`Problem Statement:`

- Ola was facing sudden rise in driver atrition rate which was significantally effecting their operational efficiency and recruitment cost.

`Objective:`

- My objective is to find the pattern between the drivers who had left their job betweeen 2019 to 2021 and Build and evaluate Machine learning models to predict driver attrition and provide insights for improving retention.

```
import pandas as pd
df=pd.read_csv(r'https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/002/492/original/ola_driver_scaler.csv')
```

Understanding

```
df.info()
df=df.drop('Unnamed: 0',axis=1)#removed unnessary column
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19104 entries, 0 to 19103
Data columns (total 14 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Unnamed: 0            19104 non-null  int64
 1   MMM-YY                19104 non-null  object
 2   Driver_ID             19104 non-null  int64
 3   Age                   19043 non-null  float64
 4   Gender                19052 non-null  float64
 5   City                  19104 non-null  object
 6   Education_Level       19104 non-null  int64
 7   Income                19104 non-null  int64
 8   Dateofjoining         19104 non-null  object
 9   LastWorkingDate       1616 non-null   object
 10  Joining Designation   19104 non-null  int64
 11  Grade                 19104 non-null  int64
 12  Total Business Value  19104 non-null  int64
 13  Quarterly Rating      19104 non-null  int64
dtypes: float64(2), int64(8), object(4)
memory usage: 2.0+ MB
```

```
df.head(10)
```

```
/usr/local/lib/python3.12/dist-packages/google/colab/_dataframe_summarizer.py:88: UserWarning: Could not infer format, so each
  cast_date_col = pd.to_datetime(column, errors="coerce")
```

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Total Business Value
0	01/01/19	1	28.0	0.0	C23	2	57387	24/12/18	NaN	1	1	2381060
1	02/01/19	1	28.0	0.0	C23	2	57387	24/12/18	NaN	1	1	-665480
2	03/01/19	1	28.0	0.0	C23	2	57387	24/12/18	03/11/19	1	1	0
3	11/01/20	2	31.0	0.0	C7	2	67016	11/06/20	NaN	2	2	0
4	12/01/20	2	31.0	0.0	C7	2	67016	11/06/20	NaN	2	2	0
5	12/01/19	4	43.0	0.0	C13	2	65603	12/07/19	NaN	2	2	0
6	01/01/20	4	43.0	0.0	C13	2	65603	12/07/19	NaN	2	2	0
7	02/01/20	4	43.0	0.0	C13	2	65603	12/07/19	NaN	2	2	0
8	03/01/20	4	43.0	0.0	C13	2	65603	12/07/19	NaN	2	2	350000
9	04/01/20	4	43.0	0.0	C13	2	65603	12/07/19	27/04/20	2	2	0

```
df.describe()
```

	Driver_ID	Age	Gender	Education_Level	Income	Joining Designation	Grade	Total Business Value	Quar
count	19104.000000	19043.000000	19052.000000	19104.000000	19104.000000	19104.000000	19104.000000	1.910400e+04	19104.
mean	1415.591133	34.668435	0.418749	1.021671	65652.025126	1.690536	2.252670	5.716621e+05	2.
std	810.705321	6.257912	0.493367	0.800167	30914.515344	0.836984	1.026512	1.128312e+06	1.
min	1.000000	21.000000	0.000000	0.000000	10747.000000	1.000000	1.000000	-6.000000e+06	1.
25%	710.000000	30.000000	0.000000	0.000000	42383.000000	1.000000	1.000000	0.000000e+00	1.
50%	1417.000000	34.000000	0.000000	1.000000	60087.000000	1.000000	2.000000	2.500000e+05	2.
75%	2137.000000	39.000000	1.000000	2.000000	83969.000000	2.000000	3.000000	6.997000e+05	3.

```
df.shape
```

```
(19104, 13)
```

Converting To DateTime Datatype

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

```
/tmp/ipython-input-733293316.py:1: UserWarning: Could not infer format, so each element will be parsed individually, falling ba
  df['Dateofjoining']=pd.to_datetime(df['Dateofjoining'],errors='coerce')
/tmp/ipython-input-733293316.py:2: UserWarning: Could not infer format, so each element will be parsed individually, falling ba
  df['LastWorkingDate']=pd.to_datetime(df['LastWorkingDate'],errors='coerce')
```

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	T Busi V
0	01/01/19	1	28.0	0.0	C23	2	57387	2018-12-24	NaT	1	1	238
1	02/01/19	1	28.0	0.0	C23	2	57387	2018-12-24	NaT	1	1	-66
2	03/01/19	1	28.0	0.0	C23	2	57387	2018-12-24	2019-03-11	1	1	
3	11/01/20	2	31.0	0.0	C7	2	67016	2020-11-06	NaT	2	2	
4	12/01/20	2	31.0	0.0	C7	2	67016	2020-11-06	NaT	2	2	
...	...	...	...	...	...	...	...	...	...	...	...	
19099	08/01/20	2788	30.0	0.0	C27	2	70254	2020-06-08	NaT	2	2	74
19100	09/01/20	2788	30.0	0.0	C27	2	70254	2020-06-08	NaT	2	2	44
19101	10/01/20	2788	30.0	0.0	C27	2	70254	2020-06-08	NaT	2	2	
19102	11/01/20	2788	30.0	0.0	C27	2	70254	2020-06-08	NaT	2	2	20
19103	12/01/20	2788	30.0	0.0	C27	2	70254	2020-06-08	NaT	2	2	41

Checking NULL Values

```
#detect The Columns with null values
df.isnull().sum()
```

	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

Most of the Null values were in `LastWorkingDate`

Data Cleaning And Preparation

Filling Null Values

```
df['Age']=df['Age'].fillna(int(df['Age'].mean()))                  #filling null values of age with the mean age
mode=df['Gender'].mode()
df['Gender']=df['Gender'].fillna(int(mode[0]))                      #filling null values of gender with the mode ge
df.isnull().sum()
df=df.rename(columns={'MMM-YY':'Reportingdate'})                    #changed the mmm-yy column to reportingdate col

```

Changed To Appropriate Datatype

```
df['Gender']=df['Gender'].astype(int)
df['Age']=df['Age'].astype(int)
```

```
# IQR Method To Detect Outliers
q1 = df['Total Business Value'].quantile(0.25)
q3 = df['Total Business Value'].quantile(0.75)
iqr = q3 - q1

lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr

outliers = df[(df['Total Business Value'] < lower_bound) | (df['Total Business Value'] > upper_bound)]
print('No. Of Outliers :',outliers.shape[0])
```

```
No. Of Outliers : 1371
```

Their Is NO Point In Removing The Outlier Cause It Will Affect The Data And The Performance Of Every Driver Is Important So WE Will Keep The Outlier As It Is.

Creating `Tenure_Days` From `Last_working_date` and `joining_date`

```
df['Tenure_Days']=(df['LastWorkingDate']-df['Dateofjoining']).dt.days
df
```

	Reportingdate	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade
0	01/01/19	1	28	0	C23	2	57387	2018-12-24	NaT	1	1
1	02/01/19	1	28	0	C23	2	57387	2018-12-24	NaT	1	1
2	03/01/19	1	28	0	C23	2	57387	2018-12-24	2019-03-11	1	1
3	11/01/20	2	31	0	C7	2	67016	2020-11-06	NaT	2	2
4	12/01/20	2	31	0	C7	2	67016	2020-11-06	NaT	2	2
...	...	...	...	...	...	...	...	...	...	...	...
19099	08/01/20	2788	30	0	C27	2	70254	2020-06-08	NaT	2	2
19100	09/01/20	2788	30	0	C27	2	70254	2020-06-08	NaT	2	2
19101	10/01/20	2788	30	0	C27	2	70254	2020-06-08	NaT	2	2

Target Column

```
import numpy as np
df["Target"] = np.where(df["LastWorkingDate"].notna(), 1, 0)
```

```
gopi=df["Target"].sum()
print(f"Driver Left: {gopi}")
```

```
Driver Left: 1616
```

Target Columns contains the Drivers left and stayed Data in binary form

- `0` means Driver is Working
- `1` means Driver has Resigned

TotalBussinessValue

```
df.groupby(df['Total Business Value'] < 0)['Target'].sum()
```

	Target
Total Business Value	
False	1585
True	31

dtype: int64

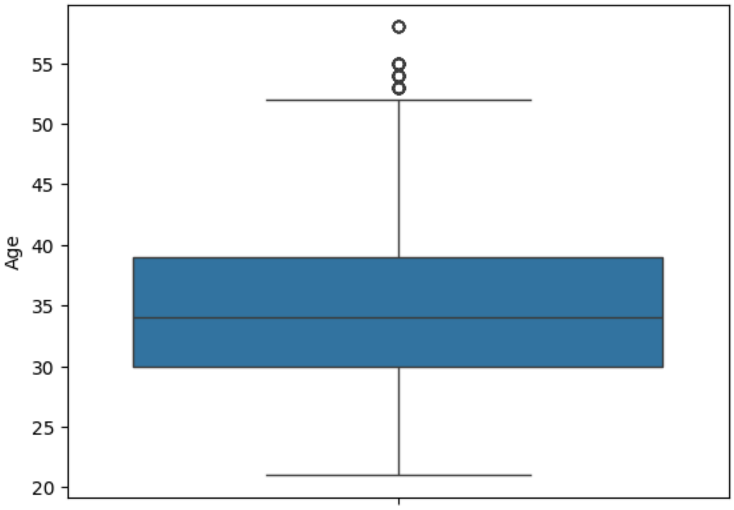
False means `Total Business Value` > `0` (Drivers Has Positive TotalBussinessValue)

True means `Total Business Value` < `0` (Drivers Has Negative TotalBussinessValue)

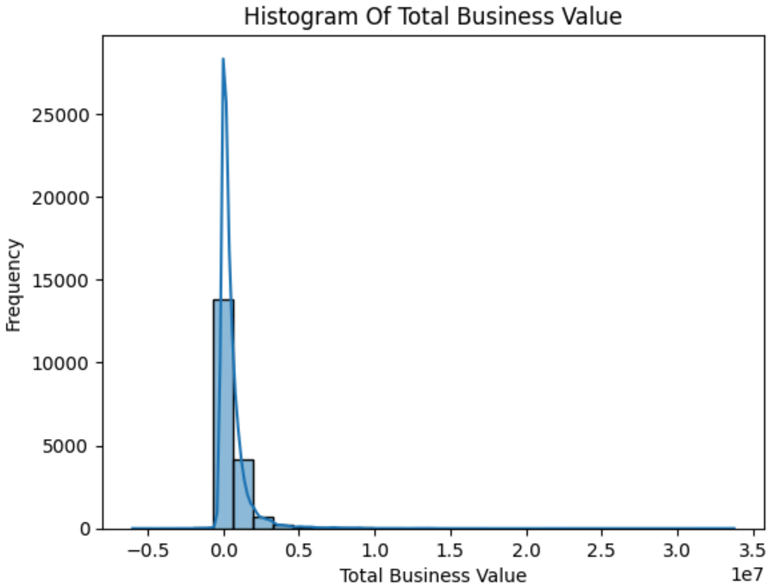
- Total Business Value alone is not a strong direct indicator of driver attrition, as both churners and non-churners can have positive or negative values.

Visulization (Univariate Analysis)

```
import matplotlib.pyplot as plt
import seaborn as sns
sns.boxplot(y=df['Age'])
plt.show()
```




```
sns.histplot(data=df,x='Total Business Value',bins=30,kde=True)
plt.title("Histogram Of Total Business Value")
plt.ylabel('Frequency')
plt.show()
```

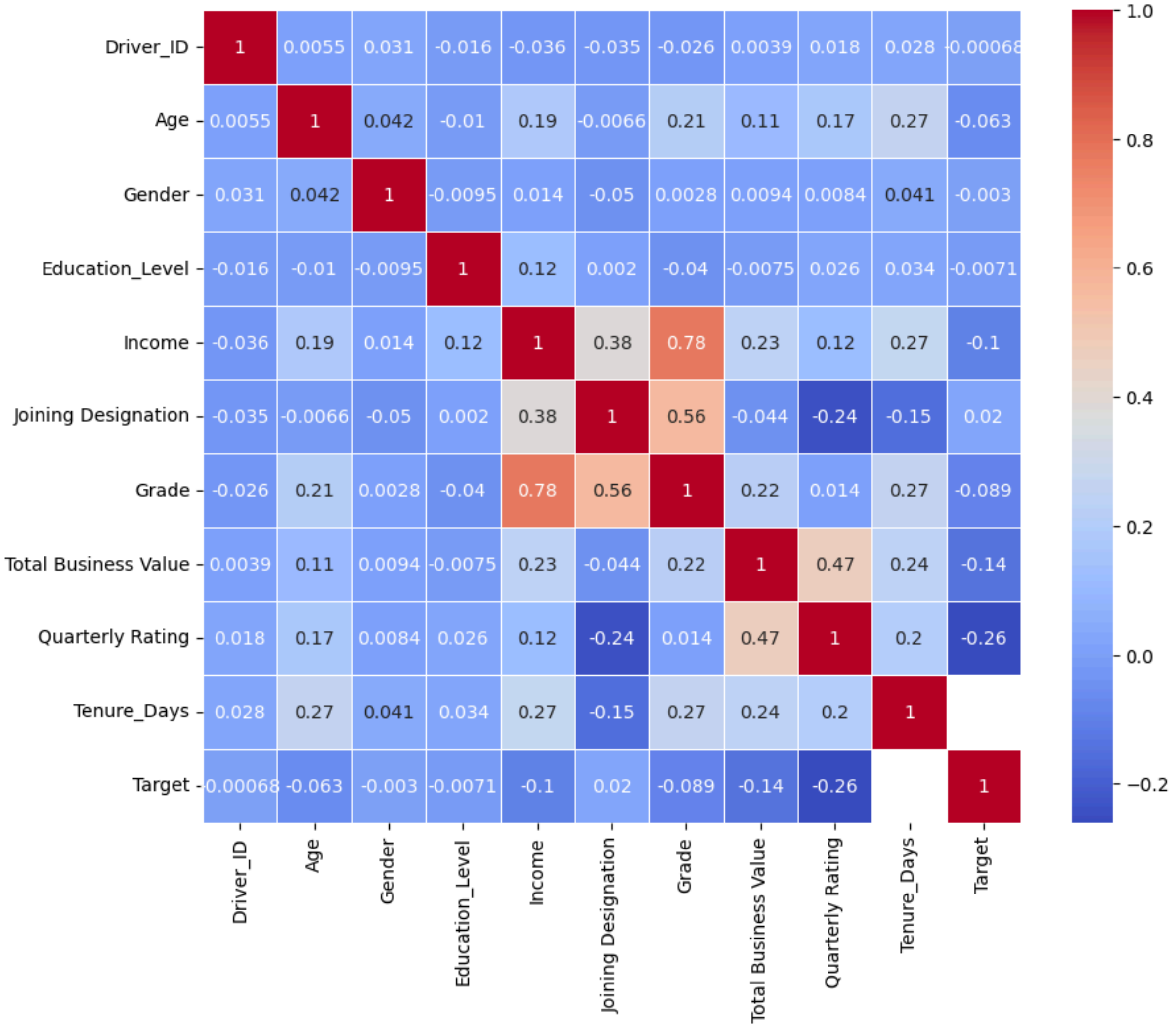


- **X-axis:** Total Business Value
- **Y-axis:** Frequency
- **Observation:** The distribution is highly skewed, suggesting the presence of outliers or extreme high values.

Visualization (Bivariate Analysis)

```
numeric_df=df.select_dtypes(include='number')
corr=numeric_df.corr()
plt.figure(figsize=(10,8))
sns.heatmap(corr,annot=True,cmap='coolwarm',linewidths=0.5)
```

```
<Axes: >
```



The Columns Are Not That Correlated :

- Most Correlated: Grade-Income
- Least Correlated: Quarterly Rating - Target

```
#converted ReportDate In Datetime Format
df['Reportingdate']=pd.to_datetime(df['Reportingdate'],errors='coerce')
df
```

```
/tmp/ipython-input-2591182952.py:2: UserWarning: Could not infer format, so each element will be parsed individually, falling b
  df['Reportingdate']=pd.to_datetime(df['Reportingdate'],errors='coerce')
```

	Reportingdate	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade
0	2019-01-01	1	28	0	C23	2	57387	2018-12-24	NaT	1	1
1	2019-02-01	1	28	0	C23	2	57387	2018-12-24	NaT	1	1
2	2019-03-01	1	28	0	C23	2	57387	2018-12-24	2019-03-11	1	1
3	2020-11-01	2	31	0	C7	2	67016	2020-11-06	NaT	2	2
4	2020-12-01	2	31	0	C7	2	67016	2020-11-06	NaT	2	2
...	...	...	...	...	...	...	...	...	...	...	...
19099	2020-08-01	2788	30	0	C27	2	70254	2020-06-08	NaT	2	2
19100	2020-09-01	2788	30	0	C27	2	70254	2020-06-08	NaT	2	2
19101	2020-10-01	2788	30	0	C27	2	70254	2020-06-08	NaT	2	2
19102	2020-11-01	2788	30	0	C27	2	70254	2020-06-08	NaT	2	2
19103	2020-12-01	2788	30	0	C27	2	70254	2020-06-08	NaT	2	2

19104 rows × 15 columns

```
df.groupby('Education_Level')['Income'].mean()
```

Education_Level	Income
0	60644.080670
1	66362.592366
2	69561.404299

dtype: float64

- Higher Education Means Higher Payment

```
#Checking If Income Is A Reasone for Driver's Attrition
df.groupby('Target')['Income'].mean()
```

Target	Income
0	66600.170631
1	55391.400990

dtype: float64

- Lower Income Is A Reason For Driver's Attrition

```
df.groupby('Target')['Age'].mean().astype(int)
```

Target	Age
0	34
1	33

dtype: int64

- The Younger Drivers are Most Likely To Leave

Made A Column `Tenure_Group` To Understand It Better

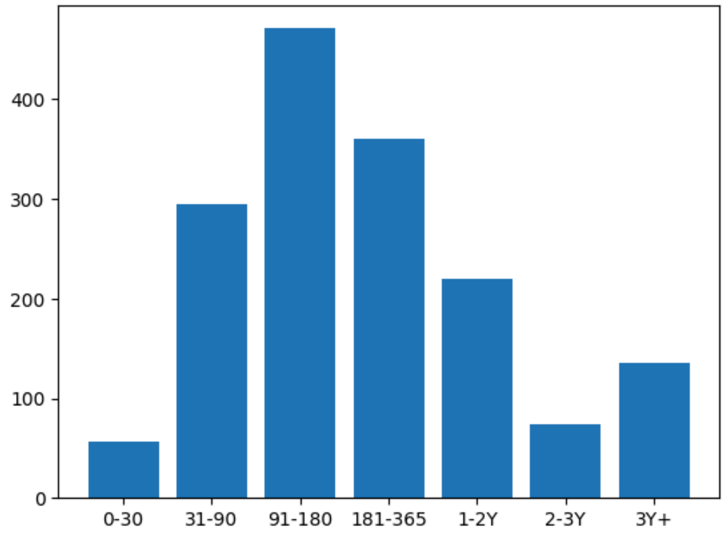
```
df['Tenure_Group'] = pd.cut(df['Tenure_Days'], bins=[0, 30, 90, 180, 365, 730, 1095, df['Tenure_Days'].max()],
                            labels=['0-30', '31-90', '91-180', '181-365', '1-2Y', '2-3Y', '3Y+'])

grouped = df.groupby('Tenure_Group', observed=False)['Target'].sum()
grouped
```

Tenure_Group	Target
0-30	56
31-90	295
91-180	471
181-365	360
1-2Y	220
2-3Y	74
3Y+	136

dtype: int64

```
plt.bar(x=grouped.index, height=grouped.values)
```

```
<BarContainer object of 7 artists>
```



Driver attrition is most likely to occur between 91 to 365 days of tenure.

- The **highest attrition** is observed in the **91–180 days** range, with 471 drivers leaving.
- The **second highest** occurs in the **181–365** days range, with 360 drivers leaving.
- This **trend suggests** that drivers are more prone to leave after **3 to 12 months of employment—possibly** due to job dissatisfaction, unmet expectations, or lack of engagement during the post-onboarding phase.

```
1 df
```

	Reportingdate	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade
0	2019-01-01	1	28	0	C23	2	57387	2018-12-24	NaT	1	1
1	2019-02-01	1	28	0	C23	2	57387	2018-12-24	NaT	1	1
2	2019-03-01	1	28	0	C23	2	57387	2018-12-24	2019-03-11	1	1
3	2020-11-01	2	31	0	C7	2	67016	2020-11-06	NaT	2	2
4	2020-12-01	2	31	0	C7	2	67016	2020-11-06	NaT	2	2
...	...	...	...	...	...	...	...	...	...	...	...
19099	2020-08-01	2788	30	0	C27	2	70254	2020-06-08	NaT	2	2
19100	2020-09-01	2788	30	0	C27	2	70254	2020-06-08	NaT	2	2
19101	2020-10-01	2788	30	0	C27	2	70254	2020-06-08	NaT	2	2
19102	2020-11-01	2788	30	0	C27	2	70254	2020-06-08	NaT	2	2
19103	2020-12-01	2788	30	0	C27	2	70254	2020-06-08	NaT	2	2

19104 rows × 16 columns

```
1 df["Reportingdate"]
```

	Reportingdate
0	2019-01-01
1	2019-02-01
2	2019-03-01
3	2020-11-01
4	2020-12-01
...	...
19099	2020-08-01
19100	2020-09-01
19101	2020-10-01
19102	2020-11-01
19103	2020-12-01

19104 rows × 1 columns

dtype: datetime64[ns]

```
df["Tenure_Days"] = df["Tenure_Days"].fillna(
abs((pd.to_datetime("2020-12-01") - pd.to_datetime(df["Dateofjoining"])).dt.days)
)

```

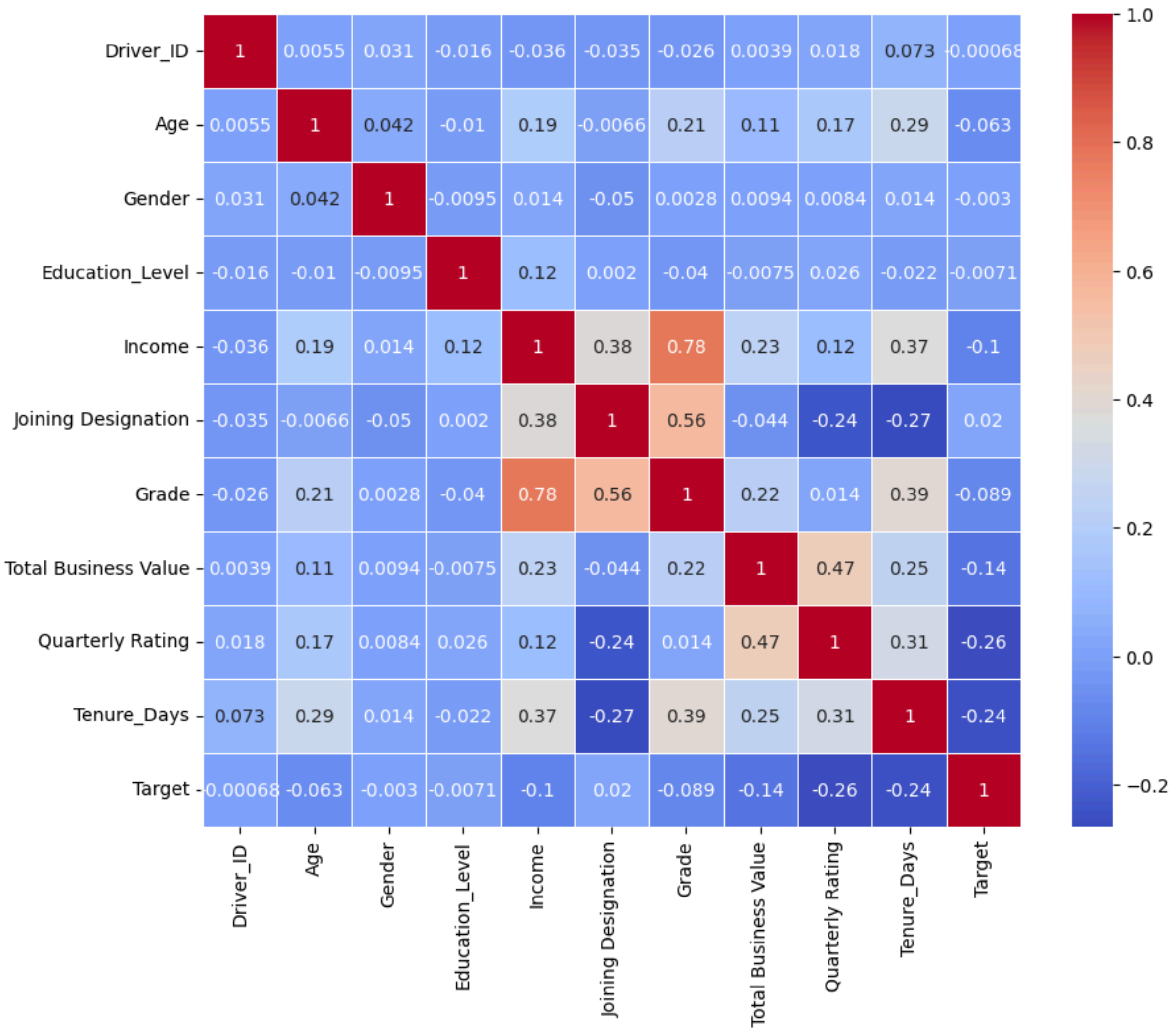
```
df['Tenure_Group'] = pd.cut(df['Tenure_Days'], bins=[0, 30, 90, 180, 365, 730, 1095, df['Tenure_Days'].max()],
                            labels=['0-30', '31-90', '91-180', '181-365', '1-2Y', '2-3Y', '3Y+'])

grouped = df.groupby('Tenure_Group', observed=False)['Target'].sum()
grouped
```

Tenure_Group	Target
0-30	56
31-90	295
91-180	471
181-365	360
1-2Y	220
2-3Y	74
3Y+	136

dtype: int64

```
numeric_df=df.select_dtypes(include='number')
corr=numeric_df.corr()
plt.figure(figsize=(10,8))
sns.heatmap(corr,annot=True,cmap='coolwarm',linewidths=0.5)
```

```
<Axes: >
```



Correlation Heatmap Analysis

The heatmap below shows the **pairwise correlation** between features in the dataset. This visualization helps identify which variables are strongly related, weakly related, or inversely related.

Key Observations:

- `Income`, `Grade`, and `Joining Designation` are **highly correlated** with each other:
  - **Income vs Grade**: 0.78
  - **Income vs Joining Designation**: 0.38
  - **Grade vs Joining Designation**: 0.56
- `Target` has **negative correlations** with:
  - `Quarterly Rating`: **-0.26**
  - `Tenure_Days`: **-0.24**
  - `Total Business Value`: **-0.14**
- `Age` and `Tenure_Days` show a **moderate positive correlation**: **0.29**
- `Driver_ID` shows almost **no meaningful correlation**, as expected since it's just an identifier.

Conclusion:

- Variables like `Income`, `Grade`, `Quarterly Rating`, and `Tenure_Days` could be **important features** when predicting the `Target`.
- Features with high correlation between each other (e.g., `Income` and `Grade`) may require **multicollinearity checks** before using in regression models.

```
df = pd.get_dummies(df, columns=['Joining Designation', 'Education_Level', 'City'], drop_first=True)
```

```
df
```

	Reportingdate	Driver_ID	Age	Gender	Income	Dateofjoining	LastWorkingDate	Grade	Total Business Value	Quarterly Rating	...	City_C27
0	2019-01-01	1	28	0	57387	2018-12-24	NaT	1	2381060	2	...	False
1	2019-02-01	1	28	0	57387	2018-12-24	NaT	1	-665480	2	...	False
2	2019-03-01	1	28	0	57387	2018-12-24	2019-03-11	1	0	2	...	False
3	2020-11-01	2	31	0	67016	2020-11-06	NaT	2	0	1	...	False
4	2020-12-01	2	31	0	67016	2020-11-06	NaT	2	0	1	...	False
...	...	...	...	...	...	...	...	...	...	...	...	...
19099	2020-08-01	2788	30	0	70254	2020-06-08	NaT	2	740280	3	...	True
19100	2020-09-01	2788	30	0	70254	2020-06-08	NaT	2	448370	3	...	True
19101	2020-10-01	2788	30	0	70254	2020-06-08	NaT	2	0	2	...	True
19102	2020-11-01	2788	30	0	70254	2020-06-08	NaT	2	200420	2	...	True
19103	2020-12-01	2788	30	0	70254	2020-06-08	NaT	2	411480	2	...	True

19104 rows × 47 columns

```
#removing irrelevent columns
# List of columns to remove
cols_to_drop = ['Reportingdate', 'Driver_ID', 'Dateofjoining', 'LastWorkingDate']

# Drop the columns
df = df.drop(columns=cols_to_drop)
```

```
df
```

	Age	Gender	Income	Grade	Total Business Value	Quarterly Rating	Tenure_Days	Target	Tenure_Group	Joining Designation_2	...	City_C27	City_C2
0	28	0	57387	1	2381060	2	708.0	0	1-2Y	False	...	False	Fals
1	28	0	57387	1	-665480	2	708.0	0	1-2Y	False	...	False	Fals
2	28	0	57387	1	0	2	77.0	1	31-90	False	...	False	Fals
3	31	0	67016	2	0	1	25.0	0	0-30	True	...	False	Fals
4	31	0	67016	2	0	1	25.0	0	0-30	True	...	False	Fals
...	...	...	...	...	...	...	...	...	...	...	...	...	
19099	30	0	70254	2	740280	3	176.0	0	91-180	True	...	True	Fals
19100	30	0	70254	2	448370	3	176.0	0	91-180	True	...	True	Fals
19101	30	0	70254	2	0	2	176.0	0	91-180	True	...	True	Fals
19102	30	0	70254	2	200420	2	176.0	0	91-180	True	...	True	Fals
19103	30	0	70254	2	411480	2	176.0	0	91-180	True	...	True	Fals

19104 rows × 43 columns

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19104 entries, 0 to 19103
Data columns (total 43 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Age                    19104 non-null  int64
 1   Gender                 19104 non-null  int64
 2   Income                 19104 non-null  int64
 3   Grade                  19104 non-null  int64
 4   Total Business Value   19104 non-null  int64
 5   Quarterly Rating       19104 non-null  int64
 6   Tenure_Days            19104 non-null  float64
 7   Target                 19104 non-null  int64
 8   Tenure_Group           19100 non-null  category
 9   Joining Designation_2  19104 non-null  bool
 10  Joining Designation_3  19104 non-null  bool
 11  Joining Designation_4  19104 non-null  bool
 12  Joining Designation_5  19104 non-null  bool
```

```
 13  Education_Level_1      19104 non-null  bool
 14  Education_Level_2      19104 non-null  bool
 15  City_C10               19104 non-null  bool
 16  City_C11               19104 non-null  bool
 17  City_C12               19104 non-null  bool
 18  City_C13               19104 non-null  bool
 19  City_C14               19104 non-null  bool
 20  City_C15               19104 non-null  bool
 21  City_C16               19104 non-null  bool
 22  City_C17               19104 non-null  bool
 23  City_C18               19104 non-null  bool
 24  City_C19               19104 non-null  bool
 25  City_C2                19104 non-null  bool
 26  City_C20               19104 non-null  bool
 27  City_C21               19104 non-null  bool
 28  City_C22               19104 non-null  bool
 29  City_C23               19104 non-null  bool
 30  City_C24               19104 non-null  bool
 31  City_C25               19104 non-null  bool
 32  City_C26               19104 non-null  bool
 33  City_C27               19104 non-null  bool
 34  City_C28               19104 non-null  bool
 35  City_C29               19104 non-null  bool
 36  City_C3                19104 non-null  bool
 37  City_C4                19104 non-null  bool
 38  City_C5                19104 non-null  bool
 39  City_C6                19104 non-null  bool
 40  City_C7                19104 non-null  bool
 41  City_C8                19104 non-null  bool
 42  City_C9                19104 non-null  bool
dtypes: bool(34), category(1), float64(1), int64(7)
memory usage: 1.8 MB
```

```
df=df.drop(columns=['Tenure_Group'])
```

Model

`Libraries & Their Usage`

1. **sklearn.model_selection**
   - `train_test_split`: Split dataset into training & testing sets.
   - `GridSearchCV`: Hyperparameter tuning with cross-validation.
   - `StratifiedKFold`: Cross-validation that preserves class balance in each fold.
2. **sklearn.preprocessing**
   - `StandardScaler`: Standardize numerical features (mean=0, std=1).
   - `OneHotEncoder`: Convert categorical variables into binary vectors.
3. **sklearn.compose**
   - `ColumnTransformer`: Apply different preprocessing steps to numeric vs categorical columns.
4. **sklearn.pipeline**
   - `Pipeline`: Chain preprocessing + model into one workflow.
5. **sklearn.impute**
   - `KNNImputer`: Fill missing values using nearest neighbors.
6. **sklearn.metrics**
   - `classification_report`: Precision, recall, f1-score summary.
   - `roc_auc_score`: ROC AUC metric (model discrimination ability).
   - `roc_curve`: Get points for ROC curve plot.
   - `confusion_matrix`: Count TP, TN, FP, FN.
   - `ConfusionMatrixDisplay`: Visual display of confusion matrix.
7. **sklearn.linear_model**
   - `LogisticRegression`: Logistic regression classifier.
8. **imblearn.over_sampling**
   - `SMOTE`: Handle class imbalance by generating synthetic minority samples.
9. **imblearn.pipeline**
   - `Pipeline (ImbPipeline)`: Similar to sklearn's pipeline, but supports imbalanced-learn steps like SMOTE.

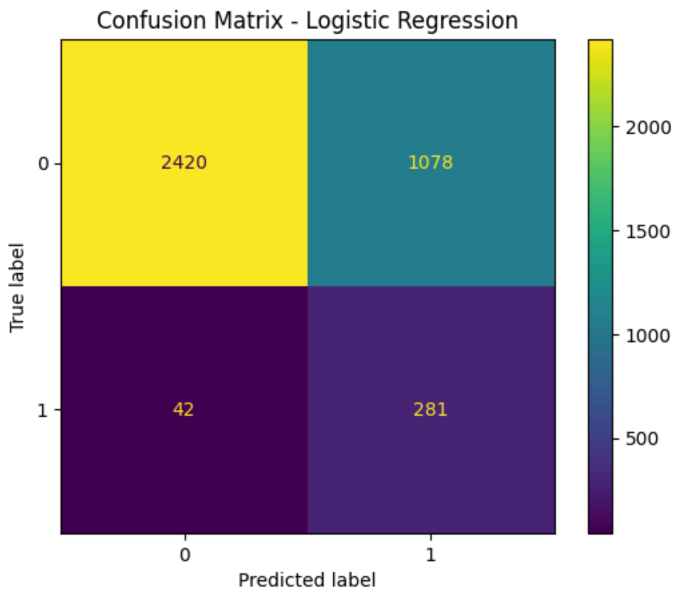
10. **matplotlib.pyplot**
    - For plotting ROC curves, confusion matrices, and feature importance graphs.

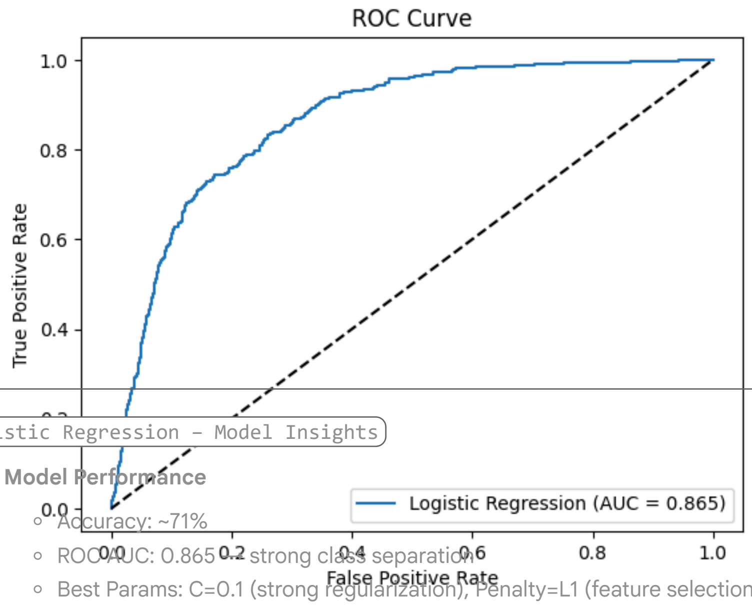
Logistic Regression

```
from sklearn.model_selection import train_test_split, GridSearchCV, StratifiedKFold
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import KNNImputer
from sklearn.metrics import classification_report, roc_auc_score, roc_curve, confusion_matrix, ConfusionMatrixDisplay
from sklearn.linear_model import LogisticRegression
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline as ImbPipeline
import matplotlib.pyplot as plt

# ==== 2. Load data (aggregated driver features) ====
agg_final = df # use the aggregated dataset from previous step

# ==== 3. Split X/y ====
y = agg_final['Target']
X = agg_final.drop(columns=['Target'])

# ==== 4. Identify numeric and categorical features ====
numeric_features = X.select_dtypes(include=['number']).columns.tolist()
cat_features = X.select_dtypes(include=['object','category']).columns.tolist()

# ==== 5. Preprocessing pipelines ====
numeric_transformer = Pipeline([
    ('imputer', KNNImputer(n_neighbors=5)),
    ('scaler', StandardScaler())
])

cat_transformer = Pipeline([
    ('onehot', OneHotEncoder(handle_unknown='ignore', sparse_output=False))
])

preprocessor = ColumnTransformer(transformers=[
    ('num', numeric_transformer, numeric_features),
    ('cat', cat_transformer, cat_features)
], remainder='drop')

# ==== 6. Train-test split (stratified) ====
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

# ==== 7. Logistic Regression inside pipeline with SMOTE ====
steps = [
    ('preproc', preprocessor),
    ('smote', SMOTE(random_state=42)),
    ('clf', LogisticRegression(solver='liblinear', class_weight='balanced', max_iter=1000))
]

pipeline = ImbPipeline(steps=steps)

# ==== 8. Hyperparameter tuning (optional) ====
param_grid = {
    'clf__C': [0.01, 0.1, 1, 10],   # regularization strength
    'clf__penalty': ['l1','l2']
}

cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
grid = GridSearchCV(pipeline, param_grid, cv=cv, scoring='roc_auc', n_jobs=-1, verbose=1)
grid.fit(X_train, y_train)

best_model_lr = grid.best_estimator_
print("Best hyperparameters:", grid.best_params_)

# ==== 9. Predict & evaluate ====
y_pred = best_model_lr.predict(X_test)
y_proba = best_model_lr.predict_proba(X_test)[:,1]
y_pred_new = (y_proba >= 0.4).astype(int)
# Classification report
print("\nClassification Report:\n", classification_report(y_test, y_pred, digits=4))

# ROC AUC
auc = roc_auc_score(y_test, y_proba)
print("ROC AUC:", auc)
```

```

# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()
plt.title("Confusion Matrix - Logistic Regression")
plt.show()

# ROC curve
fpr, tpr, _ = roc_curve(y_test, y_proba)
plt.plot(fpr, tpr, label=f'Logistic Regression (AUC = {auc:.3f})')
plt.plot([0,1],[0,1],'k--')
plt.xlabel('False Positive Rate'); plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.show()

```

```
Fitting 5 folds for each of 8 candidates, totalling 40 fits
Best hyperparameters: {'clf__C': 0.1, 'clf__penalty': 'l1'}

Classification Report:
              precision    recall  f1-score   support

           0     0.9829    0.6918    0.8121      3498
           1     0.2068    0.8700    0.3341       323

    accuracy                         0.7069      3821
   macro avg     0.5949    0.7809    0.5731      3821
weighted avg     0.9173    0.7069    0.7717      3821

ROC AUC: 0.8648135068778798
```





`Logistic Regression – Model Insights`

1. **Model Performance**
   - Accuracy: ~71%
   - ROC-AUC: 0.865 → strong class separation
   - Best Params: C=0.1 (strong regularization), Penalty=L1 (feature selection effect)
2. **Class-wise Results**
   - Class 0: Precision = 0.98, Recall = 0.69 → some false positives

- Class 1: Precision = 0.21, Recall = 0.87 → high recall, many false positives
- Model prioritizes recall for minority class (1)

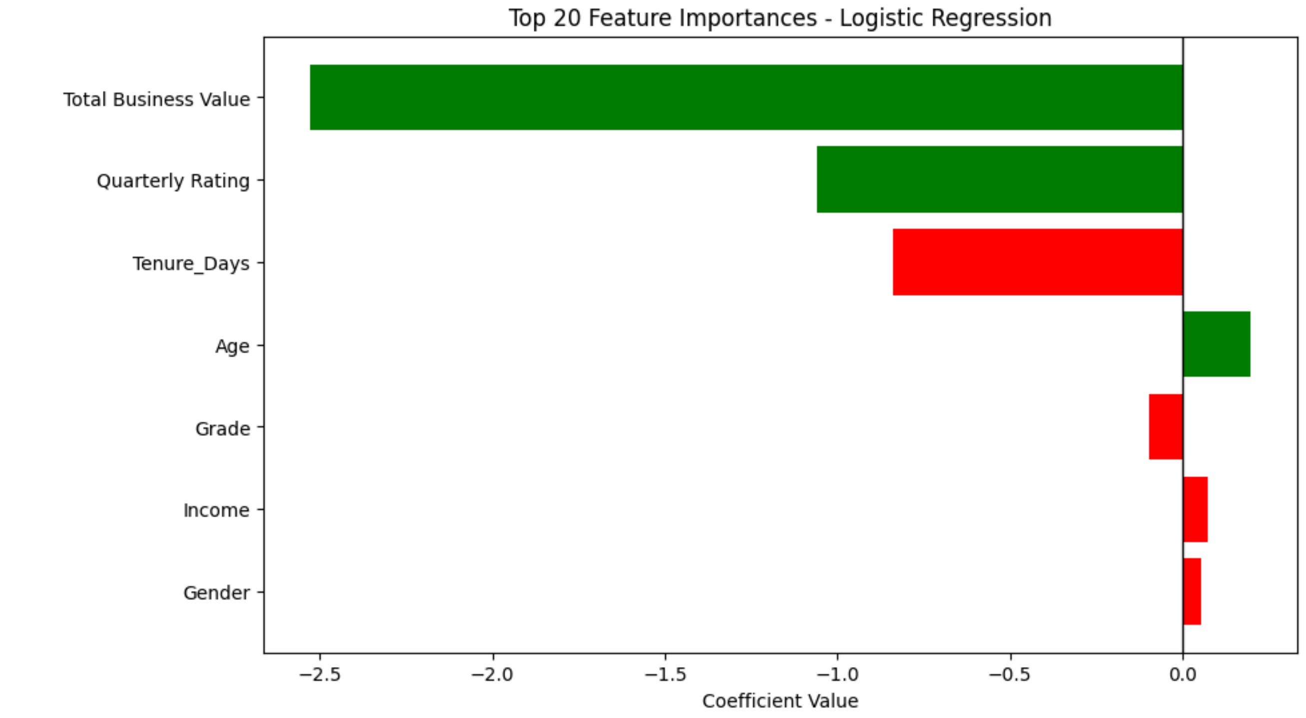
3. **Confusion Matrix Behavior**
   - Few false negatives → positives are rarely missed
   - Higher false positives → negatives often misclassified as positives

4. **Feature Importance**
   - Positive coefficients → increase probability of class 1
   - Negative coefficients → decrease probability of class 1
   - L1 penalty zeroed out irrelevant features, leaving only key drivers

5. **Business Interpretation**
   - ✅ Good when missing positives is costly (e.g., fraud, churn, safety incidents)
   - ⚠️ Not ideal if false alarms (false positives) are expensive
   - Threshold tuning can improve precision-recall balance

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

# ==== 1. Get feature names (numeric + encoded categorical) ====
numeric_features = X.select_dtypes(include=['number']).columns.tolist()
cat_features = X.select_dtypes(include=['object','category']).columns.tolist()

# Get one-hot encoded categorical feature names from pipeline
# Access the fitted preprocessor from the best_model_lr pipeline
try:
    fitted_preprocessor = best_model_lr.named_steps['preproc']
    fitted_onehot = fitted_preprocessor.named_transformers_['cat'].named_steps['onehot']
    cat_features_encoded = fitted_onehot.get_feature_names_out(cat_features)
except AttributeError:
    print("Error: 'best_model_lr' or its components are not fitted. Please run the Logistic Regression model training cel
    cat_features_encoded = [] # Initialize as empty to avoid further errors


all_features = np.concatenate([numeric_features, cat_features_encoded])

# Filter out 'Target' if it somehow ended up in all_features (shouldn't happen with the way X is created, but as a safegu
if 'Target' in all_features:
    all_features = all_features[all_features != 'Target']


# ==== 2. Extract coefficients from Logistic Regression ====
# Ensure the classifier is fitted before accessing coef_
try:
    coef = best_model_lr.named_steps['clf'].coef_[0]   # coefficients for class 1
    importances = coef  # keep sign (positive/negative impact)
except AttributeError:
    print("Error: Logistic Regression classifier is not fitted. Please run the Logistic Regression model training cell fi
    importances = [] # Initialize as empty

# Make sure importances and all_features have the same length before creating DataFrame
if len(all_features) > 0 and len(importances) == len(all_features):
    # ==== 3. Create dataframe ====
    feat_df = pd.DataFrame({'feature': all_features, 'importance': importances})
    feat_df['abs_importance'] = np.abs(feat_df['importance'])

    # Top 20 features by absolute importance
    feat_df = feat_df.sort_values(by='abs_importance', ascending=False).head(20)

    # ==== 4. Plot ====
    plt.figure(figsize=(10,6))
    colors = ['green' if x > 0 else 'red' for x in feat_df['importance']]  # green = positive impact, red = negative impa
    plt.barh(feat_df['feature'][::-1], feat_df['importance'][::-1], color=colors)
    plt.xlabel('Coefficient Value')
    plt.title('Top 20 Feature Importances - Logistic Regression')
    plt.axvline(0, color='black', linewidth=1)
    plt.show()
else:
    print("Could not generate feature importances plot due to previous errors or mismatch in feature/importance counts.")
```

```
Error: 'best_model_lr' or its components are not fitted. Please run the Logistic Regression model training cell first.
```



`Top 20 Feature Importances - Logistic Regression`

`Main Points`

- **Total Business Value** has the strongest negative impact → pushes prediction toward the **negative class**.
- **Quarterly Rating** and **Tenure_Days** also show strong negative effects.
- **Age** has a positive influence → pushes prediction toward the **positive class**.
- **Grade**, **Income**, and **Gender** have relatively small impacts.

`Note on Positive` vs `Negative`

- 🟢 **Positive coefficient (green bar):** Increases the likelihood of the positive class.
- 🔴 **Negative coefficient (red bar):** Increases the likelihood of the negative class.

`Model Leaning`

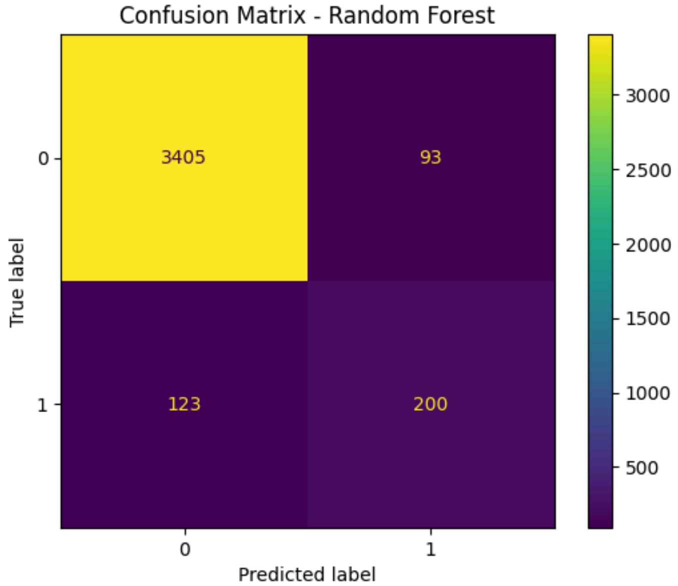
- Since most high-impact features are **negative**, the model overall leans more toward predicting the **negative class**.

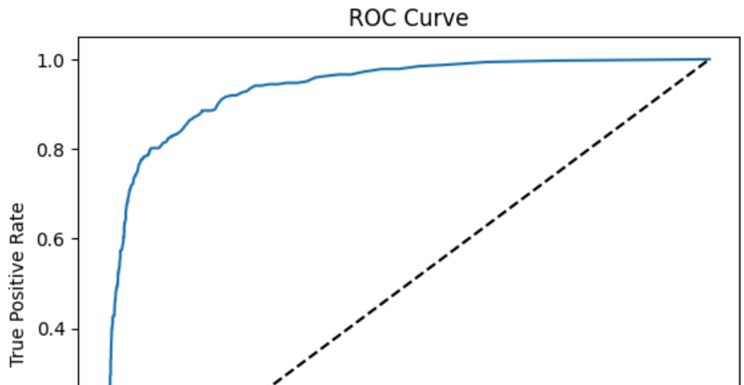
Random Forest

```
# ==== 1. Import Library ====
from sklearn.ensemble import RandomForestClassifier


# ==== 2. Load data ====
agg_final = df.copy()  # replace with your aggregated dataframe
if 'Tenure_Group' in agg_final.columns:
    agg_final = agg_final.drop(columns=['Tenure_Group'])  # remove Tenure_Group

# ==== 3. Split X/y ====
y = agg_final['Target']
X = agg_final.drop(columns=['Target'])

# ==== 4. Identify numeric and categorical features ====
numeric_features = X.select_dtypes(include=['number']).columns.tolist()
cat_features = X.select_dtypes(include=['object','category']).columns.tolist()

# ==== 5. Preprocessing pipelines ====
numeric_transformer = Pipeline([
    ('imputer', KNNImputer(n_neighbors=5)),
    ('scaler', StandardScaler())
])

cat_transformer = Pipeline([
    ('onehot', OneHotEncoder(handle_unknown='ignore', sparse_output=False))
])

```

```
preprocessor = ColumnTransformer(transformers=[
    ('num', numeric_transformer, numeric_features),
    ('cat', cat_transformer, cat_features)
], remainder='drop')

# ==== 6. Train-test split (stratified) ====
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

# ==== 7. Random Forest with SMOTE ====
steps = [
    ('preproc', preprocessor),
    ('smote', SMOTE(random_state=42)),
    ('clf', RandomForestClassifier(random_state=42, class_weight='balanced'))
]

pipeline = ImbPipeline(steps=steps)

# ==== 8. Hyperparameter tuning (optional) ====
param_grid = {
    'clf__n_estimators': [100, 200],
    'clf__max_depth': [5, 10, None],
    'clf__min_samples_split': [2, 5],
    'clf__min_samples_leaf': [1, 2]
}

cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
grid = GridSearchCV(pipeline, param_grid, cv=cv, scoring='roc_auc', n_jobs=-1, verbose=1)
grid.fit(X_train, y_train)

best_model_rf = grid.best_estimator_
print("Best hyperparameters:", grid.best_params_)

# ==== 9. Predict & evaluate ====
y_pred = best_model_rf.predict(X_test)
y_proba = best_model_rf.predict_proba(X_test)[:,1]

# Classification report
print("\nClassification Report:\n", classification_report(y_test, y_pred, digits=4))

# ROC AUCQXXAA
auc = roc_auc_score(y_test, y_proba)
print("ROC AUC:", auc)

# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()
plt.title("Confusion Matrix - Random Forest")
plt.show()

# ROC curve
fpr, tpr, _ = roc_curve(y_test, y_proba)
plt.plot(fpr, tpr, label=f'Random Forest (AUC = {auc:.3f})')
plt.plot([0,1],[0,1],'k--')
plt.xlabel('False Positive Rate'); plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.show()
```

```
Fitting 5 folds for each of 24 candidates, totalling 120 fits
Best hyperparameters: {'clf__max_depth': None, 'clf__min_samples_leaf': 1, 'clf__min_samples_split': 2, 'clf__n_estimators': 2

Classification Report:
              precision    recall  f1-score   support

           0     0.9651    0.9734    0.9693      3498
           1     0.6826    0.6192    0.6494       323

    accuracy                         0.9435      3821
   macro avg     0.8239    0.7963    0.8093      3821
weighted avg     0.9413    0.9435    0.9422      3821

ROC AUC: 0.9401347430729989
```





Random Forest – Summary

Explanation The Random Forest model achieved high accuracy (94.35%) and a strong ROC AUC (0.94), showing excellent overall predictive power.
It performs very well on the majority class (0), while moderately handling the minority class (1).
This indicates good discrimination ability but some impact from class imbalance.

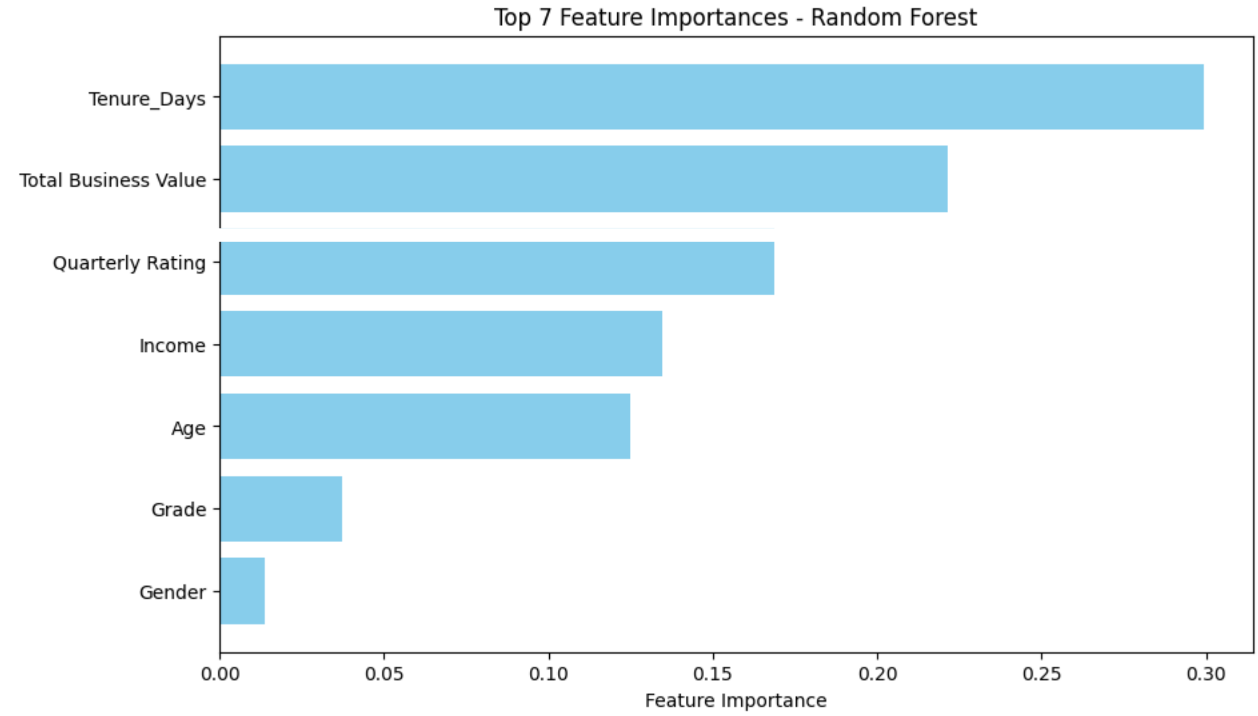
Key Insights

1. High accuracy and ROC AUC confirm strong overall model performance.
2. Excellent precision and recall for the majority class (0).
3. Moderate recall for the minority class (1) → some positives are missed.
4. Precision for class 1 is decent, indicating controlled false positives.
5. Model shows robustness to complex patterns, outperforming Logistic Regression.

```


# Identify numeric and categorical features
numeric_features = X.select_dtypes(include=['number']).columns.tolist()
cat_features = X.select_dtypes(include=['object', 'category', 'bool']).columns.tolist() # Include boolean as they were cr

# Categorical features after one-hot encoding - access from the fitted pipeline
# Ensure best_model_rf has been fitted (e.g., by running the Random Forest cell)
try:
    cat_features_encoded = best_model_rf.named_steps['preproc']\
        .named_transformers_['cat']\
```

```
        .named_steps['onehot'].get_feature_names_out(cat_features)
except AttributeError:
    print("Error: 'best_model_rf' or its components are not fitted. Please run the Random Forest model training cell firs
    cat_features_encoded = [] # Initialize as empty to avoid further errors


# Combine all feature names
all_features = np.concatenate([numeric_features, cat_features_encoded])

# Filter out 'Target' if it somehow ended up in all_features (shouldn't happen with the way X is created, but as a safegu
if 'Target' in all_features:
    all_features = all_features[all_features != 'Target']


# ==== 2. Get feature importances ====
# Ensure the classifier is fitted before accessing feature_importances_
try:
    importances = best_model_rf.named_steps['clf'].feature_importances_
except AttributeError:
    print("Error: Random Forest classifier is not fitted. Please run the Random Forest model training cell first.")
    importances = [] # Initialize as empty

# Make sure importances and all_features have the same length before creating DataFrame
if len(all_features) > 0 and len(importances) == len(all_features):
    # ==== 3. Create dataframe for plotting ====
    feat_df = pd.DataFrame({'feature': all_features, 'importance': importances})
    feat_df = feat_df.sort_values(by='importance', ascending=False).head(20)  # top 20

    # ==== 4. Plot ====
    plt.figure(figsize=(10,6))
    plt.barh(feat_df['feature'][::-1], feat_df['importance'][::-1], color='skyblue')
    plt.xlabel('Feature Importance')
    plt.title('Top 7 Feature Importances - Random Forest')
    plt.show()
else:
    print("Could not generate feature importances plot due to previous errors or mismatch in feature/importance counts.")
```

```
Error: 'best_model_rf' or its components are not fitted. Please run the Random Forest model training cell first.
```



`Random Forest Feature Importance Analysis`

The chart shows the **Top 7 most important features** identified by the Random Forest model. Feature importance reflects how much each feature contributes to predicting the target variable. Higher importance values indicate stronger influence.

`Key Observations:`

1. **Tenure_Days (~0.30)**
    - Most influential predictor.
    - Suggests that the length of tenure strongly impacts the outcome.
2. **Total Business Value (~0.22)**

   - Second most important feature.
   - Indicates customer/business value plays a major role in predictions.

3. **Quarterly Rating (~0.17)**
   - Performance or satisfaction measured quarterly has significant predictive power.

4. **Income (~0.13)** and **Age (~0.12)**
   - Both demographic/economic factors contribute moderately.
   - Income slightly outweighs Age.

5. **Grade (~0.04)** and **Gender (~0.01)**
   - Least influential features.
   - These variables add minimal value to the model's prediction.

`Insights:`

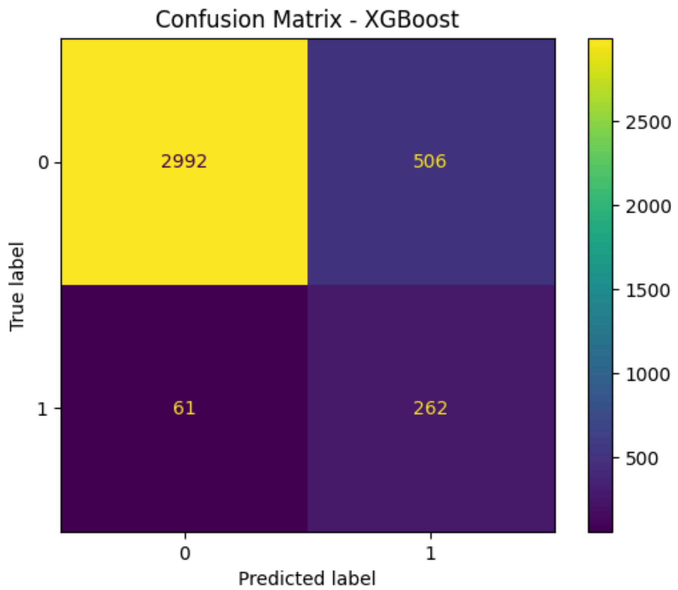
- The model relies most on **Tenure_Days** and **Business Value** for predictions.
- Features like **Gender** and **Grade** may be less relevant and could potentially be excluded without much loss in accuracy.
- The results highlight that customer longevity and value are stronger predictors compared to demographic attributes.

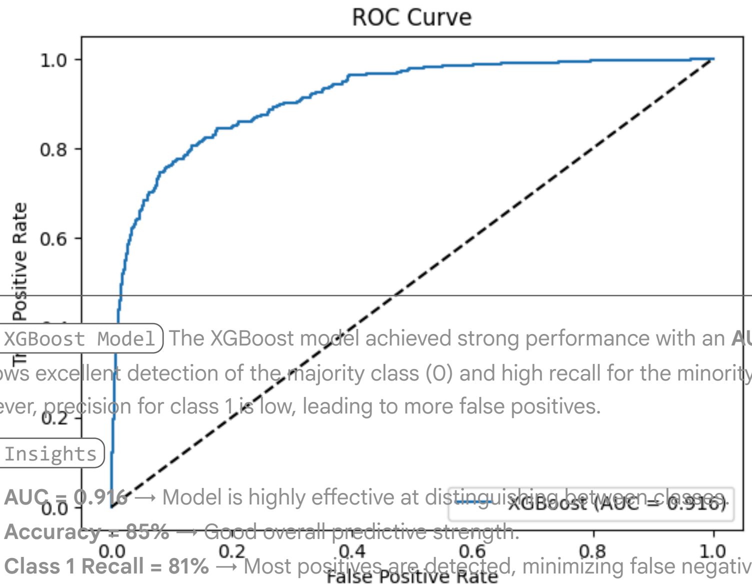
XGBoost

```
# === 1.Import Library ===
from xgboost import XGBClassifier

# ==== 2. Load data ====
agg_final = df.copy()   # replace df with your dataframe
if 'Tenure_Group' in agg_final.columns:
    agg_final = agg_final.drop(columns=['Tenure_Group'])  # remove Tenure_Group

# ==== 3. Split X / y ====
y = agg_final['Target']
X = agg_final.drop(columns=['Target'])

# ==== 4. Identify numeric and categorical features ====
numeric_features = X.select_dtypes(include=['number']).columns.tolist()
cat_features = X.select_dtypes(include=['object','category']).columns.tolist()

# ==== 5. Preprocessing pipelines ====
numeric_transformer = Pipeline([
    ('imputer', KNNImputer(n_neighbors=5)),
    ('scaler', StandardScaler())
])

cat_transformer = Pipeline([
    ('onehot', OneHotEncoder(handle_unknown='ignore', sparse_output=False))
])

preprocessor = ColumnTransformer(transformers=[
    ('num', numeric_transformer, numeric_features),
    ('cat', cat_transformer, cat_features)
], remainder='drop')

# ==== 6. Train-test split ====
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

# ==== 7. XGBoost with SMOTE ====
steps = [
    ('preproc', preprocessor),
    ('smote', SMOTE(random_state=42)),
    ('clf', XGBClassifier(
        use_label_encoder=False,
        eval_metric='logloss',
        random_state=42,
        scale_pos_weight=len(y_train[y_train==0]) / len(y_train[y_train==1])  # handles imbalance
    ))
]

pipeline = ImbPipeline(steps=steps)

# ==== 8. Hyperparameter tuning ====
param_grid = {
    'clf__n_estimators': [100, 200],
    'clf__max_depth': [3, 5, 7],
```

```
    'clf__learning_rate': [0.01, 0.1, 0.2],
    'clf__subsample': [0.8, 1.0],
    'clf__colsample_bytree': [0.8, 1.0]
}

cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
grid = GridSearchCV(pipeline, param_grid, cv=cv, scoring='roc_auc', n_jobs=-1, verbose=1)
grid.fit(X_train, y_train)

best_model_xgb = grid.best_estimator_
print("Best hyperparameters:", grid.best_params_)

# ==== 9. Predict & evaluate ====
y_pred = best_model_xgb.predict(X_test)
y_proba = best_model_xgb.predict_proba(X_test)[:,1]

# Classification report
print("\nClassification Report:\n", classification_report(y_test, y_pred, digits=4))

# ROC AUC
auc = roc_auc_score(y_test, y_proba)
print("ROC AUC:", auc)

# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()
plt.title("Confusion Matrix - XGBoost")
plt.show()

# ROC curve
fpr, tpr, _ = roc_curve(y_test, y_proba)
plt.plot(fpr, tpr, label=f'XGBoost (AUC = {auc:.3f})')
plt.plot([0,1],[0,1],'k--')
plt.xlabel('False Positive Rate'); plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.show()

```

```
Fitting 5 folds for each of 72 candidates, totalling 360 fits
/usr/local/lib/python3.12/dist-packages/xgboost/training.py:183: UserWarning: [22:13:41] WARNING: /workspace/src/learner.cc:738
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
Best hyperparameters: {'clf__colsample_bytree': 0.8, 'clf__learning_rate': 0.2, 'clf__max_depth': 7, 'clf__n_estimators': 200,

Classification Report:
              precision    recall  f1-score   support

           0     0.9800    0.8553    0.9134      3498
           1     0.3411    0.8111    0.4803       323

    accuracy                         0.8516      3821
   macro avg     0.6606    0.8332    0.6969      3821
weighted avg     0.9260    0.8516    0.8768      3821

ROC AUC: 0.9158466492130841
```





`For XGBoost Model` The XGBoost model achieved strong performance with an **AUC of 0.916** and overall **accuracy of 85%**.
It shows excellent detection of the majority class (0) and high recall for the minority class (1).
However, precision for class 1 is low, leading to more false positives.

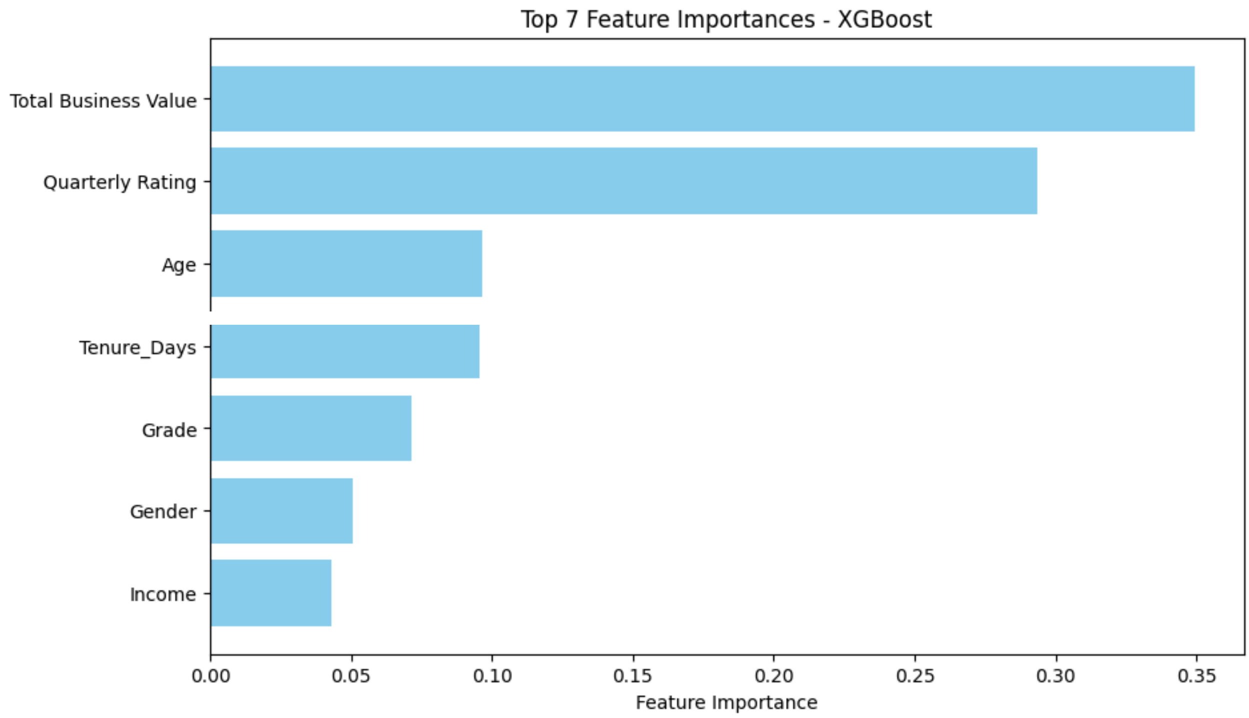
`Key Insights`

1. **AUC = 0.916** → Model is highly effective at distinguishing between classes.
2. **Accuracy ≈ 85%** → Good overall predictive strength.
3. **Class 1 Recall = 81%** → Most positives are detected, minimizing false negatives.
4. **Class 1 Precision = 34%** → Many false positives occur when predicting positives.
5. **Confusion Matrix shows imbalance** → Model favors majority class (0), but still captures minority class (1) reasonably well.

```
# Identify numeric and categorical features
numeric_features = X.select_dtypes(include=['number']).columns.tolist()
cat_features = X.select_dtypes(include=['object', 'category', 'bool']).columns.tolist() # Include boolean as they were c

# Categorical features after one-hot encoding - access from the fitted pipeline
# Ensure best_model_xgb has been fitted (e.g., by running the Random Forest cell)
try:
    cat_features_encoded = best_model_rf.named_steps['preproc']\
        .named_transformers_['cat']\
        .named_steps['onehot'].get_feature_names_out(cat_features)
except AttributeError:
    print("Error: 'best_model_rf' or its components are not fitted. Please run the Random Forest model training cell fir
    cat_features_encoded = [] # Initialize as empty to avoid further errors

```

```

# Combine all feature names
all_features = np.concatenate([numeric_features, cat_features_encoded])

# Filter out 'Target' if it somehow ended up in all_features (shouldn't happen with the way X is created, but as a safeg
if 'Target' in all_features:
    all_features = all_features[all_features != 'Target']


# ==== 2. Get feature importances ====
# Ensure the classifier is fitted before accessing feature_importances_
try:
    importances = best_model_xgb.named_steps['clf'].feature_importances_
except AttributeError:
    print("Error: Random Forest classifier is not fitted. Please run the Random Forest model training cell first.")
    importances = [] # Initialize as empty

# Make sure importances and all_features have the same length before creating DataFrame
if len(all_features) > 0 and len(importances) == len(all_features):
    # ==== 3. Create dataframe for plotting ====
    feat_df = pd.DataFrame({'feature': all_features, 'importance': importances})
    feat_df = feat_df.sort_values(by='importance', ascending=False).head(20)  # top 20

    # ==== 4. Plot ====
    plt.figure(figsize=(10,6))
    plt.barh(feat_df['feature'][::-1], feat_df['importance'][::-1], color='skyblue')
    plt.xlabel('Feature Importance')
    plt.title('Top 7 Feature Importances - XGBoost')
    plt.show()
else:
    print("Could not generate feature importances plot due to previous errors or mismatch in feature/importance counts."
```

```
Error: 'best_model_rf' or its components are not fitted. Please run the Random Forest model training cell first.
```



`XGBoost Feature Importance Analysis`

The chart shows the Top 7 most important features identified by the XGBoost model. Feature importance reflects how much each feature