OLA DRIVER ATTRITION ANALYSIS:

PROBLEM STATEMENT:

Ola struggles with a high churn rate among its drivers and it’s very easy for drivers to stop working for the service on the fly or jump to Uber depending on the rates, which leads to:

-Increased hiring cost.

-Lower operational efficency.

-Disrupted customer service quality.

PROJECT OBJECTIVE:

Use information for a segment of drivers for 2019 and 2020 to:

-Identify attrition pattern.

-Predict whether a driver is likely to leave.

-Provide actionable retention strategies.

DATA EXPLORATION:

In [32]:

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

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, roc_auc_score, roc_curve, c
```

In [33]:

```
import io
import pandas as pd
df = pd.read_csv(r"C:\Users\Swati Negi\Downloads\ola_driver.csv")
df
```

Out[33]:

	Unnamed: 0	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Incom
0	0	01/01/19	1	28.0	0.0	C23	2	5738
1	1	02/01/19	1	28.0	0.0	C23	2	5738
2	2	03/01/19	1	28.0	0.0	C23	2	5738
3	3	11/01/20	2	31.0	0.0	C7	2	6701
4	4	12/01/20	2	31.0	0.0	C7	2	6701
...	...	...	...	...	...	...	...	.
19099	19099	08/01/20	2788	30.0	0.0	C27	2	7025
19100	19100	09/01/20	2788	30.0	0.0	C27	2	7025
19101	19101	10/01/20	2788	30.0	0.0	C27	2	7025
19102	19102	11/01/20	2788	30.0	0.0	C27	2	7025
19103	19103	12/01/20	2788	30.0	0.0	C27	2	7025

19104 rows × 14 columns

INSPECTION OF THE DATA

In [34]:

```
df.shape
```

Out[34]: (19104, 14)

In [35]:

```
df.dtypes
```

Out[35]:
```
Unnamed: 0               int64
MMM-YY                  object
Driver_ID                int64
Age                    float64
Gender                 float64
City                    object
Education_Level          int64
Income                   int64
Dateofjoining           object
LastWorkingDate         object
Joining Designation      int64
Grade                    int64
Total Business Value     int64
Quarterly Rating         int64
dtype: object
```

CHECK FOR MISSING VALUES

In [36]:
```
df.isnull().sum()
```

Out[36]:
```
Unnamed: 0                  0
MMM-YY                      0
Driver_ID                   0
Age                        61
Gender                     52
City                        0
Education_Level             0
Income                      0
Dateofjoining               0
LastWorkingDate         17488
Joining Designation         0
Grade                       0
Total Business Value        0
Quarterly Rating            0
dtype: int64
```

There are large number of missing values in "lastworkingdate" column but their is no problem regarding it because it states that number of drivers are still active.

STATISTICAL SUMMARY:

In [37]:
```
df.describe()
```

Out[37]:

	Unnamed: 0	Driver_ID	Age	Gender	Education_Level
count	19104.000000	19104.000000	19043.000000	19052.000000	19104.000000
mean	9551.500000	1415.591133	34.668435	0.418749	1.021671
std	5514.994107	810.705321	6.257912	0.493367	0.800167
min	0.000000	1.000000	21.000000	0.000000	0.000000
25%	4775.750000	710.000000	30.000000	0.000000	0.000000
50%	9551.500000	1417.000000	34.000000	0.000000	1.000000
75%	14327.250000	2137.000000	39.000000	1.000000	2.000000
max	19103.000000	2788.000000	58.000000	1.000000	2.000000

NUMBER OF UNIQUE DRIVERS

In [38]:
```
df['Driver_ID'].nunique()
```

Out[38]: 2381

TEMPORAL ANALYSIS

In [59]:
```
df['Dateofjoining'] = pd.to_datetime(df['Dateofjoining'], errors='coerce')
df['LastWorkingDate'] = pd.to_datetime(df['LastWorkingDate'], errors='coerce')
```

Number of drivers joined and left each month

In [40]:
```
df['JoinMonth'] = df['Dateofjoining'].dt.to_period('M')
df['LeaveMonth'] = df['LastWorkingDate'].dt.to_period('M')

join_counts = df['JoinMonth'].value_counts().sort_index()
print(join_counts)

leave_counts = df['LeaveMonth'].value_counts().sort_index()
print(leave_counts)
```

```
JoinMonth
2013-04     31
2013-05     24
2013-06     59
2013-07     63
2013-08     33
          ...
2020-08    325
2020-09    314
2020-10    139
2020-11     93
2020-12     59
Freq: M, Name: count, Length: 85, dtype: int64
LeaveMonth
2018-12      5
2019-01     82
2019-02     85
2019-03     75
2019-04     49
2019-05     98
2019-06     61
2019-07     48
2019-08     53
2019-09     79
2019-10     70
2019-11     69
2019-12     56
2020-01     70
2020-02     70
2020-03     58
2020-04     42
2020-05     63
2020-06     77
2020-07    141
2020-08      4
2020-09     66
2020-10     62
2020-11     73
2020-12     60
Freq: M, Name: count, dtype: int64
```

Average tenure of drivers

In [41]:
```
df['LastDate'] = df['LastWorkingDate'].fillna(df['MMM-YY'])
df['Tenure_Days'] = (df['LastDate'] - df['Dateofjoining']).dt.days
df['Tenure_Days'].mean() / 30
```

Out[41]:
```
19.73729934394193
```

DATA PREPROCESSING

FEATURE ENGINEERING:

Target variable to indicate whether a driver has left the company based on LastWorkingDate?

In [42]:
```
df['Attrition'] = df['LastWorkingDate'].notna().astype(int)
print(df['Attrition'])
```

```
0        0
1        0
2        1
3        0
4        0
        ..
19099    0
19100    0
19101    0
19102    0
19103    0
Name: Attrition, Length: 19104, dtype: int32
```

If it shows 1 then it means driver has left the ola or if it shows 0 then driver is still active.

Tenure or duration of employment

In [43]:
```
df['Tenure_Days'] = (df['LastDate']-df['Dateofjoining'])
print(df['Tenure_Days'])
```

```
0         8 days
1        39 days
2        77 days
3        -5 days
4        25 days
          ...
19099    54 days
19100    85 days
19101   115 days
19102   146 days
19103   176 days
Name: Tenure_Days, Length: 19104, dtype: timedelta64[ns]
```

Changes of drivers rating and income

In [44]:
```
df.sort_values(by=['Driver_ID','MMM-YY'],inplace = True)

df['Prev_Rating'] = df.groupby('Driver_ID')['Quarterly Rating'].shift(1)
df['Rating_Increased'] = (df['Quarterly Rating']> df['Prev_Rating'])
```

```
print(df['Rating_Increased'])
```

```
0        False
1        False
2        False
3        False
4        False
         ...
19099    False
19100    False
19101    False
19102    False
19103    False
Name: Rating_Increased, Length: 19104, dtype: bool
```

In [45]:
```
df['Prev_Income'] = df.groupby('Driver_ID')['Income'].shift(1)
df['Income_Increased'] = (df['Income']>df['Prev_Income'])
print(df['Income_Increased'])
```

```
0        False
1        False
2        False
3        False
4        False
         ...
19099    False
19100    False
19101    False
19102    False
19103    False
Name: Income_Increased, Length: 19104, dtype: bool
```

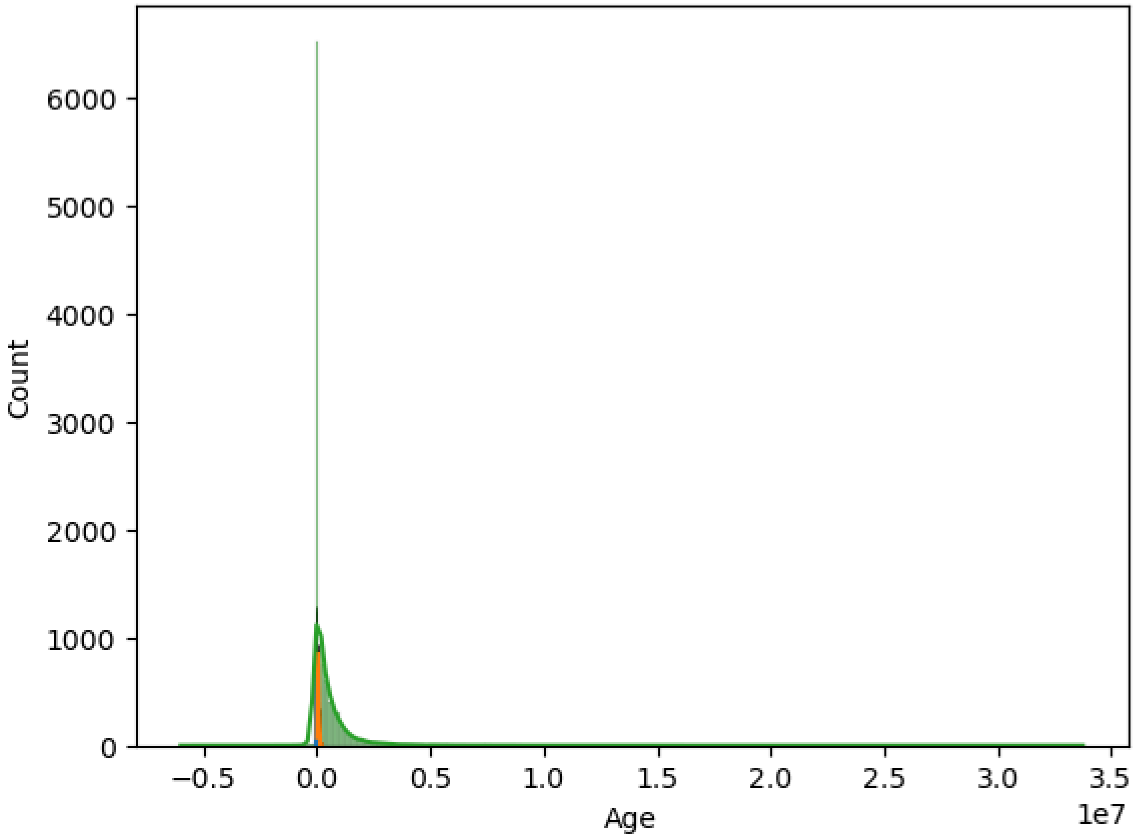
EDA (EXPLORATORY DATA ANALYSIS)

Distributions of Age, Income, and Total Business Value

In [46]:
```
sns.histplot(df['Age'],kde=True)
sns.histplot(df['Income'],kde=True)
sns.histplot(df['Total Business Value'],kde=True)
```

```
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarn
ing: use_inf_as_na option is deprecated and will be removed in a future versio
n. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarn
ing: use_inf_as_na option is deprecated and will be removed in a future versio
n. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarn
ing: use_inf_as_na option is deprecated and will be removed in a future versio
n. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```

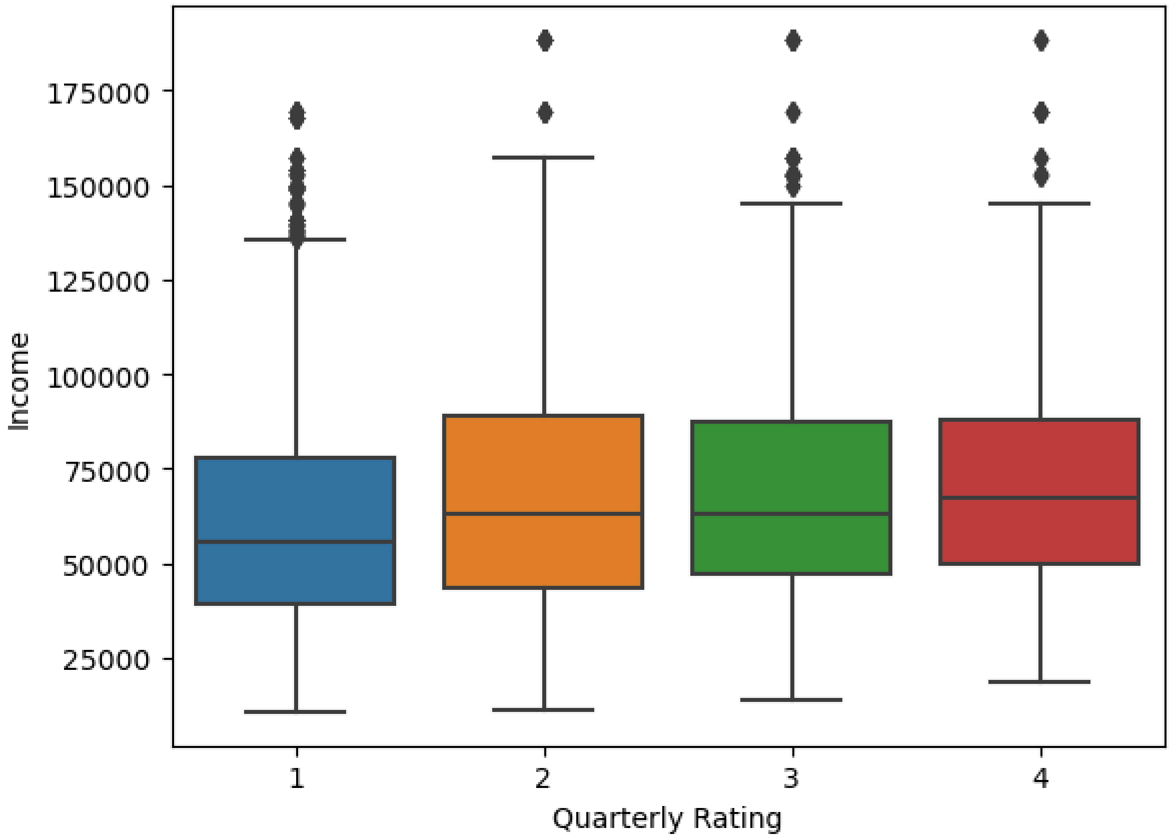
Out[46]:
```
<Axes: xlabel='Age', ylabel='Count'>
```



Quarterly Rating vary across different drivers and time periods

In [47]:
```
sns.boxplot(x='Quarterly Rating', y= 'Income', data = df)
```

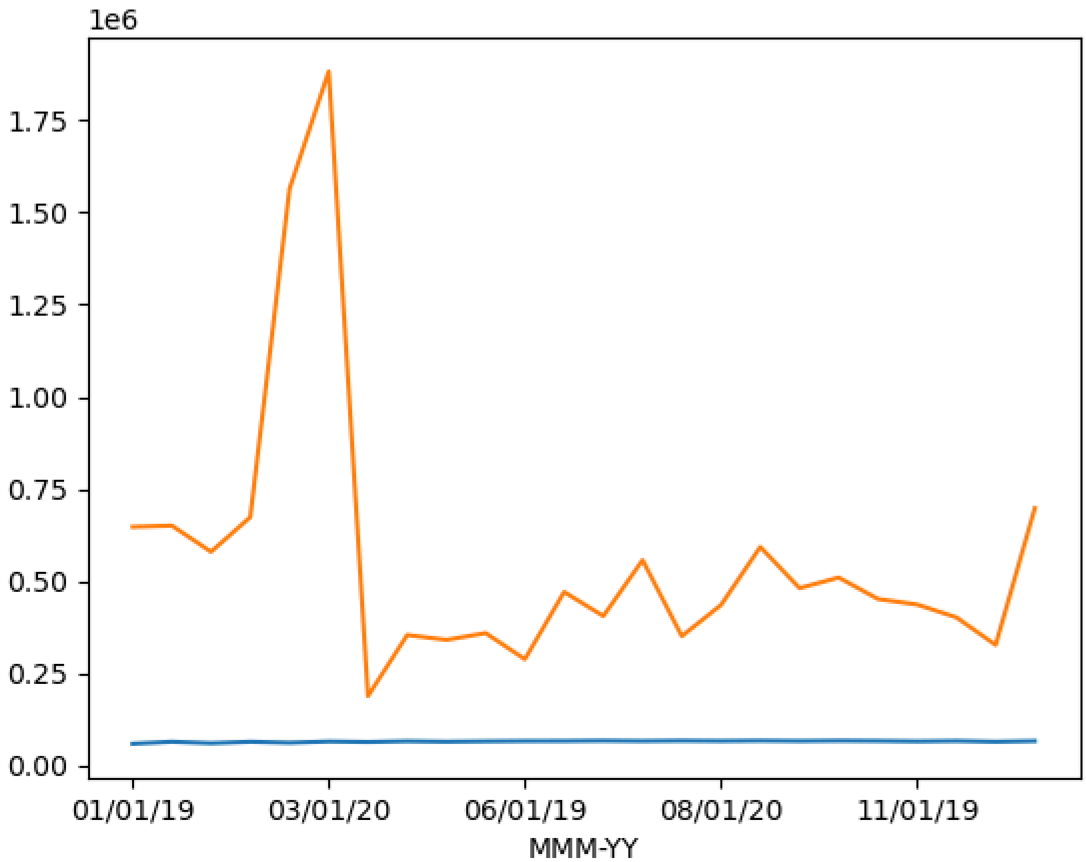
Out[47]: <Axes: xlabel='Quarterly Rating', ylabel='Income'>



Trends or patterns in the monthly income or business value acquired

In [48]:
```
df.groupby('MMM-YY')['Income'].mean().plot()
df.groupby('MMM-YY')['Total Business Value'].mean().plot()
```

Out[48]:
```
<Axes: xlabel='MMM-YY'>
```



Missing Values Handling:

In 'LastWorkingDate' their are many missing values but it is used to define the attrrition part for the projects, so we don't need to handle this type of missing values.

Other missing values like "Age" and "Gender" can be imputed using:

In [54]:
```
df['Age'].fillna(df['Age'].median(),inplace = True)
```

In [55]:
```
df['Gender'].fillna(df['Gender'].median(),inplace = True)
```

Correlation and Relationships

Correlation between Age and Income

In [56]:
```
df[['Age','Income']].corr()
```

Out[56]:

	Age	Income
Age	1.000000	0.190995
Income	0.190995	1.000000

Weak correlation between Age and Income

How do Education_Level and City affect Total Business Value

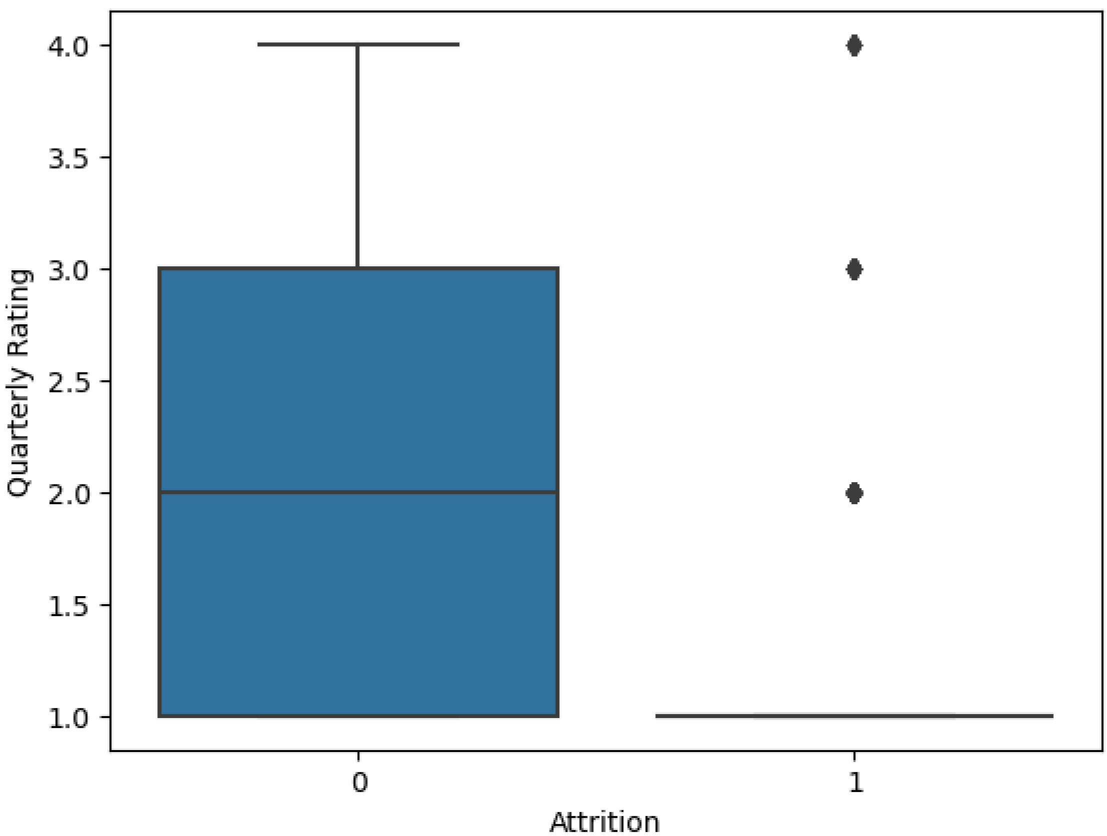
In [57]:
```
df.groupby('Education_Level')['Total Business Value'].mean()
df.groupby('City')['Total Business Value'].mean()
```

Out[57]:
```
City
C1     531560.280650
C10    540753.736559
C11    538549.145299
C12    667282.310867
C13    796263.075571
C14    607931.635802
C15    553266.636005
C16    632585.712271
C17    429160.204545
C18    550106.250000
C19    630978.151986
C2     553365.084746
C20    468535.605159
C21    572684.776119
C22    559749.431397
C23    423986.561338
C24    584712.426710
C25    507575.119863
C26    661837.445339
C27    572039.312977
C28    591406.778917
C29    736637.511111
C3     458003.940345
C4     556092.266436
C5     634855.975610
C6     566042.954545
C7     484569.228243
C8     566328.539326
C9     467914.865385
Name: Total Business Value, dtype: float64
```

Are drivers with higher Quarterly Rating more likely to stay longer

In [58]:
```
sns.boxplot(x='Attrition', y='Quarterly Rating', data = df)
```

Out[58]:
```
<Axes: xlabel='Attrition', ylabel='Quarterly Rating'>
```



Higher ratings is equal to higher retention

Actionable Insights & Recommendations

Based on the analysis, strategies Ola can implement to improve driver retention:

-Onboard support: At starting ola should provide training and bonus during the first 3 or 6 months of the joining.

-Mentor low rated driver: To reduce the churn ola can use the early support strategy.

-Incentive providation: Incentive can be given after every milestone achieved and recognition.

There are specific demographic groups or performance metrics that require targeted interventions:

-Drivers with education level 0 should be provide a support material digitally.

-Drivers who have quarterly rating<2 should be given personalized coaching or training.

-Drivers who have decreasing income trend should be offered a minimum guaranteed income.

Key factors influencing driver attrition:

-Stagnant income.

-Poor Quarterly Rating.

-Low Tenure.

THANK YOU

In [ ]:

```

```