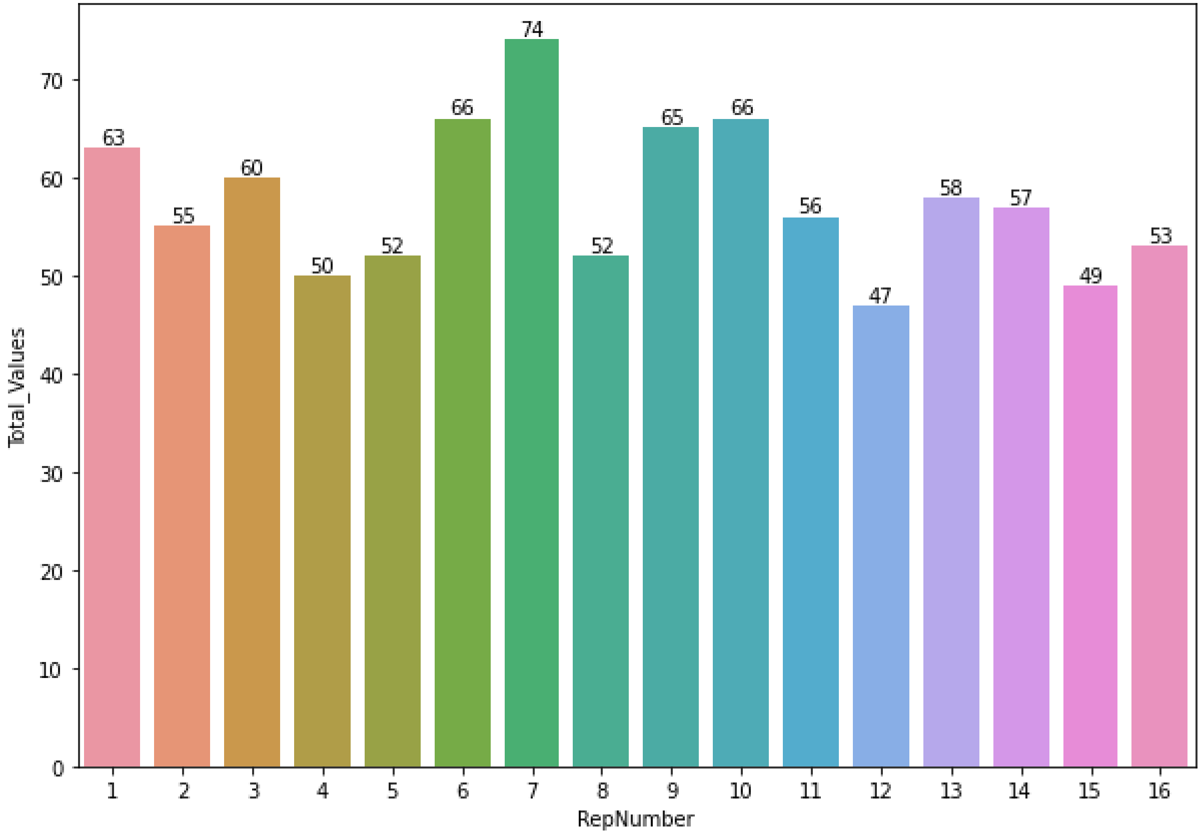
In [87]:

```
RepNumber =df.groupby('FraudFound_P').agg(Total_Values=('RepNumber', 'value_counts')).reset_index().sort_values(["Total_Values"]

plt.figure(figsize=(20,7))
ax =sns.barplot(data= RepNumber, x="RepNumber", y="Total_Values" ,hue = "FraudFound_P")
ax.bar_label(ax.containers[1])[0]
ax.bar_label(ax.containers[0])[0]
plt.show()
```



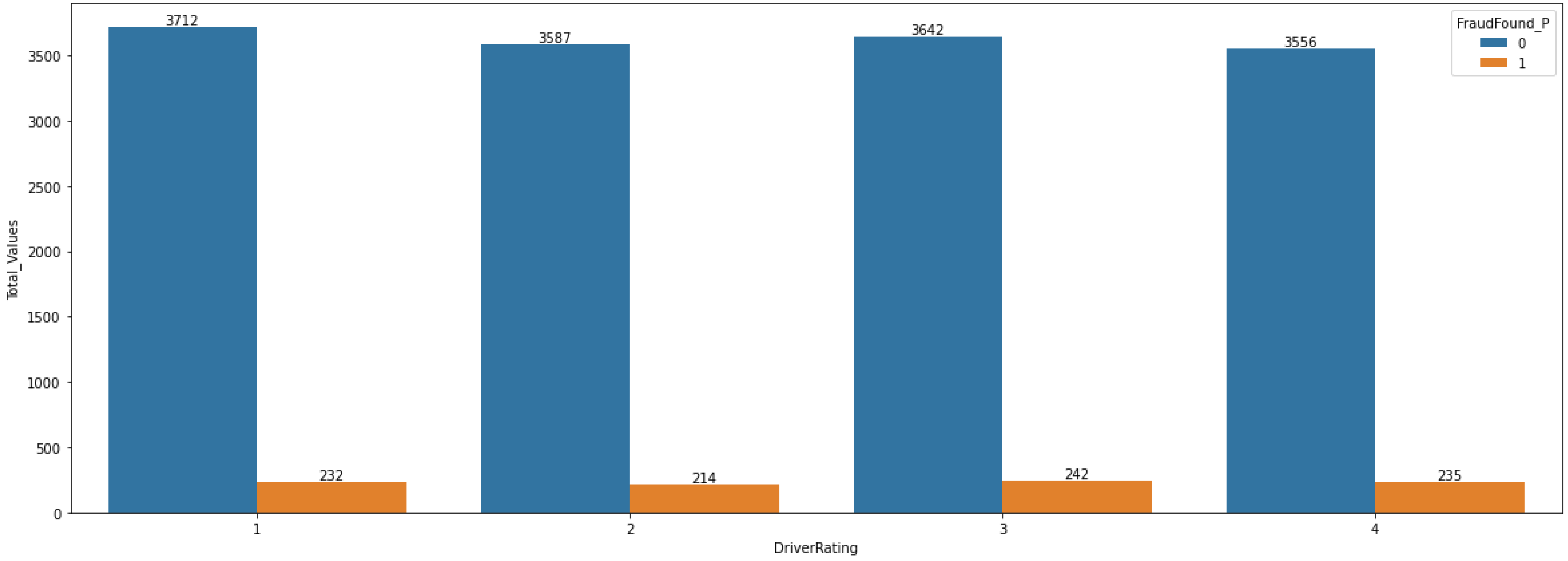
In [88]:

```
Fur_RepNumber = RepNumber[RepNumber.FraudFound_P == 1]
plt.figure(figsize=(10,7))
ax =sns.barplot(data=Fur_RepNumber, x="RepNumber", y="Total_Values" )
ax.bar_label(ax.containers[0])[0]
plt.show()
```



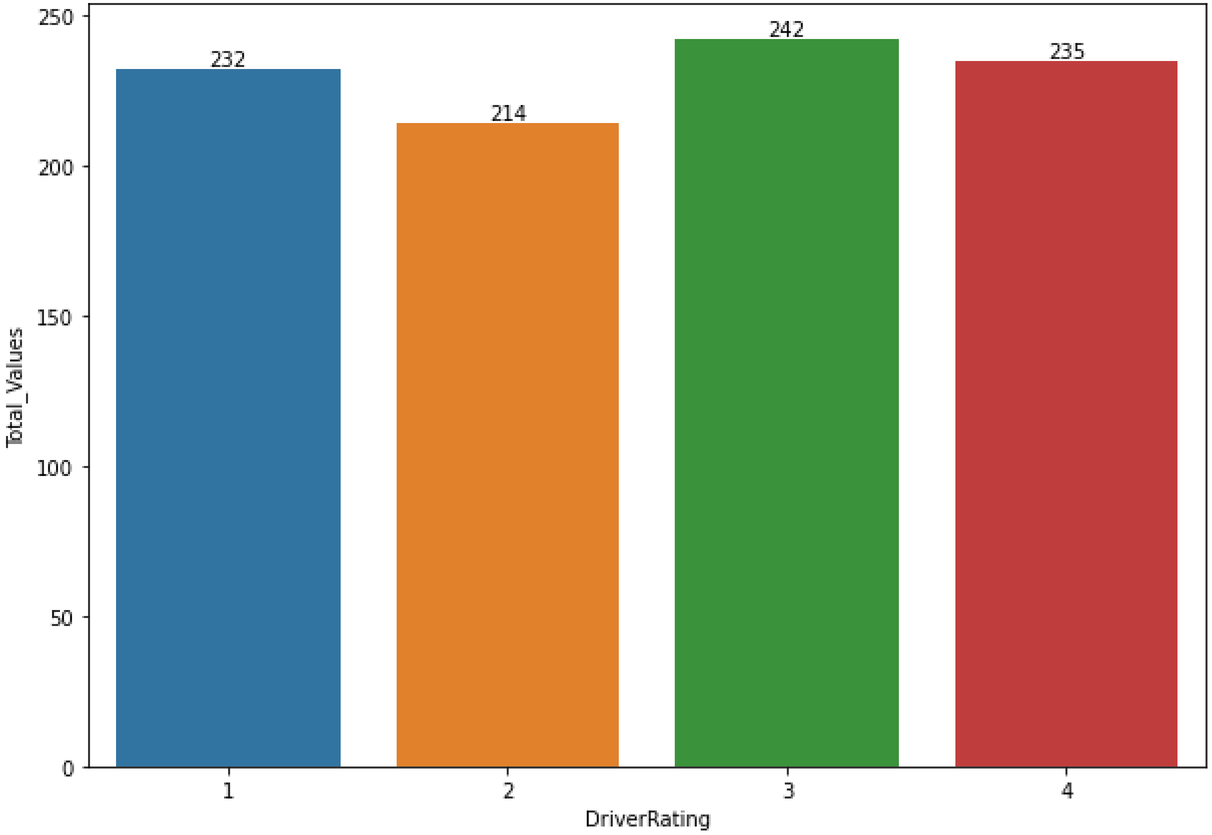
In [89]:

```
DriverRating =df.groupby('FraudFound_P').agg(Total_Values=('DriverRating', 'value_counts')).reset_index()
plt.figure(figsize=(20,7))
ax =sns.barplot(data= DriverRating, x="DriverRating", y="Total_Values" ,hue = "FraudFound_P")
ax.bar_label(ax.containers[1])[0]
ax.bar_label(ax.containers[0])[0]
plt.show()
```

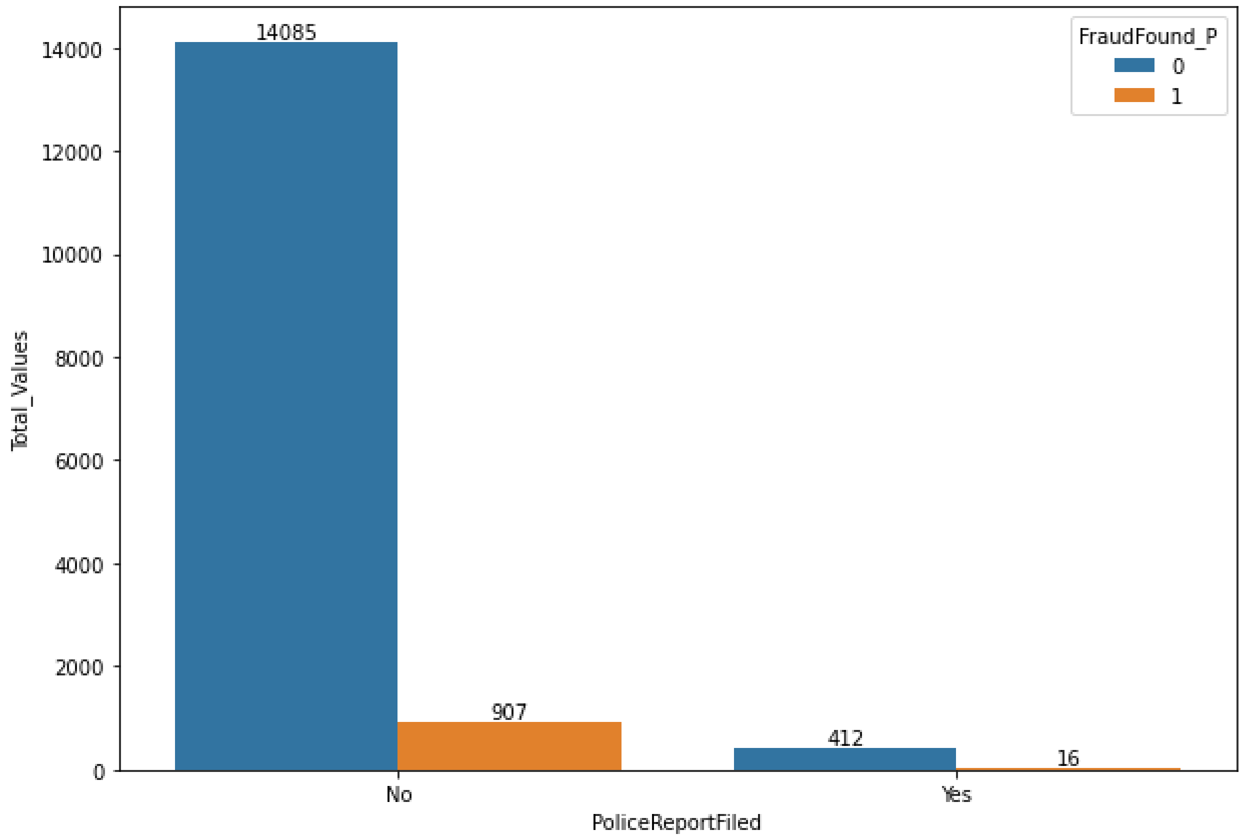


In [90]:

```
Fur_DriverRating = DriverRating[DriverRating.FraudFound_P == 1]
plt.figure(figsize=(10,7))
ax =sns.barplot(data=Fur_DriverRating, x="DriverRating", y="Total_Values" )
ax.bar_label(ax.containers[0])[0]
plt.show()
```

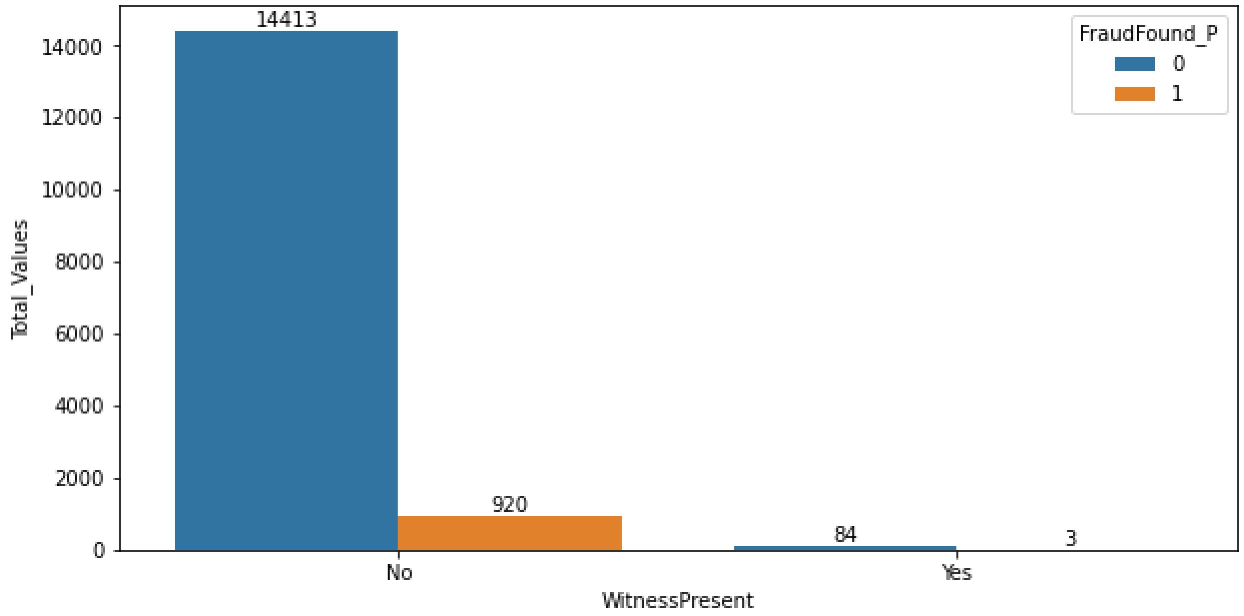


In [91]:
```
PoliceReportFiled =df.groupby('FraudFound_P').agg(Total_Values=('PoliceReportFiled', 'value_counts')).reset_index()
plt.figure(figsize=(10,7))
ax =sns.barplot(data= PoliceReportFiled, x="PoliceReportFiled", y="Total_Values" ,hue = "FraudFound_P")
ax.bar_label(ax.containers[1])[0]
ax.bar_label(ax.containers[0])[0]
plt.show()
```



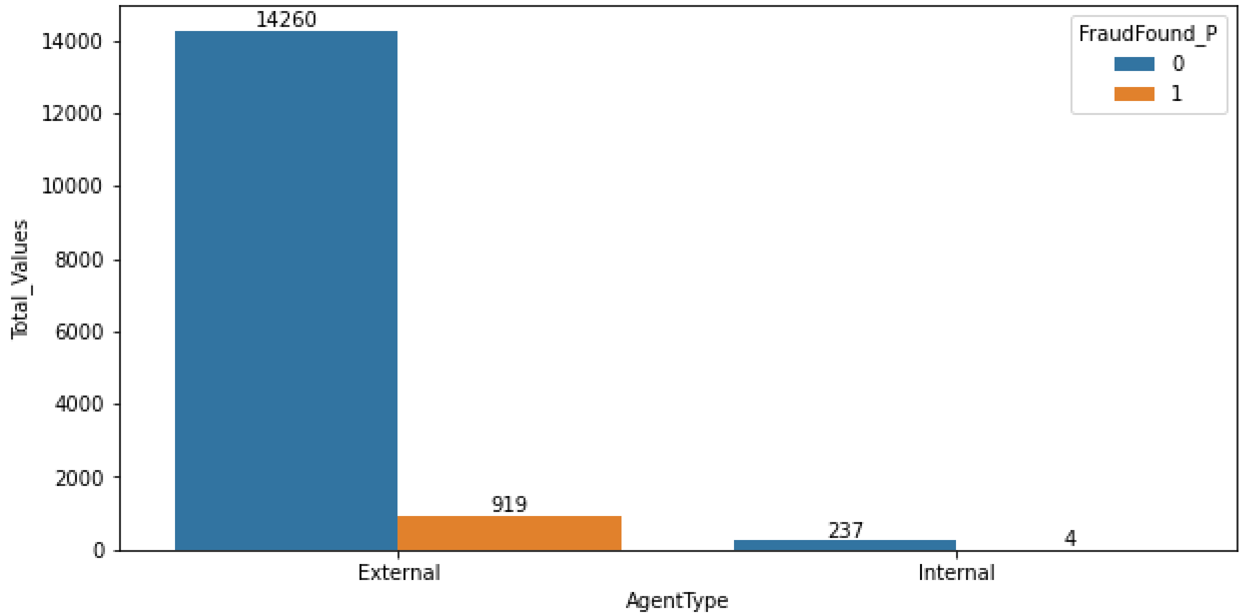
In [92]:

```
WitnessPresent =df.groupby('FraudFound_P').agg(Total_Values=('WitnessPresent', 'value_counts')).reset_index()
plt.figure(figsize=(10,5))
ax =sns.barplot(data= WitnessPresent, x="WitnessPresent", y="Total_Values" ,hue = "FraudFound_P")
ax.bar_label(ax.containers[1])[0]
ax.bar_label(ax.containers[0])[0]
plt.show()
```

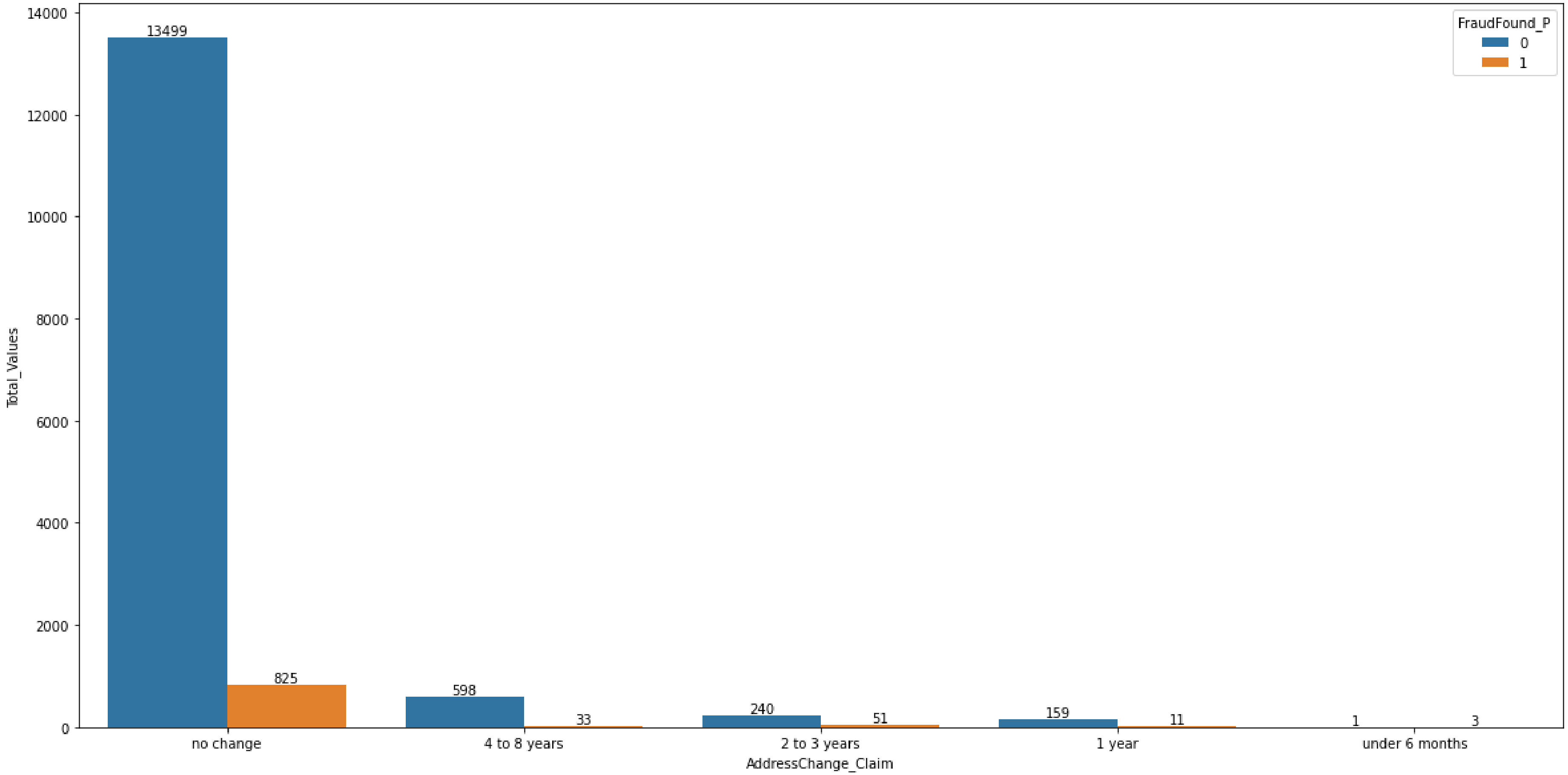


In [93]:

```
AgentType =df.groupby('FraudFound_P').agg(Total_Values=('AgentType', 'value_counts')).reset_index()
plt.figure(figsize=(10,5))
ax =sns.barplot(data= AgentType, x="AgentType", y="Total_Values" ,hue = "FraudFound_P")
ax.bar_label(ax.containers[1])[0]
ax.bar_label(ax.containers[0])[0]
plt.show()
```

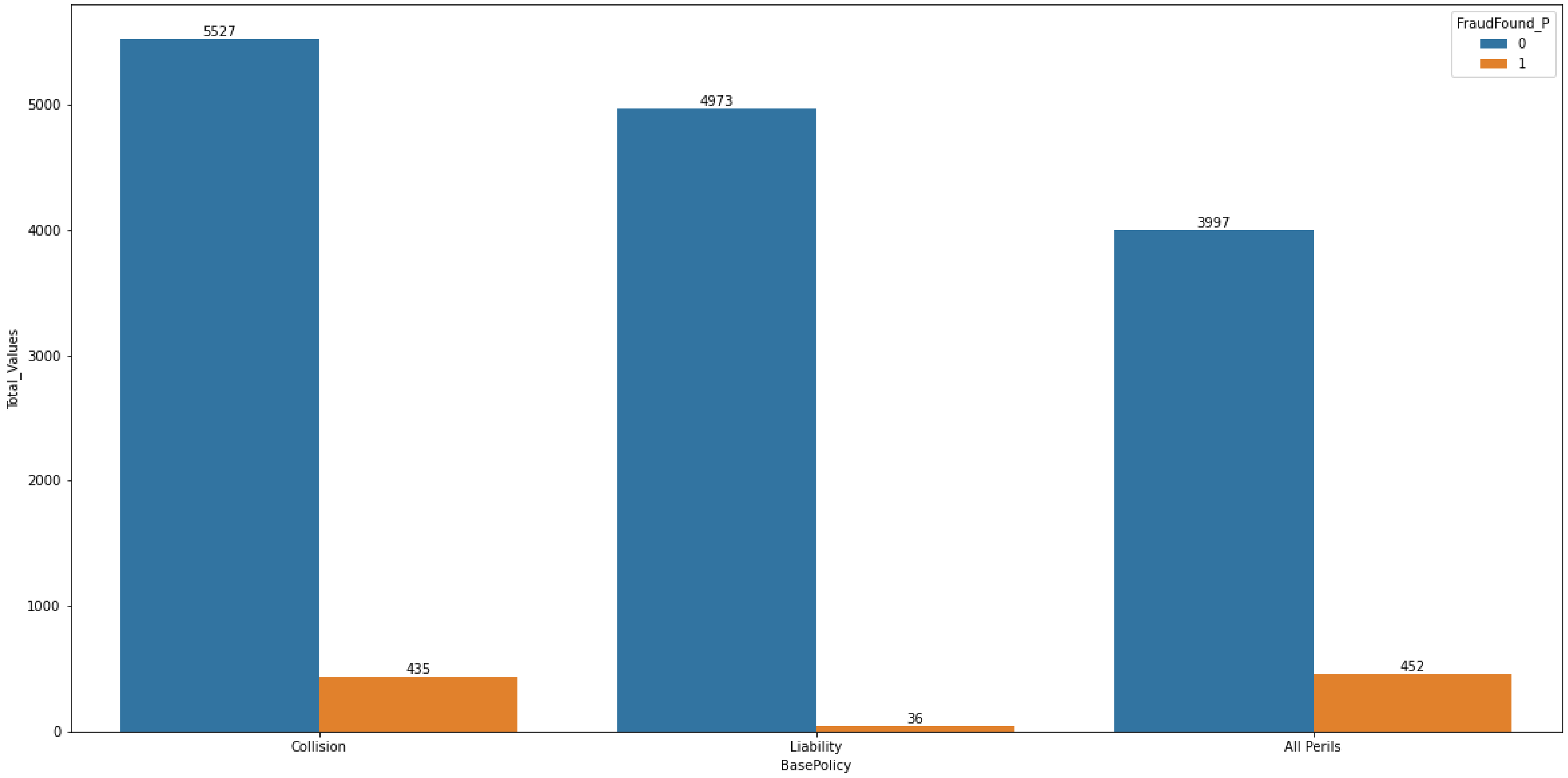


```
In [94]: AddressChange_Claim =df.groupby('FraudFound_P').agg(Total_Values=('AddressChange_Claim', 'value_counts')).reset_index()
         plt.figure(figsize=(20,10))
         ax =sns.barplot(data= AddressChange_Claim, x="AddressChange_Claim", y="Total_Values" ,hue = "FraudFound_P")
         ax.bar_label(ax.containers[1])[0]
         ax.bar_label(ax.containers[0])[0]
         plt.show()
```



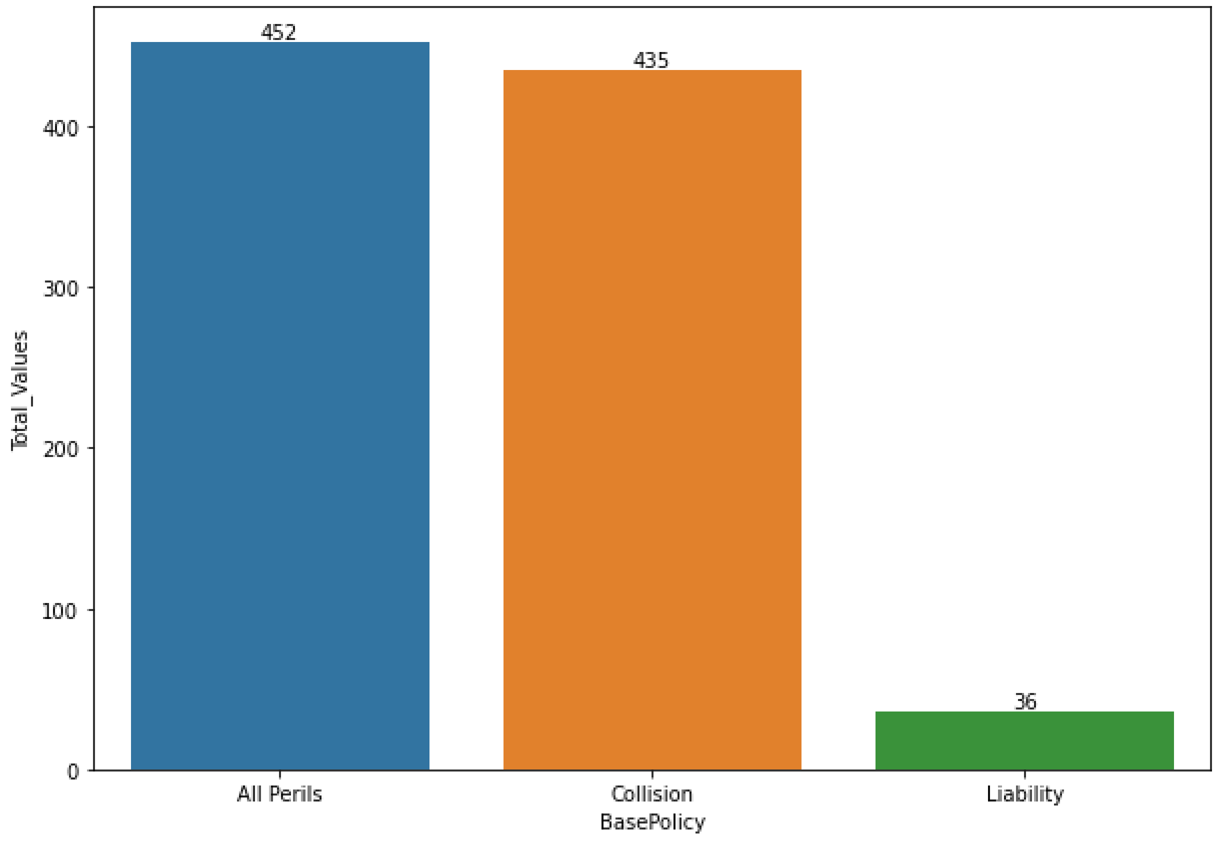
In [95]:

```
BasePolicy = df.groupby('FraudFound_P').agg(Total_Values=('BasePolicy', 'value_counts')).reset_index()
plt.figure(figsize=(20,10))
ax =sns.barplot(data= BasePolicy, x="BasePolicy", y="Total_Values" ,hue = "FraudFound_P")
ax.bar_label(ax.containers[1])[0]
ax.bar_label(ax.containers[0])[0]
plt.show()
```

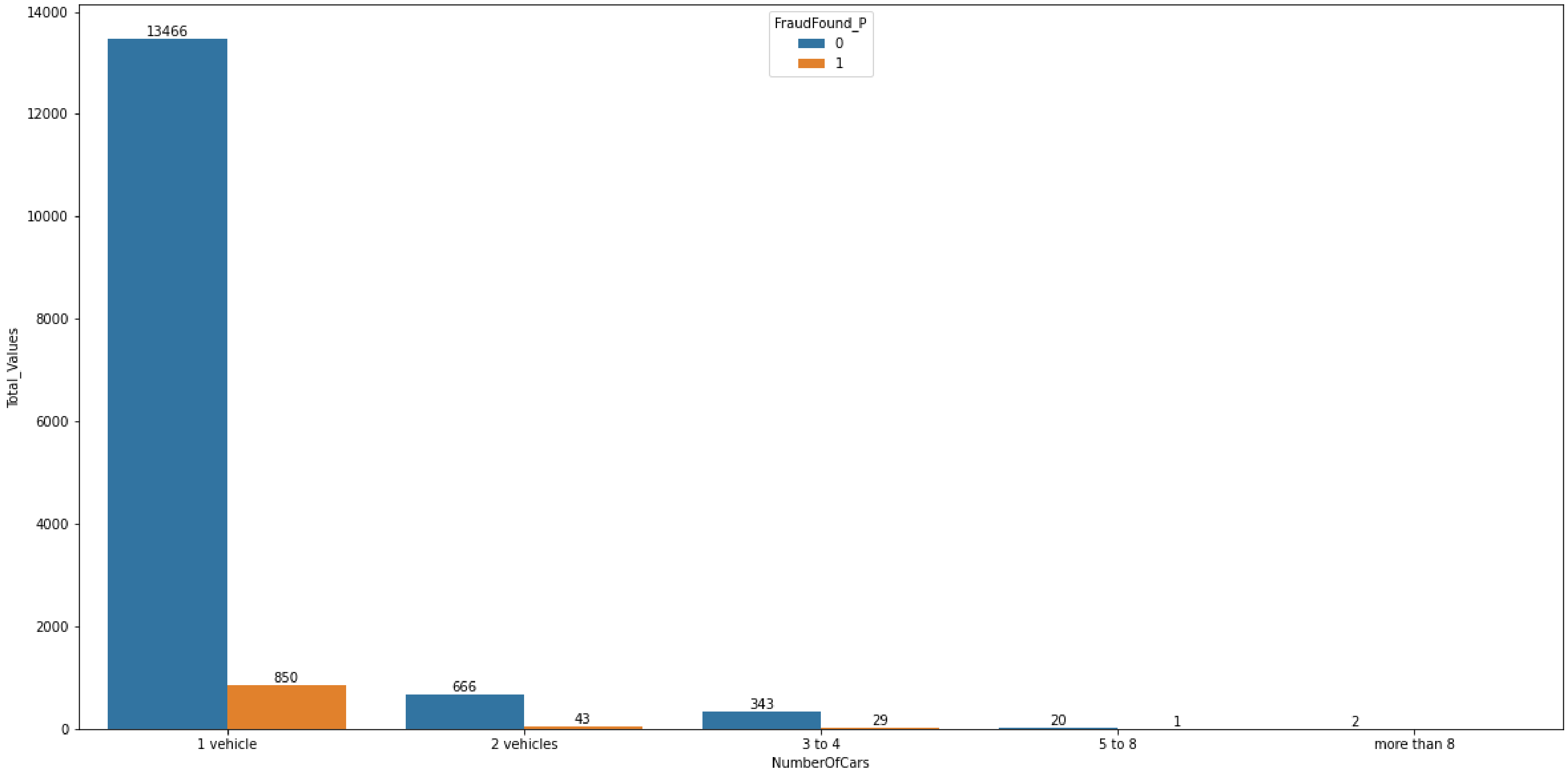


In [96]:

```
Fur_BasePolicy = BasePolicy[BasePolicy.FraudFound_P == 1]
plt.figure(figsize=(10,7))
ax =sns.barplot(data=Fur_BasePolicy, x="BasePolicy", y="Total_Values" )
ax.bar_label(ax.containers[0])[0]
plt.show()
```



```
In [97]: NumberOfCars = df.groupby('FraudFound_P').agg(Total_Values=('NumberOfCars', 'value_counts')).reset_index()
         plt.figure(figsize=(20,10))
         ax =sns.barplot(data= NumberOfCars, x="NumberOfCars", y="Total_Values" ,hue = "FraudFound_P")
         ax.bar_label(ax.containers[1])[0]
         ax.bar_label(ax.containers[0])[0]
         plt.show()
```



In [98]:

```
df.groupby('DriverRating').agg(Total_Values = ('Fault',"value_counts")).reset_index()
```

Out[98]:

	DriverRating	Fault	Total_Values
0	1	Policy Holder	2824
1	1	Third Party	1120
2	2	Policy Holder	2802
3	2	Third Party	999
4	3	Policy Holder	2827
5	3	Third Party	1057
6	4	Policy Holder	2777
7	4	Third Party	1014

In [99]:

```
corr_matrix = df.corr()
```

In [100…

```
corr_matrix.FraudFound_P
```

Out[100]:

```
WeekOfMonth           -0.011861
WeekOfMonthClaimed    -0.005761
PolicyNumber          -0.020345
Age                   -0.027389
FraudFound_P           1.000000
RepNumber             -0.007551
Deductible             0.017348
DriverRating           0.007266
Year                  -0.024760
Name: FraudFound_P, dtype: float64
```

Data Pre-Processing

In [101…

```
df.head()
```

Out[101]:

	Month	WeekOfMonth	DayOfWeek	Make	AccidentArea	DayOfWeekClaimed	MonthClaimed	WeekOfMonthClaimed	PolicyNumber	Sex	...	Ag
0	Dec	5	Wednesday	Honda	Urban	Tuesday	Jan	1	1	Female	...	
1	Jan	3	Wednesday	Honda	Urban	Monday	Jan	4	2	Male	...	
2	Oct	5	Friday	Honda	Urban	Thursday	Nov	2	3	Male	...	
3	Jun	2	Saturday	Toyota	Rural	Friday	Jul	1	4	Male	...	r
4	Jan	5	Monday	Honda	Urban	Tuesday	Feb	2	5	Female	...	

5 rows × 33 columns

In [102…

```
df['AccidentArea'].unique()
```

Out[102]:

```
array(['Urban', 'Rural'], dtype=object)
```

In [103…

```
# Converting AccidentArea into numeric :
df.AccidentArea.replace(['Urban', 'Rural'],[0,1],inplace= True)
```

In [104…

```
df['AccidentArea'].unique()
```

Out[104]:

```
array([0, 1], dtype=int64)
```

In [105…

```
df['MonthClaimed'].unique()
```

Out[105]:

```
array(['Jan', 'Nov', 'Jul', 'Feb', 'Mar', 'Dec', 'Apr', 'Aug', 'May',
       'Jun', 'Sep', 'Oct'], dtype=object)
```

In [106…

```
# Converting data in Numeric
df.MonthClaimed.replace(['Jan', 'Nov', 'Jul', 'Feb', 'Mar', 'Dec', 'Apr', 'Aug', 'May',
       'Jun', 'Sep', 'Oct'],[1,11,7,2,3,12,4,8,5,6,9,10],inplace= True)
```

In [107…

```
df['MonthClaimed'].unique()
```

Out[107]:

```
array([ 1, 11,  7,  2,  3, 12,  4,  8,  5,  6,  9, 10], dtype=int64)
```

In [108…

```
df['DayOfWeekClaimed'].unique()
```

Out[108]:
```
array(['Tuesday', 'Monday', 'Thursday', 'Friday', 'Wednesday', 'Saturday',
       'Sunday'], dtype=object)
```

In [109…
```
df['DayOfWeekClaimed'].replace(['Tuesday', 'Monday', 'Thursday', 'Friday', 'Wednesday', 'Saturday',
       'Sunday'],[2,1,4,5,3,6,7],inplace=True)
```

In [110…
```
df['DayOfWeekClaimed'].unique()
```

Out[110]:
```
array([2, 1, 4, 5, 3, 6, 7], dtype=int64)
```

In [111…
```
df['Sex'].replace(['Female', 'Male'],[0,1],inplace=True)
```

In [112…
```
df['Sex'].unique()
```

Out[112]:
```
array([0, 1], dtype=int64)
```

In [113…
```
df.Fault.unique()
```

Out[113]:
```
array(['Policy Holder', 'Third Party'], dtype=object)
```

In [114…
```
# Converting Into Numeric
df.Fault.replace(['Policy Holder', 'Third Party'],[0,1],inplace = True)
```

In [115…
```
df.Fault.unique()
```

Out[115]:
```
array([0, 1], dtype=int64)
```

In [116…
```
df.DayOfWeek.unique()
```

Out[116]:
```
array(['Wednesday', 'Friday', 'Saturday', 'Monday', 'Tuesday', 'Sunday',
       'Thursday'], dtype=object)
```

In [117…
```
df['DayOfWeek'].replace(['Tuesday', 'Monday', 'Thursday', 'Friday', 'Wednesday', 'Saturday',
       'Sunday'],[2,1,4,5,3,6,7],inplace=True)
```

In [118…
```
df.DayOfWeek.unique()
```

Out[118]:
```
array([3, 5, 6, 1, 2, 7, 4], dtype=int64)
```

In [119…

```
df.MaritalStatus.unique()
```

Out[119]:

```
array(['Single', 'Married', 'Widow', 'Divorced'], dtype=object)
```

In [120…

```
df['Month'].unique()
```

Out[120]:

```
array(['Dec', 'Jan', 'Oct', 'Jun', 'Feb', 'Nov', 'Apr', 'Mar', 'Aug',
       'Jul', 'May', 'Sep'], dtype=object)
```

In [121…

```
# Converting data in Numeric
df.Month.replace(['Jan', 'Nov', 'Jul', 'Feb', 'Mar', 'Dec', 'Apr', 'Aug', 'May',
       'Jun', 'Sep', 'Oct'],[1,11,7,2,3,12,4,8,5,6,9,10],inplace= True)
```

In [122…

```
df['Month'].unique()
```

Out[122]:

```
array([12,  1, 10,  6,  2, 11,  4,  3,  8,  7,  5,  9], dtype=int64)
```

In [123…

```
df.Days_Policy_Accident.unique()
```

Out[123]:

```
array(['more than 30', '15 to 30', '1 to 7', '8 to 15'], dtype=object)
```

In [124…

```
# Converting data in Numeric
df.Days_Policy_Accident.replace(['more than 30', '15 to 30', '1 to 7', '8 to 15'],[35,30,7,15],inplace= True)
```

In [ ]:

```

```

In [125…

```
df.AgeOfVehicle.unique()
```

Out[125]:

```
array(['3 years', '6 years', '7 years', 'more than 7', '5 years', 'new',
       '4 years', '2 years'], dtype=object)
```

In [126…

```
# Converting data in Numeric
df.AgeOfVehicle.replace(['3 years', '6 years', '7 years', 'more than 7', '5 years', 'new',
       '4 years', '2 years'],[3,6,7,8,5,0,4,2],inplace= True)
```

In [127…

```
df.Days_Policy_Claim.unique()
```

Out[127]:

```
array(['more than 30', '15 to 30', '8 to 15', 'none'], dtype=object)
```

In [128…

```
# Converting data in Numeric
df.Days_Policy_Claim.replace(['more than 30', '15 to 30', 'none', '8 to 15'],[35,30,0,15],inplace= True)
```

In [129…

```
df.PoliceReportFiled.unique()
```

Out[129]:

```
array(['No', 'Yes'], dtype=object)
```

In [130…

```
df.PoliceReportFiled.replace(['No', 'Yes'],[0,1],inplace= True)
```

In [131…

```
df.WitnessPresent.unique()
```

Out[131]:

```
array(['No', 'Yes'], dtype=object)
```

In [132…

```
df.WitnessPresent.replace(['No', 'Yes'],[0,1],inplace= True)
```

In [133…

```
df.AgentType.unique()
```

Out[133]:

```
array(['External', 'Internal'], dtype=object)
```

In [134…

```
# Converting data in Numeric
df.AgentType.replace(['External', 'Internal'],[0,1],inplace= True)
```

In [135…

```
df.NumberOfSuppliments.unique()
```

Out[135]:

```
array(['none', 'more than 5', '3 to 5', '1 to 2'], dtype=object)
```

In [136…

```
# Converting data in Numeric
df.NumberOfSuppliments.replace(['none', 'more than 5', '3 to 5', '1 to 2'],[0,6,5,3],inplace= True)
```

In [137…

```
df.AddressChange_Claim.unique()
```

Out[137]:

```
array(['1 year', 'no change', '4 to 8 years', '2 to 3 years',
       'under 6 months'], dtype=object)
```

In [138…

```
# Converting data in Numeric
df.AddressChange_Claim.replace(['1 year', 'no change', '4 to 8 years', '2 to 3 years',
       'under 6 months'],[1,0,8,3,0.6],inplace= True)
```

In [139…

```
df.NumberOfCars.unique()
```

Out[139]:

```
array(['3 to 4', '1 vehicle', '2 vehicles', '5 to 8', 'more than 8'],
      dtype=object)
```

In [140…

```
# Converting data in Numeric
df.NumberOfCars.replace(['3 to 4', '1 vehicle', '2 vehicles', '5 to 8', 'more than 8'],[4,1,2,8,9],inplace= True)
```

In [141…

```
df.NumberOfCars.unique()
```

Out[141]:

```
array([4, 1, 2, 8, 9], dtype=int64)
```

In [142…

```
corr = df.corr()
```

In [143…

```
corr.FraudFound_P
```

Out[143]:

```
Month                  -0.027278
WeekOfMonth            -0.011861
DayOfWeek               0.017452
AccidentArea            0.033499
DayOfWeekClaimed        0.007994
MonthClaimed           -0.028955
WeekOfMonthClaimed     -0.005761
PolicyNumber           -0.020345
Sex                     0.029953
Age                    -0.027389
Fault                  -0.131389
FraudFound_P            1.000000
RepNumber              -0.007551
Deductible              0.017348
DriverRating            0.007266
Days_Policy_Accident   -0.007185
Days_Policy_Claim      -0.014897
AgeOfVehicle           -0.032742
PoliceReportFiled      -0.016007
WitnessPresent         -0.008057
AgentType              -0.022978
NumberOfSuppliments    -0.032310
AddressChange_Claim     0.010940
NumberOfCars            0.008680
Year                   -0.024760
Name: FraudFound_P, dtype: float64
```

In [144…

```
ohe = pd.get_dummies(df[['Make', 'MaritalStatus','PolicyType','VehicleCategory','VehiclePrice','PastNumberOfClaims',
                         "BasePolicy"]])
```

In [145…

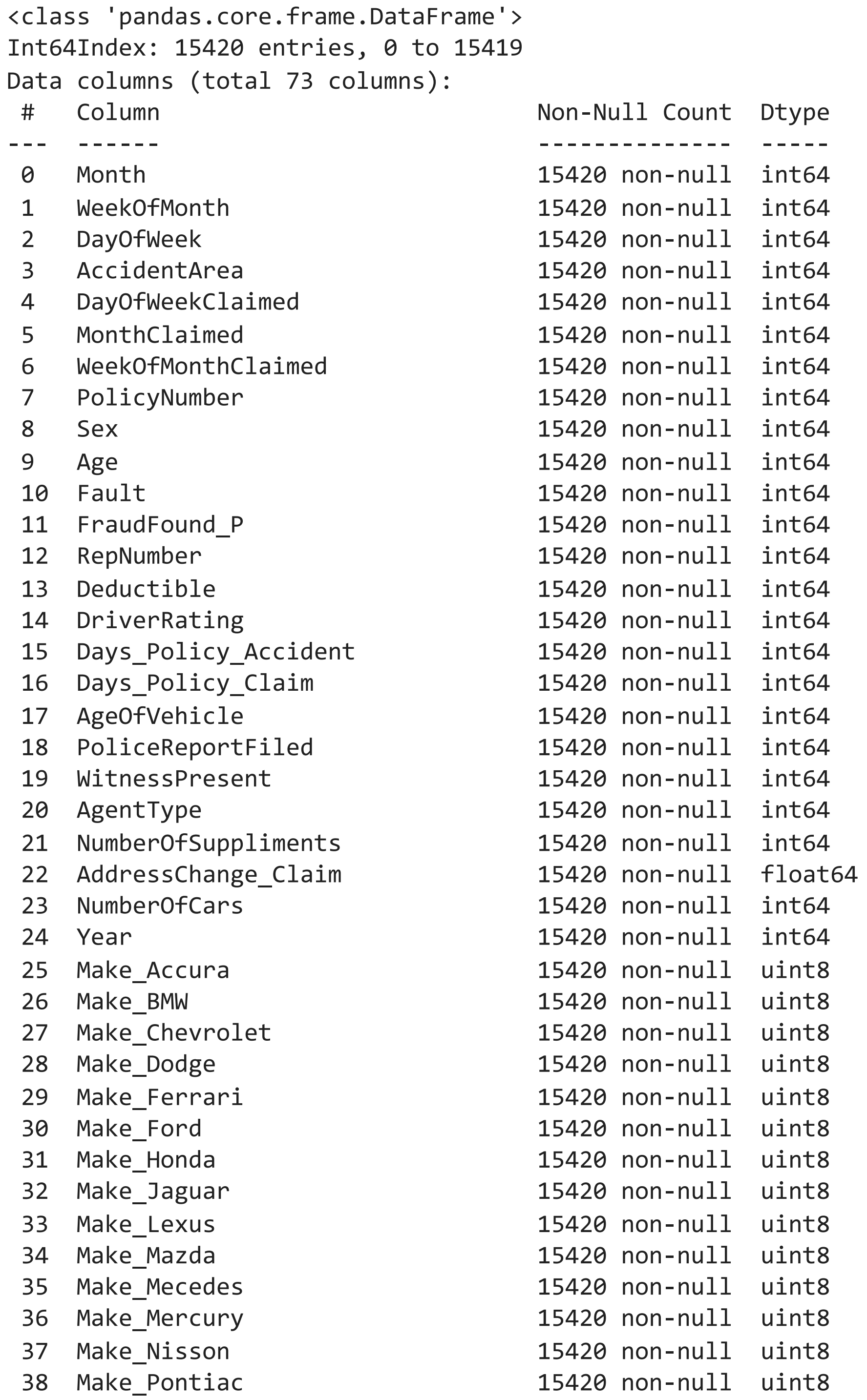
```
m_df=pd.concat([df, ohe], axis=1)
```

In [146…

```
m_df.drop(['Make', 'MaritalStatus','PolicyType','VehicleCategory','VehiclePrice','PastNumberOfClaims',
                         "BasePolicy",'AgeOfPolicyHolder'], axis=1, inplace=True)
```

In [147…

```
m_df.info()
```



```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15420 entries, 0 to 15419
Data columns (total 73 columns):
 #   Column                            Non-Null Count  Dtype  
---  ------                            --------------  -----  
 0   Month                             15420 non-null  int64  
 1   WeekOfMonth                       15420 non-null  int64  
 2   DayOfWeek                         15420 non-null  int64  
 3   AccidentArea                      15420 non-null  int64  
 4   DayOfWeekClaimed                  15420 non-null  int64  
 5   MonthClaimed                      15420 non-null  int64  
 6   WeekOfMonthClaimed                15420 non-null  int64  
 7   PolicyNumber                      15420 non-null  int64  
 8   Sex                               15420 non-null  int64  
 9   Age                               15420 non-null  int64  
 10  Fault                             15420 non-null  int64  
 11  FraudFound_P                      15420 non-null  int64  
 12  RepNumber                         15420 non-null  int64  
 13  Deductible                        15420 non-null  int64  
 14  DriverRating                      15420 non-null  int64  
 15  Days_Policy_Accident              15420 non-null  int64  
 16  Days_Policy_Claim                 15420 non-null  int64  
 17  AgeOfVehicle                      15420 non-null  int64  
 18  PoliceReportFiled                 15420 non-null  int64  
 19  WitnessPresent                    15420 non-null  int64  
 20  AgentType                         15420 non-null  int64  
 21  NumberOfSuppliments               15420 non-null  int64  
 22  AddressChange_Claim               15420 non-null  float64
 23  NumberOfCars                      15420 non-null  int64  
 24  Year                              15420 non-null  int64  
 25  Make_Accura                       15420 non-null  uint8  
 26  Make_BMW                          15420 non-null  uint8  
 27  Make_Chevrolet                    15420 non-null  uint8  
 28  Make_Dodge                        15420 non-null  uint8  
 29  Make_Ferrari                      15420 non-null  uint8  
 30  Make_Ford                         15420 non-null  uint8  
 31  Make_Honda                        15420 non-null  uint8  
 32  Make_Jaguar                       15420 non-null  uint8  
 33  Make_Lexus                        15420 non-null  uint8  
 34  Make_Mazda                        15420 non-null  uint8  
 35  Make_Mecedes                      15420 non-null  uint8  
 36  Make_Mercury                      15420 non-null  uint8  
 37  Make_Nisson                       15420 non-null  uint8  
 38  Make_Pontiac                      15420 non-null  uint8  
 39  Make_Porche                      15420 non-null  uint8
 40  Make_Saab                        15420 non-null  uint8
 41  Make_Saturn                      15420 non-null  uint8
 42  Make_Toyota                      15420 non-null  uint8
 43  Make_VW                          15420 non-null  uint8
 44  MaritalStatus_Divorced           15420 non-null  uint8
 45  MaritalStatus_Married            15420 non-null  uint8
 46  MaritalStatus_Single             15420 non-null  uint8
 47  MaritalStatus_Widow              15420 non-null  uint8
 48  PolicyType_Sedan - All Perils    15420 non-null  uint8
 49  PolicyType_Sedan - Collision     15420 non-null  uint8
 50  PolicyType_Sedan - Liability     15420 non-null  uint8
 51  PolicyType_Sport - All Perils    15420 non-null  uint8
 52  PolicyType_Sport - Collision     15420 non-null  uint8
 53  PolicyType_Sport - Liability     15420 non-null  uint8
 54  PolicyType_Utility - All Perils  15420 non-null  uint8
 55  PolicyType_Utility - Collision   15420 non-null  uint8
 56  PolicyType_Utility - Liability   15420 non-null  uint8
 57  VehicleCategory_Sedan            15420 non-null  uint8
 58  VehicleCategory_Sport            15420 non-null  uint8
 59  VehicleCategory_Utility          15420 non-null  uint8
 60  VehiclePrice_20000 to 29000      15420 non-null  uint8
 61  VehiclePrice_30000 to 39000      15420 non-null  uint8
 62  VehiclePrice_40000 to 59000      15420 non-null  uint8
 63  VehiclePrice_60000 to 69000      15420 non-null  uint8
 64  VehiclePrice_less than 20000     15420 non-null  uint8
 65  VehiclePrice_more than 69000     15420 non-null  uint8
 66  PastNumberOfClaims_1             15420 non-null  uint8
 67  PastNumberOfClaims_2 to 4        15420 non-null  uint8
 68  PastNumberOfClaims_more than 4   15420 non-null  uint8
 69  PastNumberOfClaims_none          15420 non-null  uint8
 70  BasePolicy_All Perils            15420 non-null  uint8
 71  BasePolicy_Collision             15420 non-null  uint8
 72  BasePolicy_Liability             15420 non-null  uint8
dtypes: float64(1), int64(24), uint8(48)
memory usage: 3.8 MB
```

Importing ML models

Our data is Imbalance so we try diffrent method the resolve this issue

Under Sampling

In [148…

```
legit = m_df[m_df.FraudFound_P == 0]
fraud = m_df[m_df.FraudFound_P == 1]
```

In [149…

```
legit.shape,fraud.shape
```

Out[149]:

```
((14497, 73), (923, 73))
```

In [150…

```
legit_sample = legit.sample(n = 923)
```

In [151…

```
legit_sample.shape
```

Out[151]:

```
(923, 73)
```

In [152…

```
final_df = pd.concat([legit_sample,fraud ],axis=0)
```

In [153…

```
final_df.shape
```

Out[153]:

```
(1846, 73)
```

In [154…

```
x = final_df.drop('FraudFound_P',axis =1)
y = final_df.FraudFound_P
```

In [155…

```
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size = 0.3, random_state = 2345)
```

Logistic Regression

In [156…

```
from sklearn.linear_model import LogisticRegression
```

In [157…

```
logr = LogisticRegression()
```

In [158…

```
logr.fit(x_train, y_train)
```

Out[158]:

```
LogisticRegression()
```

In [159…

```
y_pred = logr.predict(x_test)
```

In [160…

```
from sklearn.metrics import classification_report
```

In [161…

```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.69      0.68      0.68       266
           1       0.71      0.72      0.71       288

    accuracy                           0.70       554
   macro avg       0.70      0.70      0.70       554
weighted avg       0.70      0.70      0.70       554
```

In [162…

```
from sklearn.metrics import confusion_matrix, accuracy_score
```

In [163…

```
confusion_matrix(y_test,y_pred)
```

Out[163]:

```
array([[180,  86],
       [ 80, 208]], dtype=int64)
```

Random Forest

In [164…

```
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.preprocessing import StandardScaler , MinMaxScaler
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix , accuracy_score
from sklearn.ensemble import RandomForestClassifier
```

In [165…

```
x_train , x_test , y_train , y_test = train_test_split(x ,y, test_size=0.2 , random_state = 134)
```

In [166…

```
from sklearn.ensemble import RandomForestClassifier
```

In [167…

```
rf = RandomForestClassifier()
```

In [168…

```
rf.fit(x_train, y_train)
```

Out[168]:

```
RandomForestClassifier()
```

In [169…

```
y_pred=rf.predict(x_test)
```

In [170…

```
accuracy_score(y_test,y_pred)
```

Out[170]:

```
0.7648648648648648
```

In [171…

```
print(metrics.classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.81      0.67      0.74       181
           1       0.73      0.85      0.79       189

    accuracy                           0.76       370
   macro avg       0.77      0.76      0.76       370
weighted avg       0.77      0.76      0.76       370
```

Over sampling

In [172…

```
x = m_df.drop('FraudFound_P',axis =1)
y = m_df.FraudFound_P
```

In [173…

```
from imblearn.combine import SMOTETomek
```

In [174…

```
smk = SMOTETomek(random_state=42)
x,y = smk.fit_resample(x,y)
```

In [175…

```
x.shape,y.shape
```

Out[175]:

```
((28576, 72), (28576,))
```

In [176…

```
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size = 0.3, random_state = 2345)
```

Logistic Regression

In [177…

```
logr = LogisticRegression()
```

In [178…

```
logr.fit(x_train, y_train)
```

Out[178]:

```
LogisticRegression()
```

In [179…

```
y_pred = logr.predict(x_test)
```

In [180…

```
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.80      0.79      0.80      4280
           1       0.80      0.81      0.80      4293

    accuracy                           0.80      8573
   macro avg       0.80      0.80      0.80      8573
weighted avg       0.80      0.80      0.80      8573
```

In [181…

```
confusion_matrix(y_test,y_pred)
```

Out[181]:

```
array([[3395,  885],
       [ 825, 3468]], dtype=int64)
```

Random Forest

In [182…

```
x_train , x_test , y_train , y_test = train_test_split(x ,y, test_size=0.2 , random_state = 134)
```

In [183…

```
rf = RandomForestClassifier()
```

In [184…

```
rf.fit(x_train, y_train)
```

Out[184]:

```
RandomForestClassifier()
```

In [185…

```
y_pred=rf.predict(x_test)
```

In [186…

```
accuracy_score(y_test,y_pred)
```

```
Out[186]: 0.9681595521343597
```

```
In [187…  print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.94      1.00      0.97      2822
           1       1.00      0.94      0.97      2894

    accuracy                           0.97      5716
   macro avg       0.97      0.97      0.97      5716
weighted avg       0.97      0.97      0.97      5716
```

- As usual Random Forest is best algorithm with the combination of over Sampling.