Credit Score Classification

Business Proble and Objective

Business Problem:

The business problem addressed by the Credit Score Classification project is the need for a reliable system to categorize credit scores accurately. Credit score classification is pivotal in evaluating an individual's creditworthiness and determining their eligibility for financial products such as loans and credit cards. It serves as a critical component in risk assessment for financial institutions, aiding them in making prudent decisions while minimizing the risk of loan defaults.

Objective:

The objective of the Credit Score Classification project is to develop a robust model capable of accurately categorizing credit scores. The project aims to leverage data analytics and machine learning techniques to achieve this goal and provide financial institutions with a reliable tool for making informed decisions based on accurate credit score classification.

2. Import Libraries

In [2]:
```
pip install xgboost
```

```
Collecting xgboost
  Downloading xgboost-2.0.3-py3-none-win_amd64.whl (99.8 MB)
     ---------------------------------------- 99.8/99.8 MB 3.3 MB/s eta 0:00:00
Requirement already satisfied: scipy in c:\users\hp\anaconda3\lib\site-packages (fro
m xgboost) (1.10.0)
Requirement already satisfied: numpy in c:\users\hp\anaconda3\lib\site-packages (fro
m xgboost) (1.23.5)
Installing collected packages: xgboost
Successfully installed xgboost-2.0.3
Note: you may need to restart the kernel to use updated packages.
```

In [3]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import statistics

from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score
from sklearn.neighbors import KNeighborsClassifier
import xgboost as xgb
from sklearn.metrics import accuracy_score, precision_score, recall_score,classificat
```

3. Load Data

In [4]:
```python
df_train_original = pd.read_csv('D:\\Scaler\\Scaler\\Fintech Domain Course\\Credit Py
df_train = df_train_original.copy()
df_train.head()
```

```
C:\Users\hp\AppData\Local\Temp\ipykernel_20772\4168188010.py:1: DtypeWarning: Column
s (26) have mixed types. Specify dtype option on import or set low_memory=False.
  df_train_original = pd.read_csv('D:\\Scaler\\Scaler\\Fintech Domain Course\\Credit
Python EDA\\Credit_score.csv')
```

Out[4]:

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Sa
0	0x1602	CUS_0xd40	January	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843
1	0x1603	CUS_0xd40	February	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	N
2	0x1604	CUS_0xd40	March	Aaron Maashoh	-500	821-00-0265	Scientist	19114.12	N
3	0x1605	CUS_0xd40	April	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	N
4	0x1606	CUS_0xd40	May	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843

5 rows × 27 columns

4. Exploratory Data Analysis

4.1 Preview Dataset

In [4]:
```python
df_train.head()
```

Out[4]:

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Sa
0	0x1602	CUS_0xd40	January	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843
1	0x1603	CUS_0xd40	February	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	N
2	0x1604	CUS_0xd40	March	Aaron Maashoh	-500	821-00-0265	Scientist	19114.12	N
3	0x1605	CUS_0xd40	April	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	N
4	0x1606	CUS_0xd40	May	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843

5 rows × 28 columns

In [5]:
```python
#Check Data Size
print('Train Data Size : ',df_train.shape)
```

```
Train Data Size :  (100000, 27)
```

In [6]:
```python
df_train.columns
```

Out[6]:
```
Index(['ID', 'Customer_ID', 'Month', 'Name', 'Age', 'SSN', 'Occupation',
       'Annual_Income', 'Monthly_Inhand_Salary', 'Num_Bank_Accounts',
       'Num_Credit_Card', 'Interest_Rate', 'Num_of_Loan', 'Type_of_Loan',
       'Delay_from_due_date', 'Num_of_Delayed_Payment', 'Changed_Credit_Limit',
       'Num_Credit_Inquiries', 'Credit_Mix', 'Outstanding_Debt',
       'Credit_Utilization_Ratio', 'Credit_History_Age',
       'Payment_of_Min_Amount', 'Total_EMI_per_month',
       'Amount_invested_monthly', 'Payment_Behaviour', 'Monthly_Balance'],
      dtype='object')
```

In [7]:
```python
#Check Train dataset
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 27 columns):
 #   Column                    Non-Null Count   Dtype  
---  ------                    --------------   -----  
 0   ID                        100000 non-null  object 
 1   Customer_ID               100000 non-null  object 
 2   Month                     100000 non-null  object 
 3   Name                      90015 non-null   object 
 4   Age                       100000 non-null  object 
 5   SSN                       100000 non-null  object 
 6   Occupation                100000 non-null  object 
 7   Annual_Income             100000 non-null  object 
 8   Monthly_Inhand_Salary     84998 non-null   float64
 9   Num_Bank_Accounts         100000 non-null  int64  
 10  Num_Credit_Card           100000 non-null  int64  
 11  Interest_Rate             100000 non-null  int64  
 12  Num_of_Loan               100000 non-null  object 
 13  Type_of_Loan              88592 non-null   object 
 14  Delay_from_due_date       100000 non-null  int64  
 15  Num_of_Delayed_Payment    92998 non-null   object 
 16  Changed_Credit_Limit      100000 non-null  object 
 17  Num_Credit_Inquiries      98035 non-null   float64
 18  Credit_Mix                100000 non-null  object 
 19  Outstanding_Debt          100000 non-null  object 
 20  Credit_Utilization_Ratio  100000 non-null  float64
 21  Credit_History_Age        90970 non-null   object 
 22  Payment_of_Min_Amount     100000 non-null  object 
 23  Total_EMI_per_month       100000 non-null  float64
 24  Amount_invested_monthly   95521 non-null   object 
 25  Payment_Behaviour         100000 non-null  object 
 26  Monthly_Balance           98800 non-null   object 
dtypes: float64(4), int64(4), object(19)
memory usage: 20.6+ MB
```

Observations :

1. There are missing values present in dataset.
2. Train dataset has both numerical and string values.

In [8]:
```python
#Check statistical values for fields with numerical datatype
df_train.describe().T
```

Out[8]:

	count	mean	std	min	25%	50%	
Monthly_Inhand_Salary	84998.0	4194.170850	3183.686167	303.645417	1625.568229	3093.745000	5957.4
Num_Bank_Accounts	100000.0	17.091280	117.404834	-1.000000	3.000000	6.000000	7.0
Num_Credit_Card	100000.0	22.474430	129.057410	0.000000	4.000000	5.000000	7.0
Interest_Rate	100000.0	72.466040	466.422621	1.000000	8.000000	13.000000	20.0
Delay_from_due_date	100000.0	21.068780	14.860104	-5.000000	10.000000	18.000000	28.0
Num_Credit_Inquiries	98035.0	27.754251	193.177339	0.000000	3.000000	6.000000	9.0
Credit_Utilization_Ratio	100000.0	32.285173	5.116875	20.000000	28.052567	32.305784	36.4
Total_EMI_per_month	100000.0	1403.118217	8306.041270	0.000000	30.306660	69.249473	161.2

In [9]:
```python
#Check statistical values for fields with other than numerical datatype
df_train.describe(exclude=np.number).T
```

Out[9]:

	count	unique	top	freq
ID	100000	100000	0x1602	1
Customer_ID	100000	12500	CUS_0xd40	8
Month	100000	8	January	12500
Name	90015	10139	Langep	44
Age	100000	1788	38	2833
SSN	100000	12501	#F%$D@*&8	5572
Occupation	100000	16	_______	7062
Annual_Income	100000	18940	36585.12	16
Num_of_Loan	100000	434	3	14386
Type_of_Loan	88592	6260	Not Specified	1408
Num_of_Delayed_Payment	92998	749	19	5327
Changed_Credit_Limit	100000	4384	_	2091
Credit_Mix	100000	4	Standard	36479
Outstanding_Debt	100000	13178	1360.45	24
Credit_History_Age	90970	404	15 Years and 11 Months	446
Payment_of_Min_Amount	100000	3	Yes	52326
Amount_invested_monthly	95521	91049	__10000__	4305
Payment_Behaviour	100000	7	Low_spent_Small_value_payments	25513
Monthly_Balance	98800	98792	__-333333333333333333333333333__	9
Credit_Score	100000	3	Standard	53174

Observations

1. Customer_ID has 12500 unique values. It means we have data of 12500 customers.
2. Month has only 8 unique values. Better to analyse further which months are present.
3. Age has 1788 unique values. This looks strange as general age range is from 0-100.
4. SSN has 12501 unique values, whereas Customer_ID only has only 12500 unique values. There is a possibility that incorrect SSN value is entered for one of the customer as same person can't have

multiple SSN.

Buidling Common Functions for Data Cleaning

Created following functions that will help in exploring,analysing & cleaning of the data

In [10]:
```
def get_column_details(df,column):
    print("Details of",column,"column")

    #DataType of column
    print("\nDataType: ",df[column].dtype)

    #Check if null values are present
    count_null = df[column].isnull().sum()
    if count_null==0:
        print("\nThere are no null values")
    elif count_null>0:
        print("\nThere are ",count_null," null values")

    #Get Number of Unique Values
    print("\nNumber of Unique Values: ",df[column].nunique())

    #Get Distribution of Column
    print("\nDistribution of column:\n")
    print(df[column].value_counts())
```

In [11]:
```
def fill_missing_with_group_mode(df, groupby, column):
    print("\nNo. of missing values before filling with group mode:",df[column].isnull

    # Fill with local mode
    mode_per_group = df.groupby(groupby)[column].transform(lambda x: x.mode().iat[0])
    df[column] = df[column].fillna(mode_per_group)

    print("\nNo. of missing values after filling with group mode:",df[column].isnull(
```

In [12]:
```
#Method to clean categorical field

def clean_categorical_field(df,groupby,column,replace_value=None):
    print("\n-----------------------------------------------------")
    print("\nCleaning steps ")

    #Replace with np.nan
    if replace_value!=None:
        df[column] = df[column].replace(replace_value,np.nan)
        print(f"\nGarbage value {replace_value} is replaced with np.nan")

    #For each Customer_ID, assign same value for the column
    fill_missing_with_group_mode(df,groupby,column)
```

In [13]:
```
# Handle Outliers and null values
def fix_inconsistent_values(df, groupby, column):
    print("\nExisting Min, Max Values:", df[column].apply([min, max]), sep='\n', end=

    df_dropped = df[df[column].notna()].groupby(groupby)[column].apply(list)
    x, y = df_dropped.apply(lambda x: stats.mode(x)).apply([min, max])
    mini, maxi = x[0][0], y[0][0]

    # assign Wrong Values to NaN
    col = df[column].apply(lambda x: np.NaN if ((x<mini)|(x>maxi)|(x<0)) else x)

    # fill with local mode
    mode_by_group = df.groupby(groupby)[column].transform(lambda x: x.mode()[0] if no
    df[column] = col.fillna(mode_by_group)
    df[column].fillna(df[column].mean(),inplace=True)

    print("\nAfter Cleaning Min, Max Values:", df[column].apply([min, max]), sep='\n'
    print("\nNo. of Unique values after Cleaning:",df[column].nunique())
    print("\nNo. of Null values after Cleaning:",df[column].isnull().sum())
```

In [14]:
```
#Method to clean Numerical Field
def clean_numerical_field(df,groupby,column,strip=None,datatype=None,replace_value=No
    print("\n-----------------------------------------------------")
    print("\nCleaning steps ")

    #Replace with np.nan
    if replace_value!=None:
        df[column] = df[column].replace(replace_value,np.nan)
        print(f"\nGarbage value {replace_value} is replaced with np.nan")

    # Remove trailing & leading special characters
    if df[column].dtype == object and strip is not None:
        df[column] = df[column].str.strip(strip)
        print(f"\nTrailing & leading {strip} are removed")

    # Change datatype
    if datatype is not None:
        df[column] = df[column].astype(datatype)
        print(f"\nDatatype of {column} is changed to {datatype}")

    fix_inconsistent_values(df, groupby, column)
```

In [15]:
```
def plot_countplot(df,column,user_friendly_column_name,rotation=0):
    print("\n-----------------------------------------------------")
    print(f'\n{user_friendly_column_name} Distribution')
    palette = "deep"
    sns.set_palette(palette)

    sns.countplot(data=df, x=column)

    plt.xlabel(f'{user_friendly_column_name}')
    plt.ylabel('Number of Records')
    plt.title(f'{user_friendly_column_name} Distribution')
    plt.xticks(rotation=rotation)

    plt.show()
```

In [16]:
```
def plot_displot(df,column,user_friendly_column_name,rotation=0,bins=20):
    print("\n-----------------------------------------------------")
    print(f'\n{user_friendly_column_name} Distribution')
    palette = "deep"
    sns.set_palette(palette)

    sns.displot(data=df, x=column, kde=True, bins=bins)

    plt.xlabel(f'{user_friendly_column_name}')
    plt.ylabel('Number of Records')
    plt.title(f'{user_friendly_column_name} Distribution')
    plt.xticks(rotation=rotation)

    plt.show()
```

In [17]:
```
def plot_stacked_bar(df,column1,column2,rotation=0):
    print("\n-----------------------------------------------------")
    print(f'\n{column1} & {column2} Distribution')
    palette = "deep"
    sns.set_palette(palette)

    pd.crosstab(df[column1], df[column2]).plot(kind='bar', stacked=True)

    plt.xlabel(f'{column1}')
    plt.ylabel('Number of Records')
    plt.title(f'{column1} & {column2} Distribution')
    plt.xticks(rotation=rotation)

    plt.show()
```

4.3 Categorical Variables

Credit Score

Summary

1. There are 3 different Credit Score - Standard, Good & Poor.
2. Distribution of credit score -

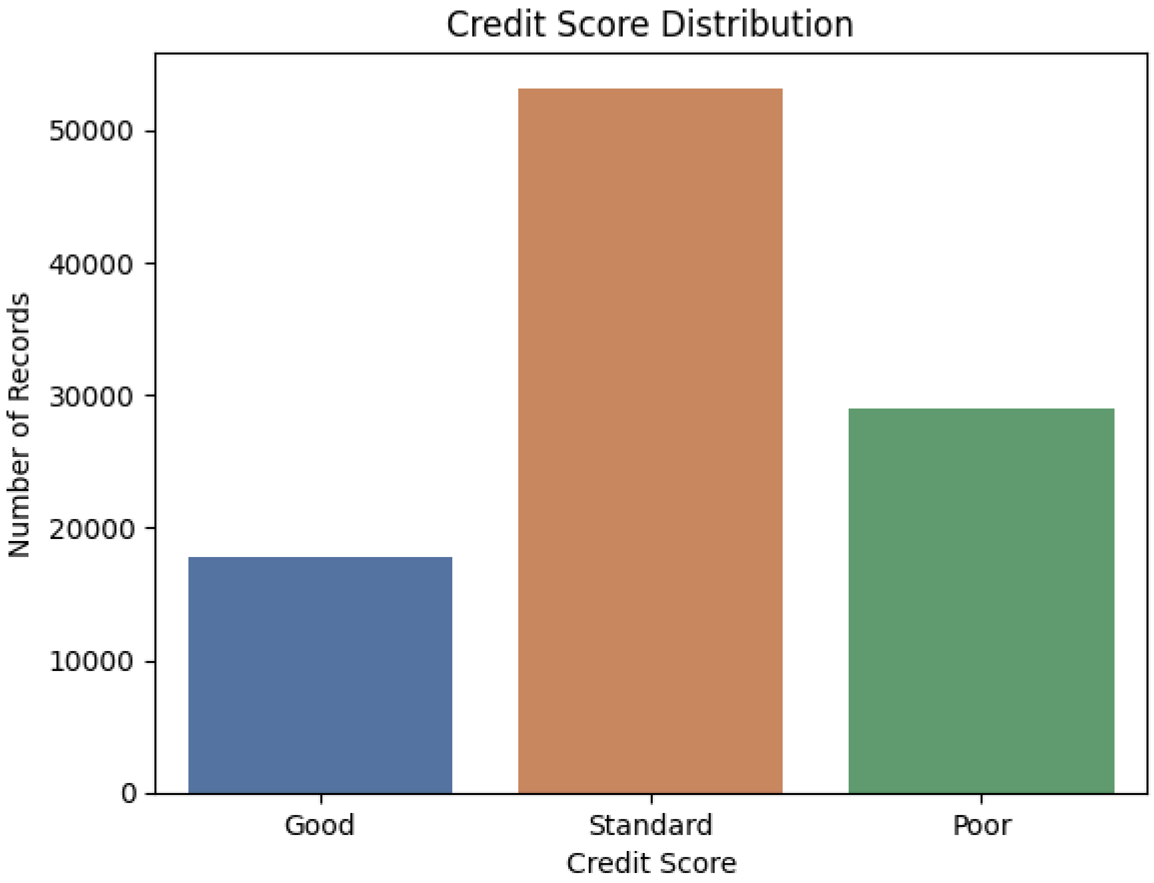
   a) Standard - 53%

   b) Poor - 29%

   c) Good - 17%
3. There are no null values for Credit Score.

In [18]:
```python
column_name = 'Credit_Score'
user_friendly_name = 'Credit Score'

#Get Details
get_column_details(df_train,column_name)

#Plot Graph
plot_countplot(df_train,column_name,user_friendly_name)
```

```
Details of Credit_Score column

DataType:  object

There are no null values

Number of Unique Values:  3

Distribution of column:

Standard    53174
Poor        28998
Good        17828
Name: Credit_Score, dtype: int64

-----------------------------------------------------

Credit Score Distribution
```



ID

Summary

1. There are 100000 distinct records and no null values present.

In [19]:
```
#Get Details
get_column_details(df_train,'ID')
```

```
Details of ID column

DataType:  object

There are no null values

Number of Unique Values:  100000

Distribution of column:

0x1602     1
0x19c88    1
0x19caa    1
0x19ca5    1
0x19ca4    1
          ..
0xd94d     1
0xd94c     1
0xd94b     1
0xd94a     1
0x25fed    1
Name: ID, Length: 100000, dtype: int64
```

Customer ID

Summary

1. We have record of 12500 unique customers.
2. Same customer can have different credit score. It means that on the basis of other values customer credit score can change.

In [20]:
```
#Get Details
get_column_details(df_train,'Customer_ID')
```

```
Details of Customer_ID column

DataType:  object

There are no null values

Number of Unique Values:  12500

Distribution of column:

CUS_0xd40     8
CUS_0x9bf4    8
CUS_0x5ae3    8
CUS_0xbe9a    8
CUS_0x4874    8
             ..
CUS_0x2eb4    8
CUS_0x7863    8
CUS_0x9d89    8
CUS_0xc045    8
CUS_0x942c    8
Name: Customer_ID, Length: 12500, dtype: int64
```

In [21]:
```python
#Check if same customer can have different credit score
df_train.groupby(['Customer_ID'])['Credit_Score'].nunique()
```

Out[21]:
```
Customer_ID
CUS_0x1000    2
CUS_0x1009    1
CUS_0x100b    2
CUS_0x1011    1
CUS_0x1013    1
             ..
CUS_0xff3     2
CUS_0xff4     1
CUS_0xff6     2
CUS_0xffc     2
CUS_0xffd     2
Name: Credit_Score, Length: 12500, dtype: int64
```

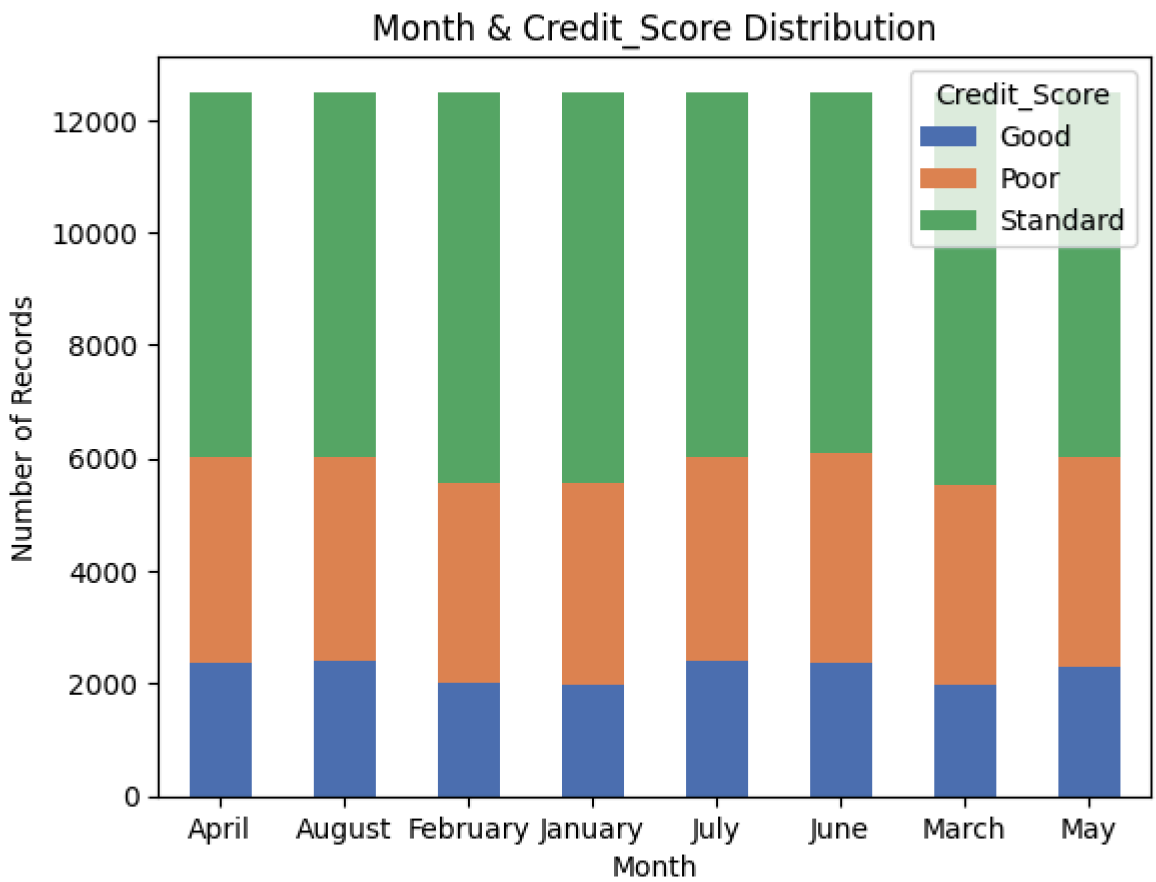
Month

Summary

1. In the training dataset, we have credit score for each customer over the course of 8 months(from January to August).
2. Converted Month column from object to datetime value so that it can be further use for model building.
3. Distribution of Credit_Scrore across different months is similar.

In [22]:
```
column_name = 'Month'

#Get Details
get_column_details(df_train,column_name)

#Plot Distrbution with Credit_Score
plot_stacked_bar(df_train,column_name,'Credit_Score')
```

```
Details of Month column

DataType:  object

There are no null values

Number of Unique Values:  8

Distribution of column:

January     12500
February    12500
March       12500
April       12500
May         12500
June        12500
July        12500
August      12500
Name: Month, dtype: int64

-----------------------------------------------------

Month & Credit_Score Distribution
```



In [23]:
```
#Convert Month to datetime object
df_train['Month'] = pd.to_datetime(df_train.Month, format='%B').dt.month
```

Name

Summary

1. There are 9985 null values.
2. Cleaning Step - Assign same Name value to each Customer_ID

In [24]:
```
column_name = 'Name'
group_by = 'Customer_ID'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_categorical_field(df_train,group_by,column_name)
```

```
Details of Name column

DataType:  object

There are  9985  null values

Number of Unique Values:  10139

Distribution of column:

Langep            44
Stevex            44
Vaughanl          39
Jessicad          39
Raymondr          38
                  ..
Alina Selyukhg     4
Habboushg          4
Mortimerq          4
Ronaldf            4
Timothyl           3
Name: Name, Length: 10139, dtype: int64

-----------------------------------------------------

Cleaning steps

No. of missing values before filling with group mode: 9985

No. of missing values after filling with group mode: 0
```

SSN

Summary

1. There are 12501 unique SSN values in training dataset.
2. 5572 entries has random/garbage value as SSN value
3. Steps to Clean SSN -

   i. Replace garbage value with np.nan

ii. Assign same SSN value for each customer ID

In [25]:
```
column_name = 'SSN'
group_by = 'Customer_ID'
garbage_value = '#F%$D@*&8'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_categorical_field(df_train,group_by,column_name,garbage_value)
```

```
Details of SSN column

DataType:  object

There are no null values

Number of Unique Values:  12501

Distribution of column:

#F%$D@*&8      5572
078-73-5990       8
486-78-3816       8
750-67-7525       8
903-50-0305       8
               ...
856-06-6147       4
753-72-2651       4
331-28-1921       4
604-62-6133       4
286-44-9634       4
Name: SSN, Length: 12501, dtype: int64

-----------------------------------------------------

Cleaning steps

Garbage value #F%$D@*&8 is replaced with np.nan

No. of missing values before filling with group mode: 5572

No. of missing values after filling with group mode: 0
```

Occupation

Summary

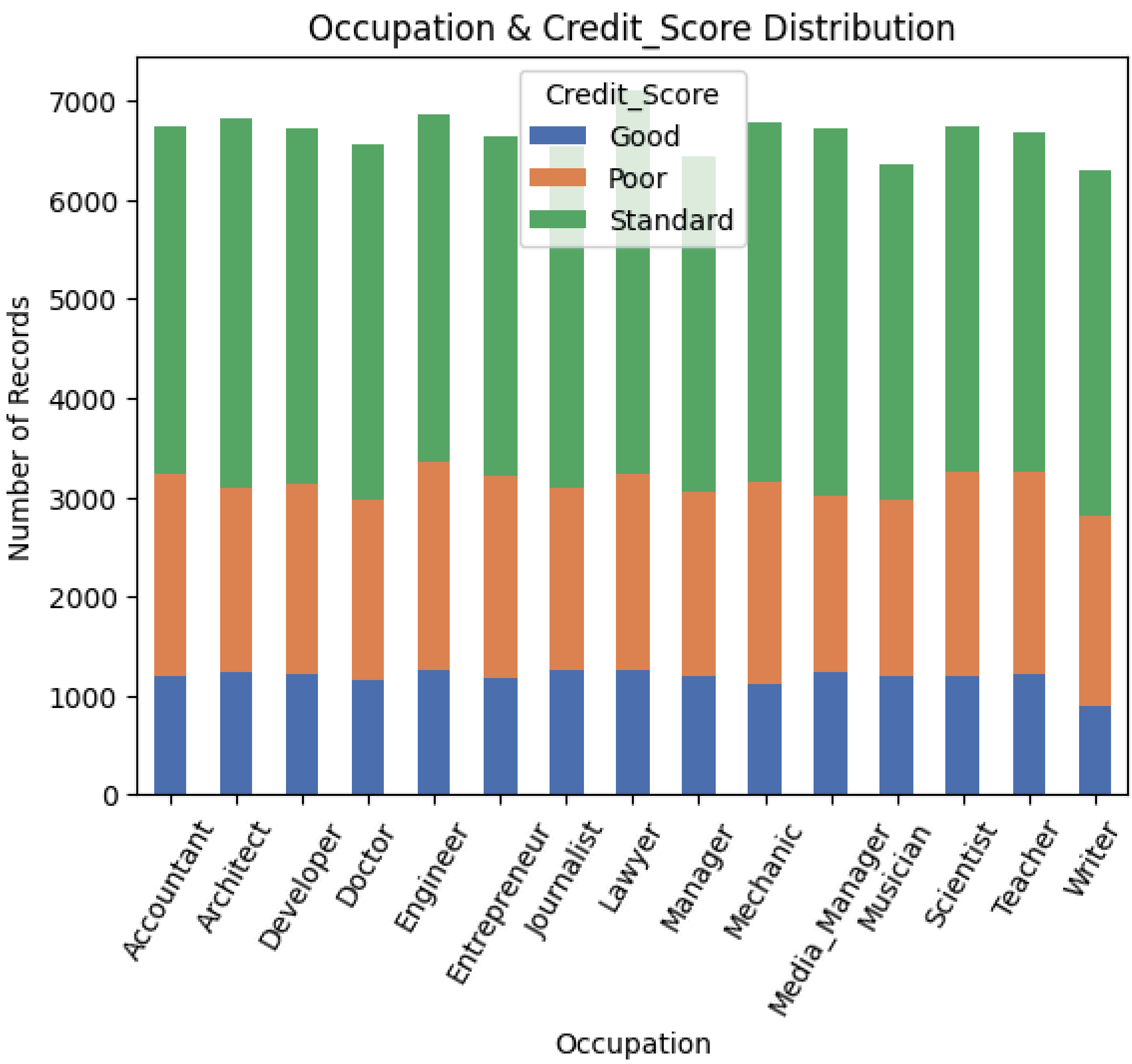
1. There are 16 unique Occupation values.
2. 7062 records are marked with garbage value.
3. Steps to Clean Occupation -

   i. Replace garbage value with np.nan

   ii. Assign same Occupation value for each customer ID
4. Distribution of Credit_Scrore across different occupation is similar.

In [26]:
```
column_name = 'Occupation'
group_by = 'Customer_ID'
garbage_value = '_______'
user_friendly_name = 'Occupation'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_categorical_field(df_train,group_by,column_name,garbage_value)

#Plot Distribution with Credit_Score
plot_stacked_bar(df_train,column_name,'Credit_Score',rotation=60)
```

```
Details of Occupation column

DataType:  object

There are no null values

Number of Unique Values:  16

Distribution of column:

_______          7062
Lawyer           6575
Architect        6355
Engineer         6350
Scientist        6299
Mechanic         6291
Accountant       6271
Developer        6235
Media_Manager    6232
Teacher          6215
Entrepreneur     6174
Doctor           6087
Journalist       6085
Manager          5973
Musician         5911
Writer           5885
Name: Occupation, dtype: int64

-----------------------------------------------------

Cleaning steps

Garbage value _______ is replaced with np.nan

No. of missing values before filling with group mode: 7062

No. of missing values after filling with group mode: 0

-----------------------------------------------------

Occupation & Credit_Score Distribution
```



Type of Loan

Summary

1. There are 6260 unique values present for Type of Loan and there are null values present.
2. Mapped all null values to *Not Specificed* for Type of Loan column.

In [27]:
```
#Get Details of Type of Loan column
get_column_details(df_train,'Type_of_Loan')
```

```
Details of Type_of_Loan column

DataType:  object

There are  11408  null values

Number of Unique Values:  6260

Distribution of column:

Not Specified
1408
Credit-Builder Loan
1280
Personal Loan
1272
Debt Consolidation Loan
1264
Student Loan
1240

...
Not Specified, Mortgage Loan, Auto Loan, and Payday Loan
8
Payday Loan, Mortgage Loan, Debt Consolidation Loan, and Student Loan
8
Debt Consolidation Loan, Auto Loan, Personal Loan, Debt Consolidation Loan, Student
Loan, and Credit-Builder Loan                        8
Student Loan, Auto Loan, Student Loan, Credit-Builder Loan, Home Equity Loan, Debt C
onsolidation Loan, and Debt Consolidation Loan       8
Personal Loan, Auto Loan, Mortgage Loan, Student Loan, and Student Loan
8
Name: Type_of_Loan, Length: 6260, dtype: int64
```

In [28]:
```
#Handle Type of Loan null values
df_train['Type_of_Loan'].replace([np.NaN], 'Not Specified', inplace=True)
```

Credit Mix

Summary

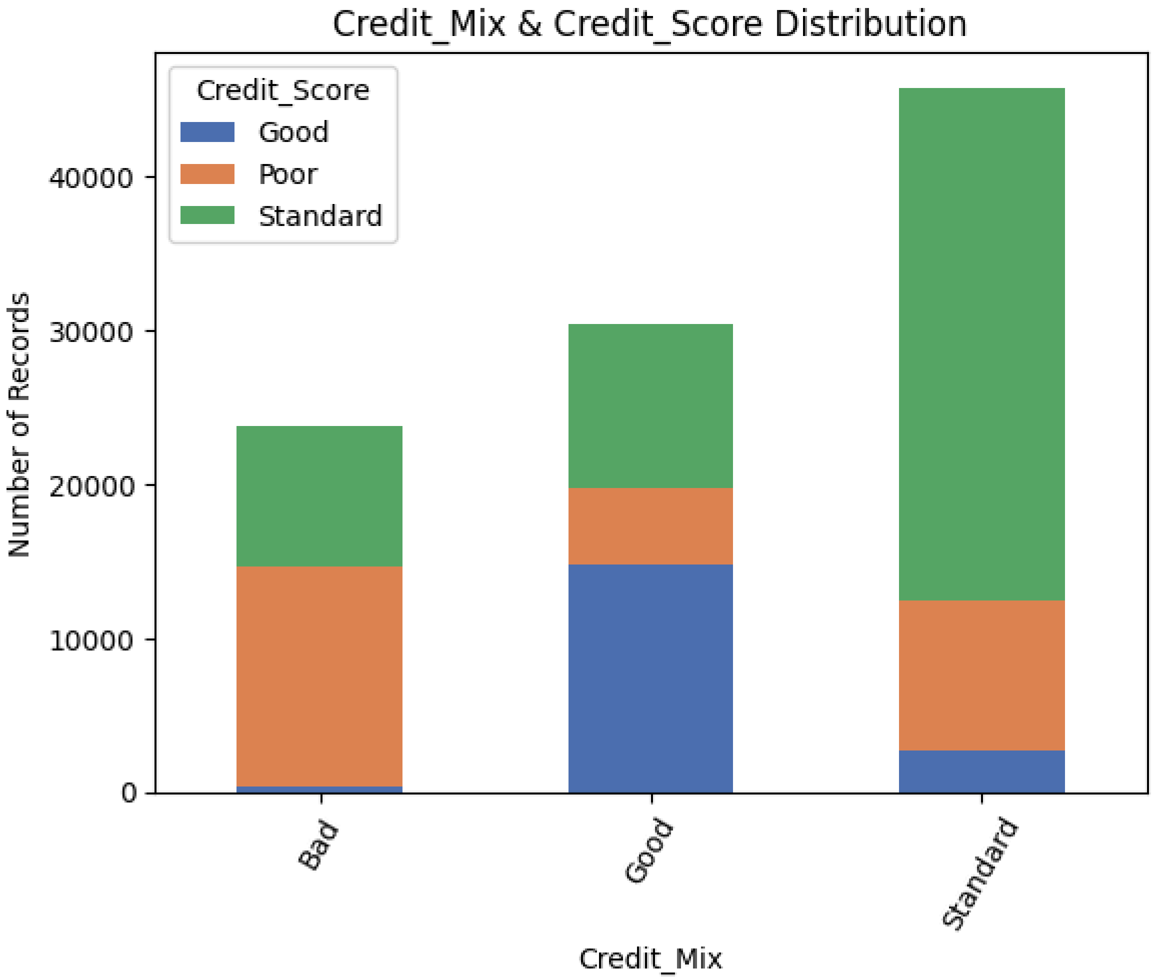
1. There are 3 types of Credit Mix - Standard, Good, Bad
2. About 20k records of Credit Mix is marked as a garbage value (_).
3. Steps to Clean Credit Mix Field -

   i. Replace garbage value with np.nan

   ii. Assign same Credit Mix value for each customer ID

In [29]:
```
column_name = 'Credit_Mix'
group_by = 'Customer_ID'
garbage_value = '_'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_categorical_field(df_train,group_by,column_name,garbage_value)

#Plot Distribution with Credit_Score
plot_stacked_bar(df_train,column_name,'Credit_Score',rotation=60)
```

```
Details of Credit_Mix column

DataType:  object

There are no null values

Number of Unique Values:  4

Distribution of column:

Standard    36479
Good        24337
_           20195
Bad         18989
Name: Credit_Mix, dtype: int64

-----------------------------------------------------

Cleaning steps

Garbage value _ is replaced with np.nan

No. of missing values before filling with group mode: 20195

No. of missing values after filling with group mode: 0

-----------------------------------------------------

Credit_Mix & Credit_Score Distribution
```



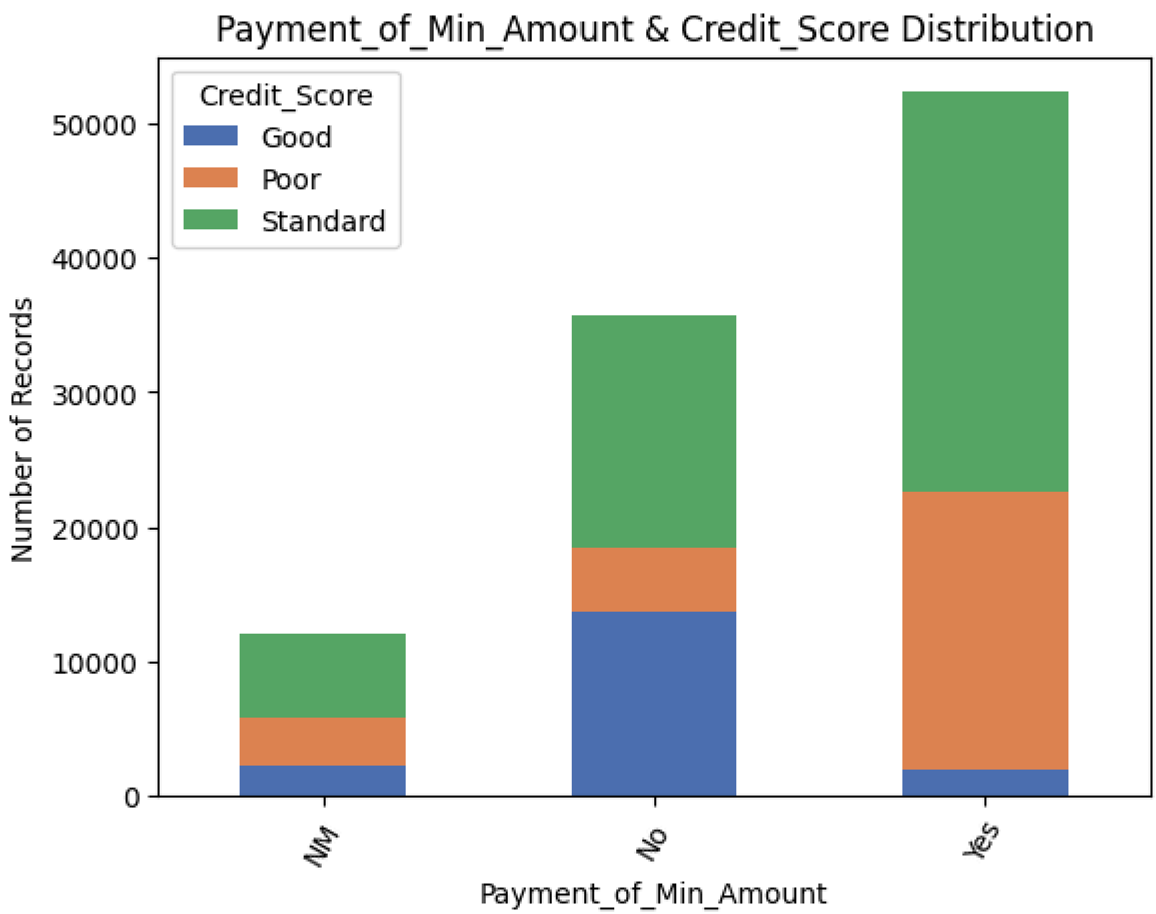
Payment of Min Amount

Summary

1. There are 3 unique values present - Yes, No & NM.
2. No missing values are present.

In [30]:
```
column_name = 'Payment_of_Min_Amount'

#Get Details
get_column_details(df_train,column_name)

#Plot Distribution with Credit_Score
plot_stacked_bar(df_train,column_name,'Credit_Score',rotation=60)
```

```
Details of Payment_of_Min_Amount column

DataType:  object

There are no null values

Number of Unique Values:   3

Distribution of column:

Yes     52326
No      35667
NM      12007
Name: Payment_of_Min_Amount, dtype: int64

-----------------------------------------------------

Payment_of_Min_Amount & Credit_Score Distribution
```



Payment Behaviour

Summary

1. There are 6 unique values of Payment Behaviour -

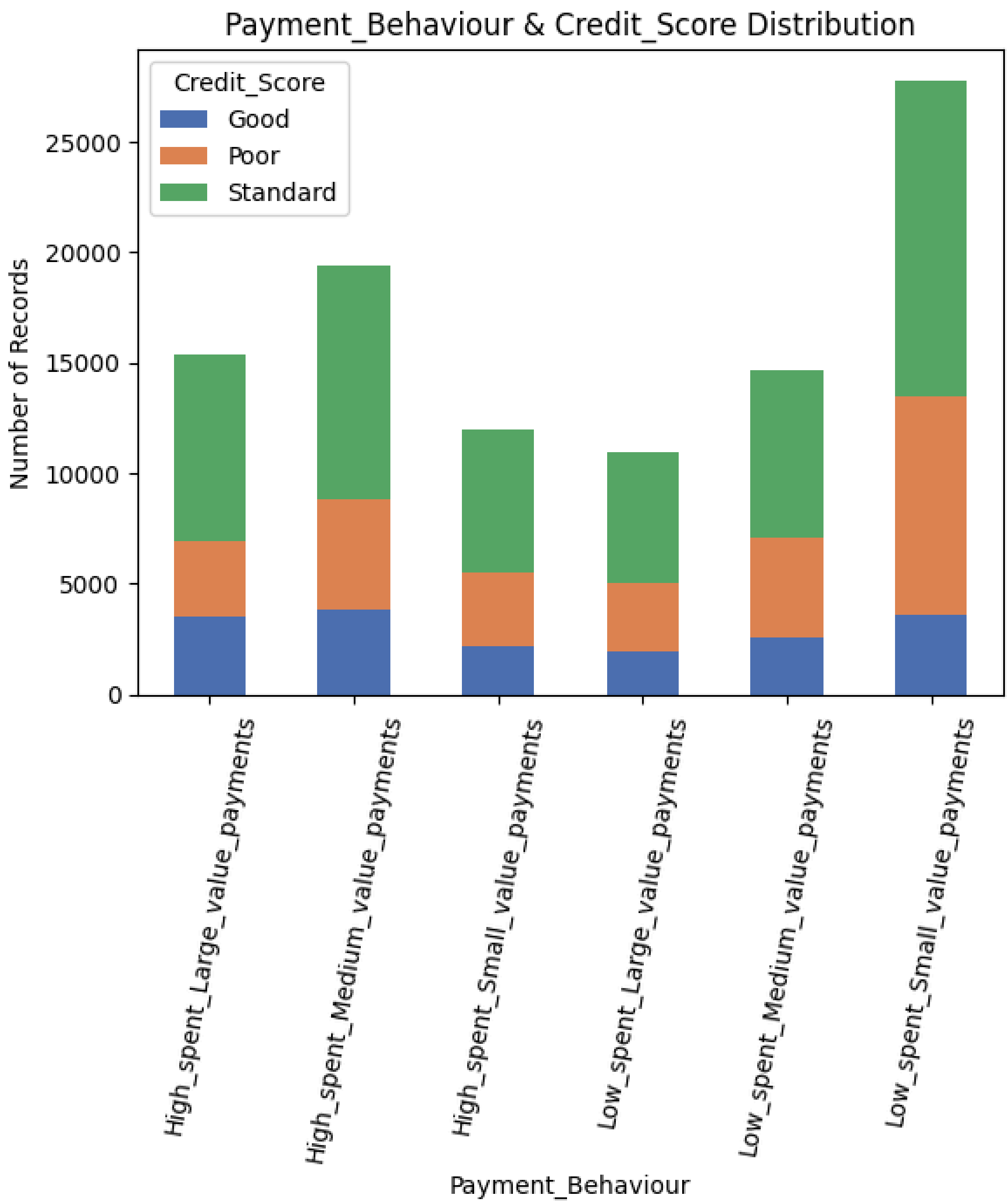
Low_spent_Small_value_payments
High_spent_Medium_value_payments
Low_spent_Medium_value_payments
High_spent_Large_value_payments
High_spent_Small_value_payments
Low_spent_Large_value_payments

2. Amount 27% of records are for Low_spent_Small_value_payments
3. For 7.6k records, Payment Behaviour is filled with garbage value
4. Steps to Clean Payment Behaviour Field -

   i. Replace garbage value with np.nan

In [31]:
```python
column_name = 'Payment_Behaviour'
group_by = 'Customer_ID'
garbage_value = '!@9#%8'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_categorical_field(df_train,group_by,column_name,garbage_value)

#Plot Distribution with Credit_Score
plot_stacked_bar(df_train,column_name,'Credit_Score',rotation=80)
```

```
Details of Payment_Behaviour column

DataType:  object

There are no null values

Number of Unique Values:  7

Distribution of column:

Low_spent_Small_value_payments      25513
High_spent_Medium_value_payments    17540
Low_spent_Medium_value_payments     13861
High_spent_Large_value_payments     13721
High_spent_Small_value_payments     11340
Low_spent_Large_value_payments      10425
!@9#%8                               7600
Name: Payment_Behaviour, dtype: int64

-----------------------------------------------------

Cleaning steps

Garbage value !@9#%8 is replaced with np.nan

No. of missing values before filling with group mode: 7600

No. of missing values after filling with group mode: 0

-----------------------------------------------------

Payment_Behaviour & Credit_Score Distribution
```



4.4 Numerical Variables

Cleaning Steps

1. Remove Trailing & Leading speical characters.
2. Convert datatype from object to int/float if required.
3. Replace null values & outliers with mode value when group by Customer_ID

Age

Summary

1. There are 1788 unique values of Age and it is stored as an object. Having 1788 distinct values of Age mean that there is a lot of dirty data.
2. After cleaning up Age value, 43 distinct Age remains.

In [32]:
```
column_name = 'Age'
group_by = 'Customer_ID'
user_friendly_name = 'Age'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_numerical_field(df_train,group_by,column_name,strip='_',datatype='int')

#Plot Graph
plot_displot(df_train,column_name,user_friendly_name,bins=40)
```

...

Annual Income

Summary

1. Annual Income has no null values.
2. Most customers have a low Annual income. Distribution is right skewed.

In [33]:
```
column_name = 'Annual_Income'
group_by = 'Customer_ID'
user_friendly_name = 'Annual Income'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_numerical_field(df_train,group_by,column_name,strip='_',datatype='float')

#Plot Graph
plot_displot(df_train,column_name,user_friendly_name,bins=40)
```

...

Monthly Inhand Salary

Summary

1. There are null values present.
2. No outliers were present for Monthly Income Salary.
3. Most customers have a low monthly income. Distribution is right skewed.

In [34]:
```
column_name = 'Monthly_Inhand_Salary'
group_by = 'Customer_ID'
user_friendly_name = 'Monthly Inhand Salary'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_numerical_field(df_train,group_by,column_name)

#Plot Graph
plot_displot(df_train,column_name,user_friendly_name,bins=40)
```

...

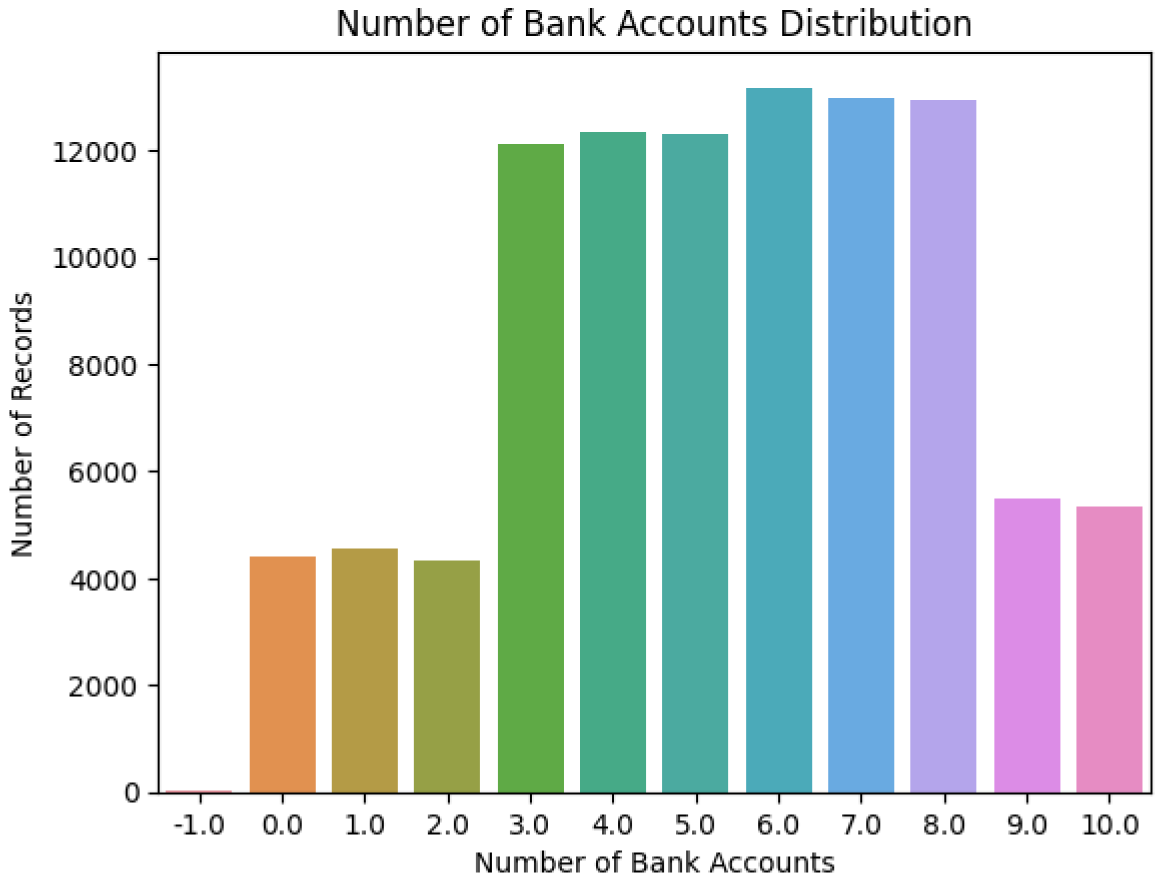
Num Bank Accounts

Summary

1. There are some outliers,negative values in Num Bank Accounts
2. After cleaning, there are 11 possible value of this field - Num Bank Accounts ranging from 0 to 10.
3. Majority of customers has no. of bank accounts between 3 to 8.

In [35]:
```python
column_name = 'Num_Bank_Accounts'
group_by = 'Customer_ID'
user_friendly_name = 'Number of Bank Accounts'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_numerical_field(df_train,group_by,column_name)

#Plot Graph
plot_countplot(df_train,column_name,user_friendly_name)
```

```
Details of Num_Bank_Accounts column

DataType:  int64

There are no null values

Number of Unique Values:  943

Distribution of column:

6       13001
7       12823
8       12765
4       12186
5       12118
        ...
1626        1
1470        1
887         1
211         1
697         1
Name: Num_Bank_Accounts, Length: 943, dtype: int64

-----------------------------------------------------

Cleaning steps

Existing Min, Max Values:
min      -1
max    1798
Name: Num_Bank_Accounts, dtype: int64

After Cleaning Min, Max Values:
min    -1.0
max    10.0
Name: Num_Bank_Accounts, dtype: float64

No. of Unique values after Cleaning: 12

No. of Null values after Cleaning: 0

-----------------------------------------------------

Number of Bank Accounts Distribution
```



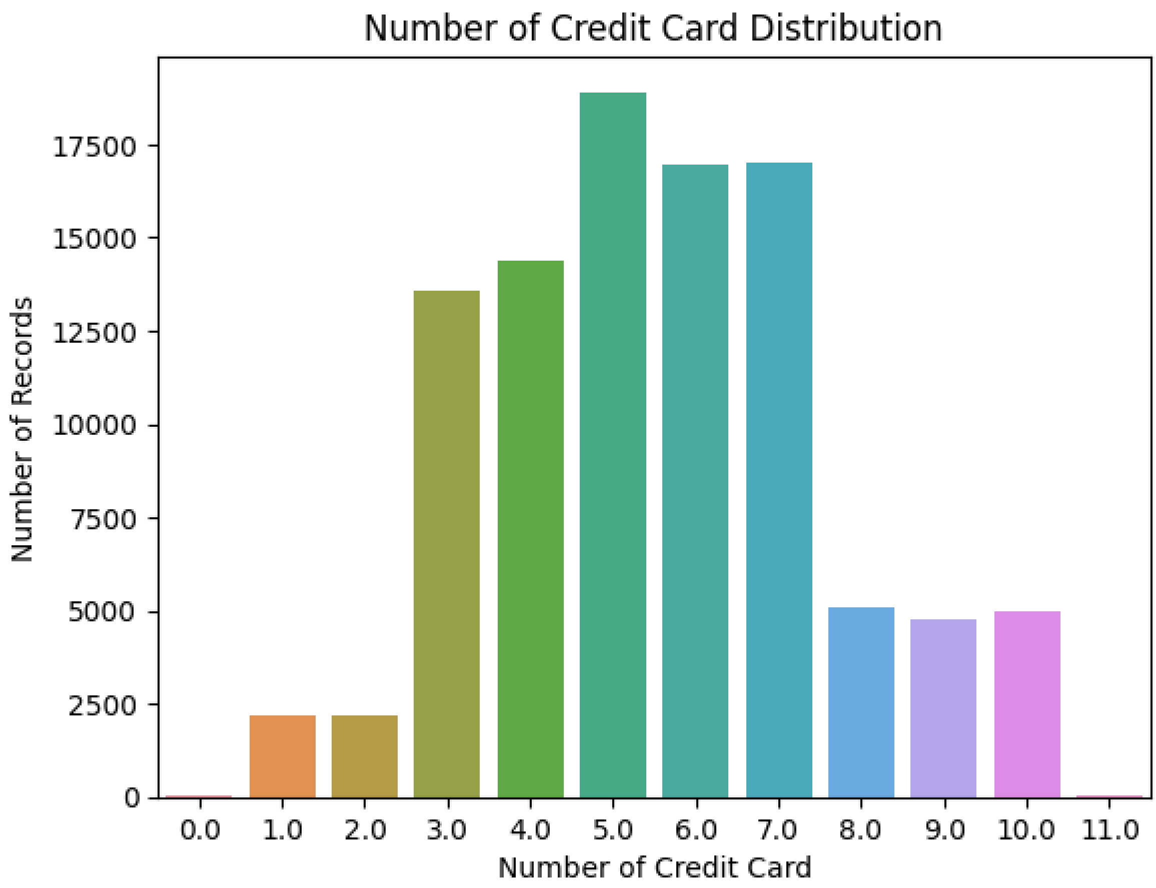
Num Credit Cards

Summary

1. There are outliers present in the field as there are 1179 unique values of number of credit card.
2. After removing outliers, number of credit cards range from 0 to 11 with most of the customers having credit cards in the range of 3 to 7 with peak at 5.

In [36]:
```python
column_name = 'Num_Credit_Card'
group_by = 'Customer_ID'
user_friendly_name = 'Number of Credit Card'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_numerical_field(df_train,group_by,column_name)

#Plot Graph
plot_countplot(df_train,column_name,user_friendly_name)
```

```
Details of Num_Credit_Card column

DataType:  int64

There are no null values

Number of Unique Values:  1179

Distribution of column:

5       18459
7       16615
6       16559
4       14030
3       13277
        ...
791         1
1118        1
657         1
640         1
679         1
Name: Num_Credit_Card, Length: 1179, dtype: int64

-----------------------------------------------------

Cleaning steps

Existing Min, Max Values:
min       0
max    1499
Name: Num_Credit_Card, dtype: int64

After Cleaning Min, Max Values:
min     0.0
max    11.0
Name: Num_Credit_Card, dtype: float64

No. of Unique values after Cleaning: 12

No. of Null values after Cleaning: 0

-----------------------------------------------------

Number of Credit Card Distribution
```



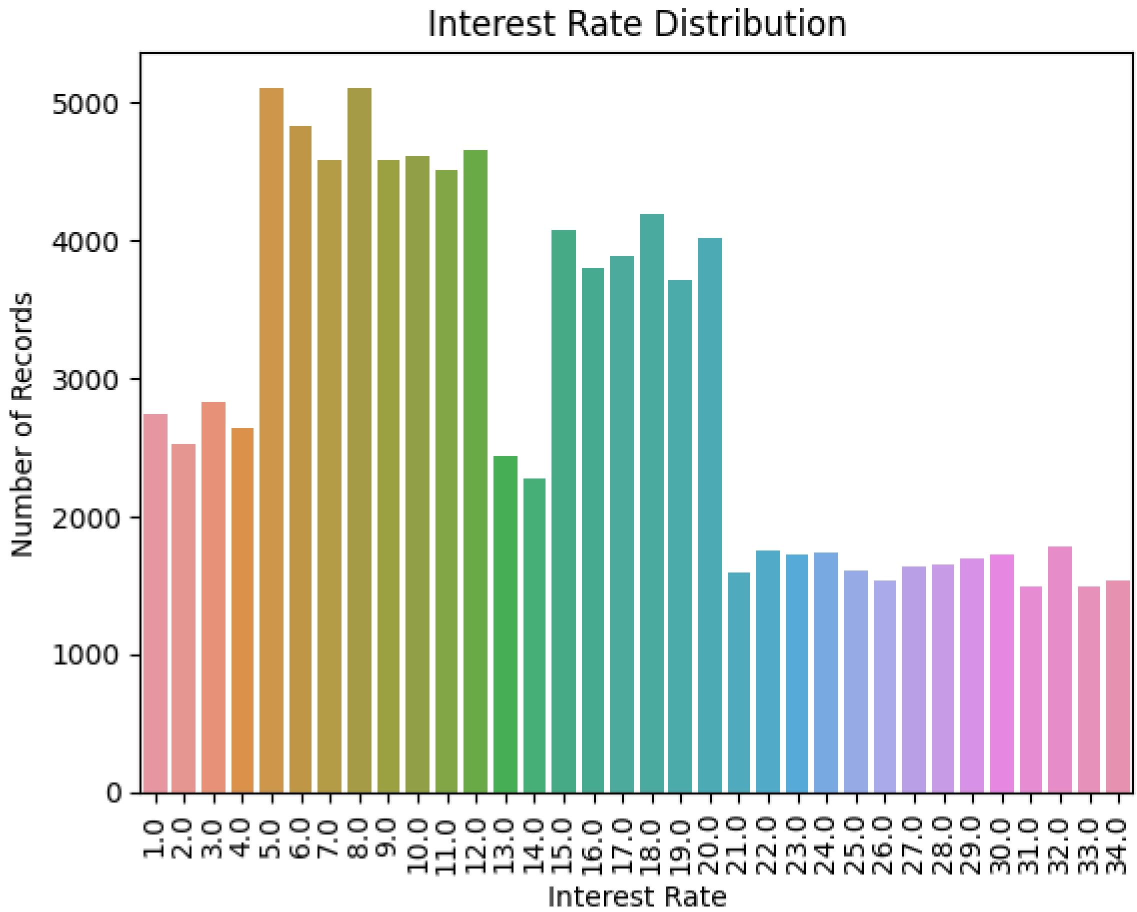
Interest Rate

Summary

1. There were outliers present, after cleaning them up, interest rate ranges from 1% to 34%

In [37]:
```python
column_name = 'Interest_Rate'
group_by = 'Customer_ID'
user_friendly_name = 'Interest Rate'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_numerical_field(df_train,group_by,column_name)

#Plot Graph
plot_countplot(df_train,column_name,user_friendly_name,rotation=90)
```

```
Details of Interest_Rate column

DataType:  int64

There are no null values

Number of Unique Values:  1750

Distribution of column:

8       5012
5       4979
6       4721
12      4540
10      4540
        ...
4995       1
1899       1
2120       1
5762       1
5729       1
Name: Interest_Rate, Length: 1750, dtype: int64

-----------------------------------------------------

Cleaning steps

Existing Min, Max Values:
min       1
max    5797
Name: Interest_Rate, dtype: int64

After Cleaning Min, Max Values:
min     1.0
max    34.0
Name: Interest_Rate, dtype: float64

No. of Unique values after Cleaning: 34

No. of Null values after Cleaning: 0

-----------------------------------------------------

Interest Rate Distribution
```



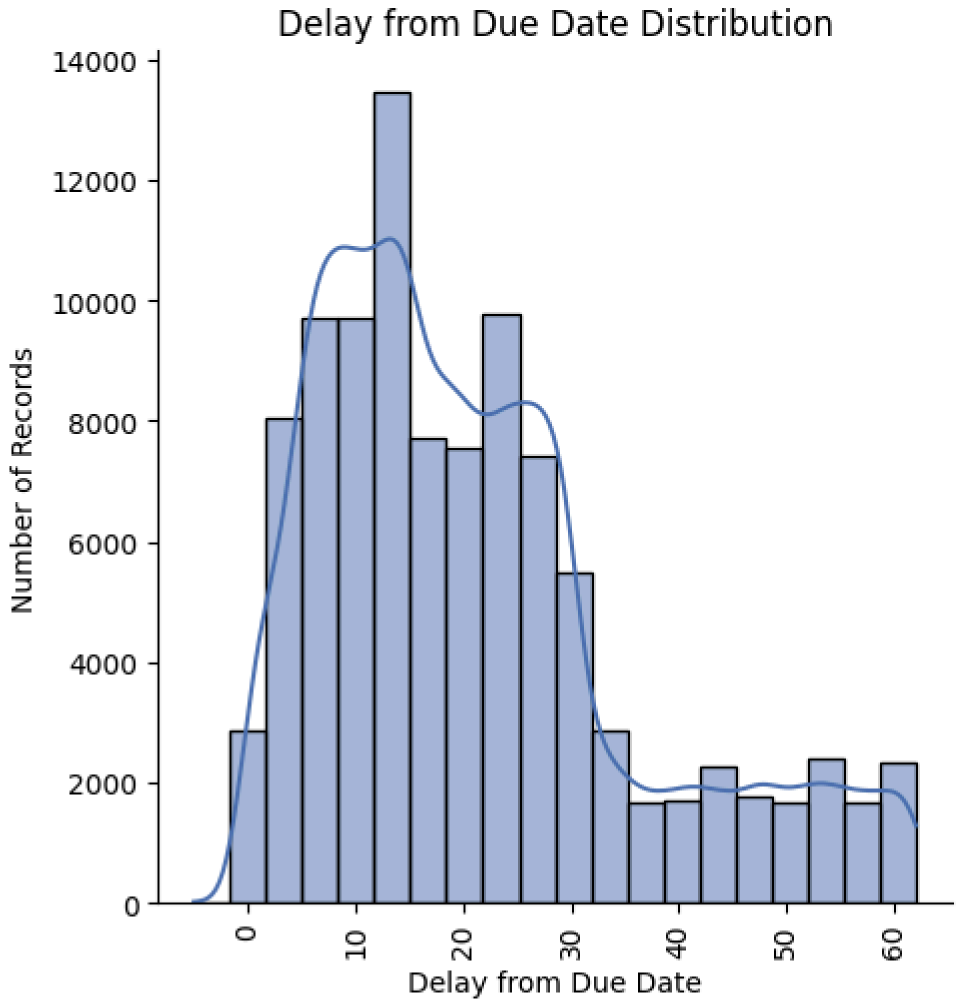
Delay from Due Date

Summary

1. Delay from due date is concentrated between 0 to 30 days.

In [38]:
```
column_name = 'Delay_from_due_date'
group_by = 'Customer_ID'
user_friendly_name = 'Delay from Due Date'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_numerical_field(df_train,group_by,column_name)

#Plot Graph
plot_displot(df_train,column_name,user_friendly_name,rotation=90)
```

```
Details of Delay_from_due_date column

DataType:  int64

There are no null values

Number of Unique Values:  73

Distribution of column:

 15    3596
 13    3424
 8     3324
 14    3313
 10    3281
       ...
-4       62
 65      56
-5       33
 66      32
 67      22
Name: Delay_from_due_date, Length: 73, dtype: int64

-----------------------------------------------------

Cleaning steps

Existing Min, Max Values:
min    -5
max    67
Name: Delay_from_due_date, dtype: int64

After Cleaning Min, Max Values:
min    -5.0
max    62.0
Name: Delay_from_due_date, dtype: float64

No. of Unique values after Cleaning: 68

No. of Null values after Cleaning: 0

-----------------------------------------------------

Delay from Due Date Distribution
```

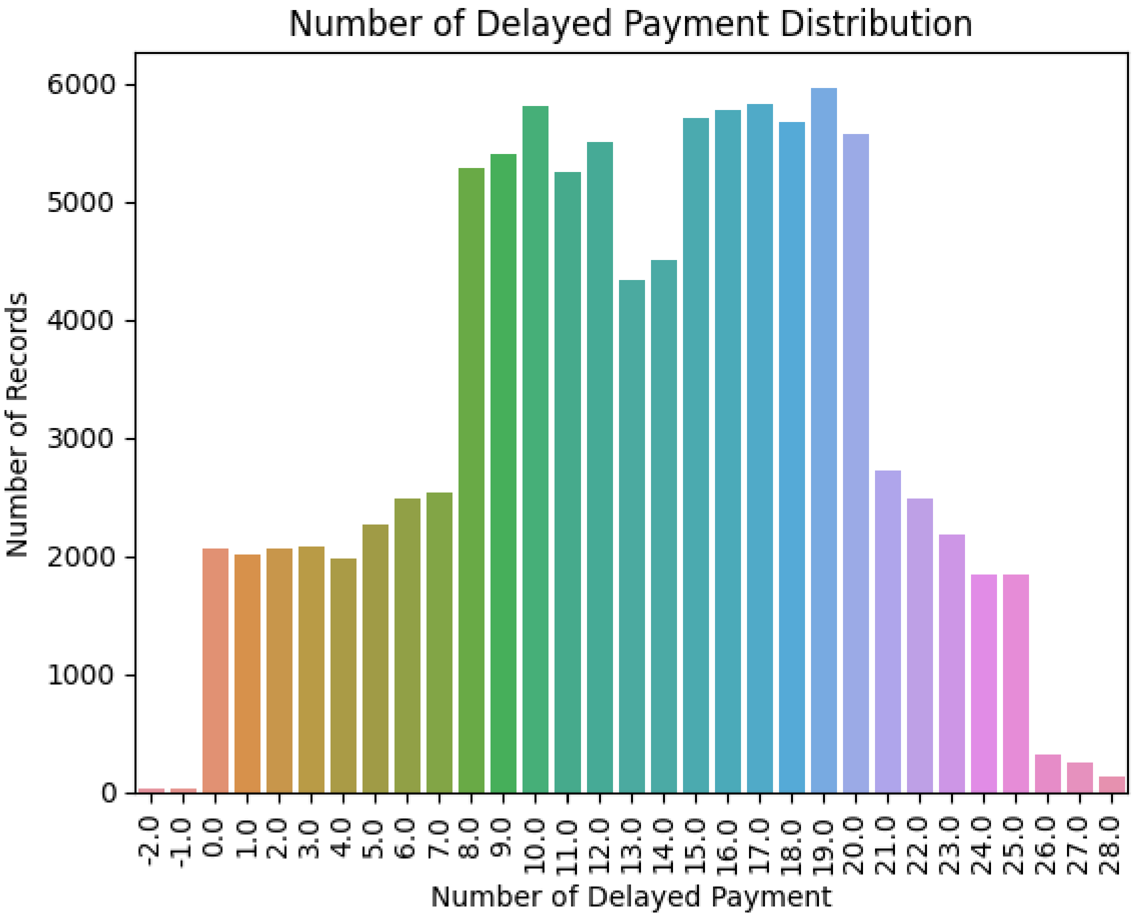


Number of Delayed Payment

Summary

In [39]:
```
column_name = 'Num_of_Delayed_Payment'
group_by = 'Customer_ID'
user_friendly_name = 'Number of Delayed Payment'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_numerical_field(df_train,group_by,column_name,strip='_',datatype='float')

#Plot Graph
plot_countplot(df_train,column_name,user_friendly_name,rotation=90)
```

```
Details of Num_of_Delayed_Payment column

DataType:  object

There are  7002  null values

Number of Unique Values:  749

Distribution of column:

19      5327
17      5261
16      5173
10      5153
18      5083
        ...
848_       1
4134       1
1530       1
1502       1
2047       1
Name: Num_of_Delayed_Payment, Length: 749, dtype: int64

-----------------------------------------------------

Cleaning steps

Trailing & leading _ are removed

Datatype of Num_of_Delayed_Payment is changed to float

Existing Min, Max Values:
min      -3.0
max    4397.0
Name: Num_of_Delayed_Payment, dtype: float64

After Cleaning Min, Max Values:
min    -2.0
max    28.0
Name: Num_of_Delayed_Payment, dtype: float64

No. of Unique values after Cleaning: 31

No. of Null values after Cleaning: 0

-----------------------------------------------------

Number of Delayed Payment Distribution
```

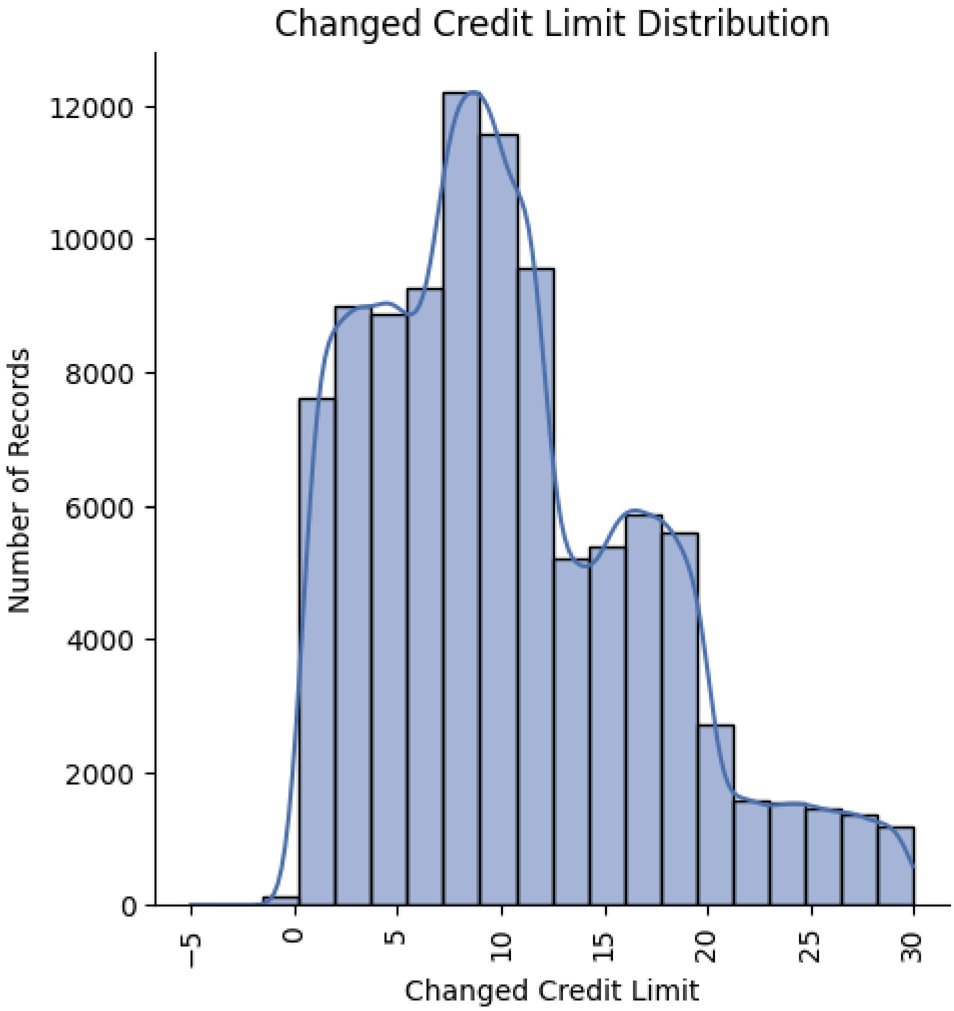


Changed Credit Limit

Summary

In [40]:
```
column_name = 'Changed_Credit_Limit'
group_by = 'Customer_ID'
user_friendly_name = 'Changed Credit Limit'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_numerical_field(df_train,group_by,column_name,strip='_',datatype='float',replac

#Plot Graph
plot_displot(df_train,column_name,user_friendly_name,rotation=90)
```

```
Details of Changed_Credit_Limit column

DataType:  object

There are no null values

Number of Unique Values:  4384

Distribution of column:

_                     2091
8.22                   133
11.5                   127
11.32                  126
7.35                   121
                      ...
-1.84                    1
0.8899999999999999       1
28.06                    1
1.5599999999999996       1
21.17                    1
Name: Changed_Credit_Limit, Length: 4384, dtype: int64

-----------------------------------------------------

Cleaning steps

Garbage value _ is replaced with np.nan

Trailing & leading _ are removed

Datatype of Changed_Credit_Limit is changed to float

Existing Min, Max Values:
min    -6.49
max    36.97
Name: Changed_Credit_Limit, dtype: float64

After Cleaning Min, Max Values:
min    -5.01
max    29.98
Name: Changed_Credit_Limit, dtype: float64

No. of Unique values after Cleaning: 3532

No. of Null values after Cleaning: 0

-----------------------------------------------------

Changed Credit Limit Distribution
```

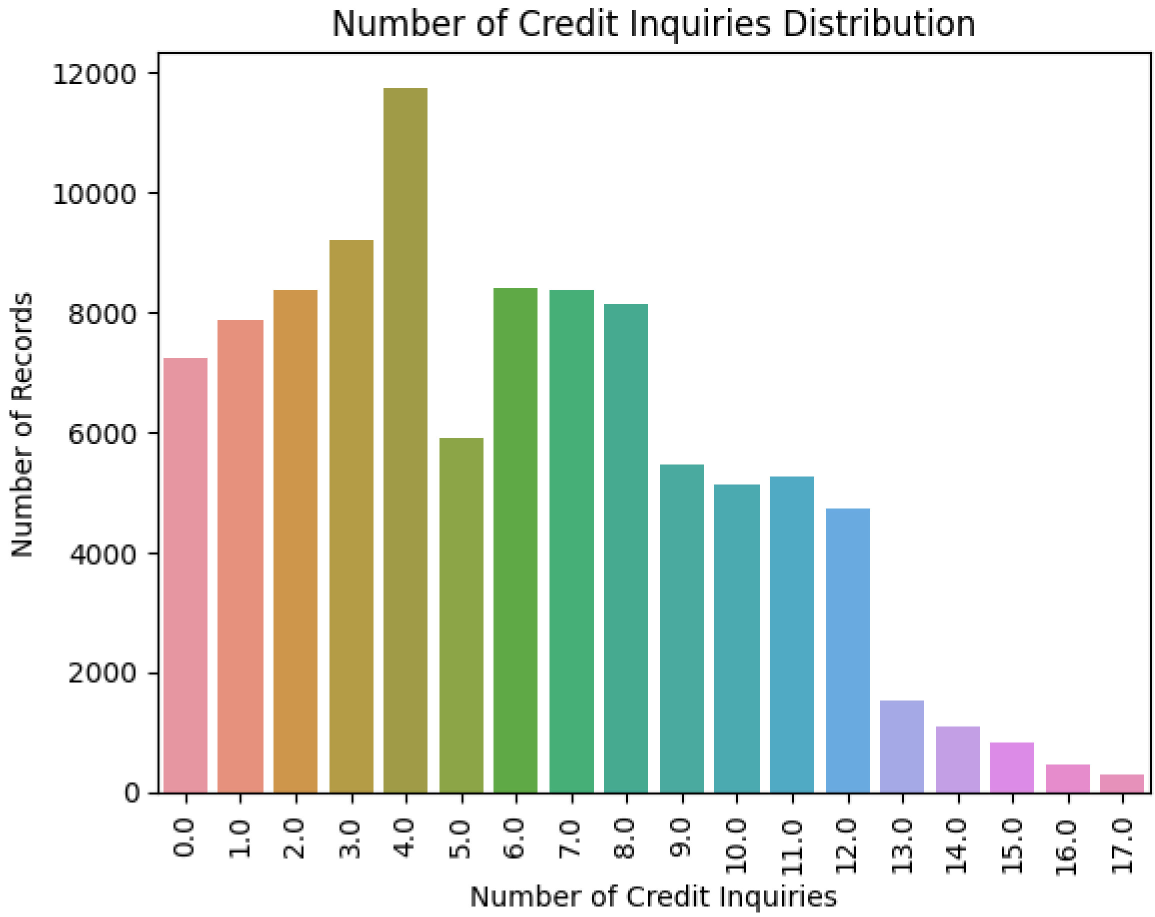


Number of Credit Inquiries

Summary

In [41]:
```
column_name = 'Num_Credit_Inquiries'
group_by = 'Customer_ID'
user_friendly_name = 'Number of Credit Inquiries'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_numerical_field(df_train,group_by,column_name)

#Plot Graph
plot_countplot(df_train,column_name,user_friendly_name,rotation=90)
```

```
Details of Num_Credit_Inquiries column

DataType:  float64

There are  1965  null values

Number of Unique Values:  1223

Distribution of column:

4.0       11271
3.0        8890
6.0        8111
7.0        8058
2.0        8028
          ...
1721.0        1
1750.0        1
2397.0        1
621.0         1
74.0          1
Name: Num_Credit_Inquiries, Length: 1223, dtype: int64

------------------------------------------------------

Cleaning steps

Existing Min, Max Values:
min       0.0
max    2597.0
Name: Num_Credit_Inquiries, dtype: float64

After Cleaning Min, Max Values:
min     0.0
max    17.0
Name: Num_Credit_Inquiries, dtype: float64

No. of Unique values after Cleaning: 18

No. of Null values after Cleaning: 0

------------------------------------------------------

Number of Credit Inquiries Distribution
```

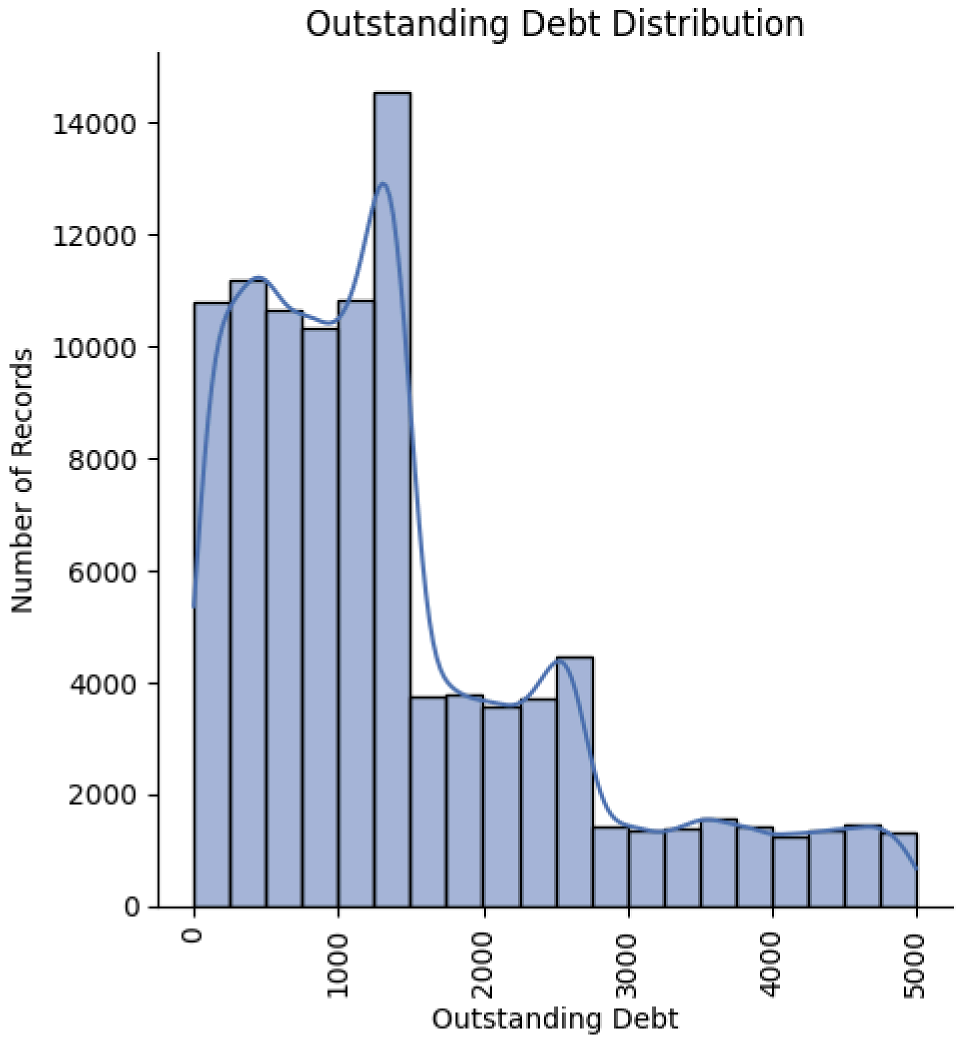


Outstanding Debt

Summary

In [42]:
```
column_name = 'Outstanding_Debt'
group_by = 'Customer_ID'
user_friendly_name = 'Outstanding Debt'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_numerical_field(df_train,group_by,column_name,strip='_',datatype=float)

#Plot Graph
plot_displot(df_train,column_name,user_friendly_name,rotation=90)
```

```
Details of Outstanding_Debt column

DataType:  object

There are no null values

Number of Unique Values:  13178

Distribution of column:

1360.45     24
460.46      23
1151.7      23
1109.03     23
467.7       16
            ..
245.46_      1
645.77_      1
174.79_      1
1181.13_     1
1013.53_     1
Name: Outstanding_Debt, Length: 13178, dtype: int64

-----------------------------------------------------

Cleaning steps

Trailing & leading _ are removed

Datatype of Outstanding_Debt is changed to <class 'float'>

Existing Min, Max Values:
min       0.23
max    4998.07
Name: Outstanding_Debt, dtype: float64

After Cleaning Min, Max Values:
min       0.23
max    4998.07
Name: Outstanding_Debt, dtype: float64

No. of Unique values after Cleaning: 12203

No. of Null values after Cleaning: 0

-----------------------------------------------------

Outstanding Debt Distribution
```



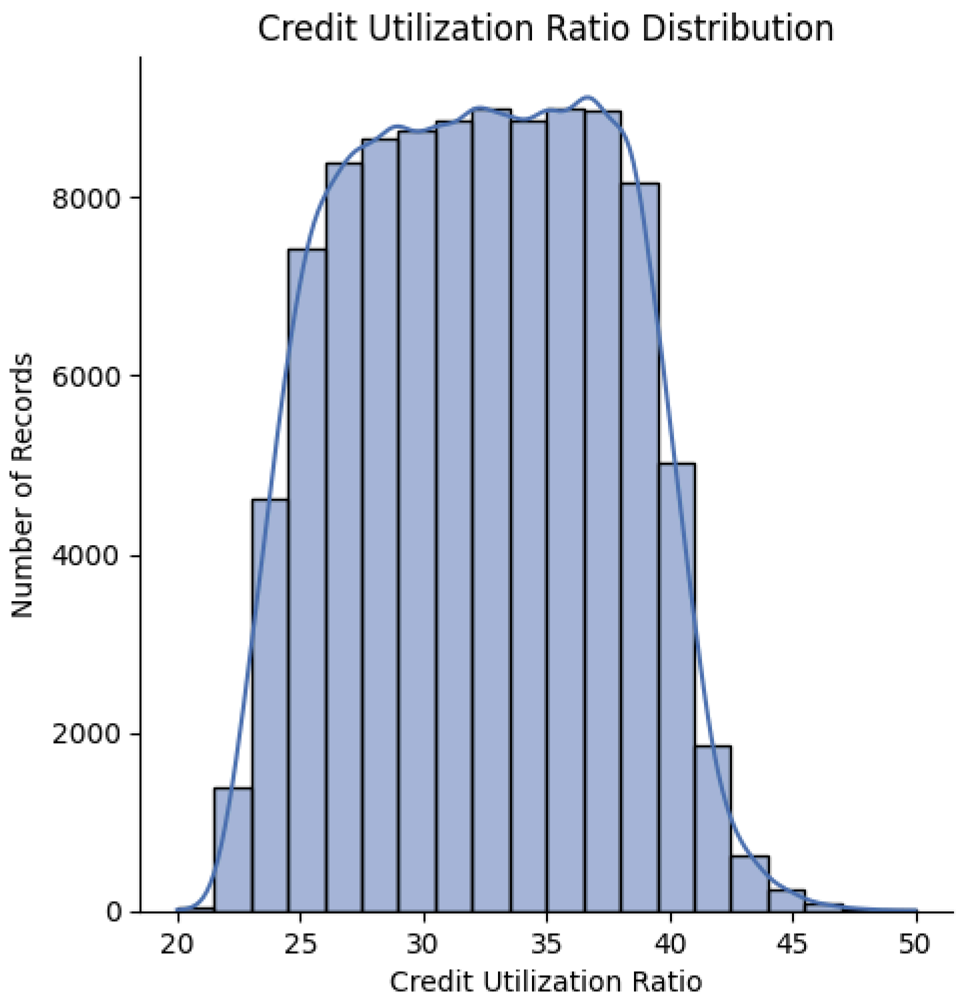
Credit Utilization Ratio

Summary

1. No cleaning is required

In [43]:
```
column_name = 'Credit_Utilization_Ratio'
group_by = 'Customer_ID'
user_friendly_name = 'Credit Utilization Ratio'

#Get Details
get_column_details(df_train,column_name)

#Plot Graph
plot_displot(df_train,column_name,user_friendly_name)
```

```
Details of Credit_Utilization_Ratio column

DataType:  float64

There are no null values

Number of Unique Values:  100000

Distribution of column:

26.822620    1
28.327949    1
30.016576    1
25.478841    1
33.933755    1
            ..
30.687138    1
38.730069    1
30.017515    1
27.279794    1
34.192463    1
Name: Credit_Utilization_Ratio, Length: 100000, dtype: int64

-----------------------------------------------------

Credit Utilization Ratio Distribution
```



Credit History Age

Summary

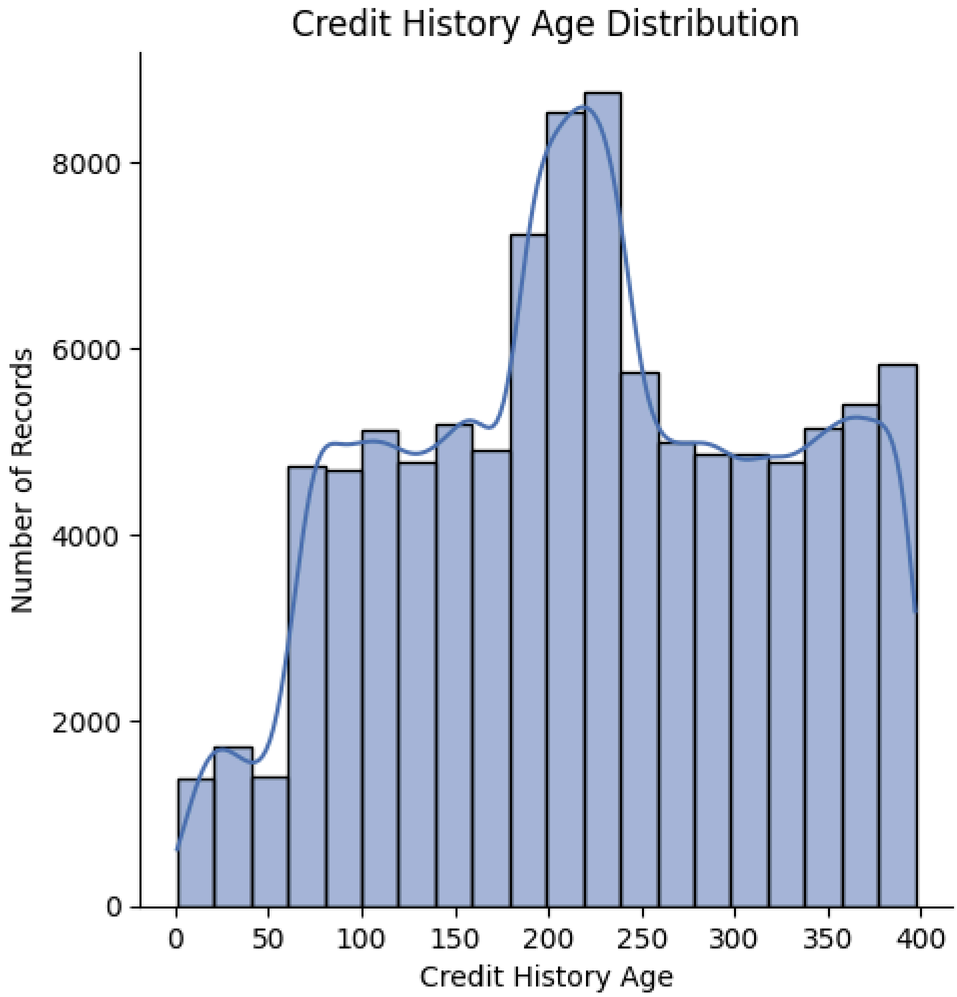
In [44]:
```
df_train['Credit_History_Age'].value_counts()
```

Out[44]:
```
15 Years and 11 Months    446
19 Years and 4 Months     445
19 Years and 5 Months     444
17 Years and 11 Months    443
19 Years and 3 Months     441
                         ...
0 Years and 3 Months       20
0 Years and 2 Months       15
33 Years and 7 Months      14
33 Years and 8 Months      12
0 Years and 1 Months        2
Name: Credit_History_Age, Length: 404, dtype: int64
```

In [45]:
```
def Month_Converter(val):
    if pd.notnull(val):
        years = int(val.split(' ')[0])
        month = int(val.split(' ')[3])
        return (years*12)+month
    else:
        return val

df_train['Credit_History_Age'] = df_train['Credit_History_Age'].apply(lambda x: Month
```

In [46]:
```
column_name = 'Credit_History_Age'
group_by = 'Customer_ID'
user_friendly_name = 'Credit History Age'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_numerical_field(df_train,group_by,column_name,datatype=float)

#Plot Graph
plot_displot(df_train,column_name,user_friendly_name)
```

```
Details of Credit_History_Age column

DataType:  float64

There are  9030  null values

Number of Unique Values:  404

Distribution of column:

191.0    446
232.0    445
233.0    444
215.0    443
231.0    441
        ...
3.0       20
2.0       15
403.0     14
404.0     12
1.0        2
Name: Credit_History_Age, Length: 404, dtype: int64

-----------------------------------------------------

Cleaning steps

Datatype of Credit_History_Age is changed to <class 'float'>

Existing Min, Max Values:
min      1.0
max    404.0
Name: Credit_History_Age, dtype: float64

After Cleaning Min, Max Values:
min      1.0
max    397.0
Name: Credit_History_Age, dtype: float64

No. of Unique values after Cleaning: 397

No. of Null values after Cleaning: 0

-----------------------------------------------------

Credit History Age Distribution
```

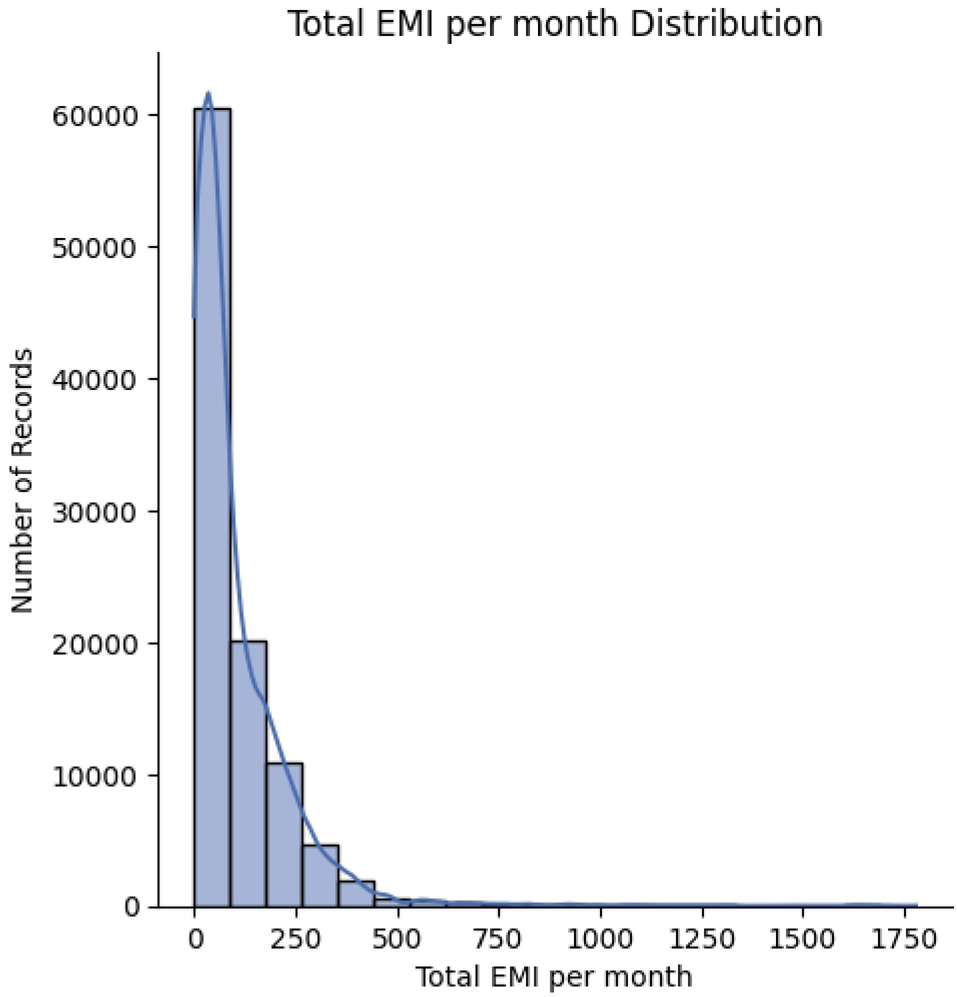


Total EMI per month

Summary

In [47]:
```
column_name = 'Total_EMI_per_month'
group_by = 'Customer_ID'
user_friendly_name = 'Total EMI per month'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_numerical_field(df_train,group_by,column_name)

#Plot Graph
plot_displot(df_train,column_name,user_friendly_name)
```

```
Details of Total_EMI_per_month column

DataType:  float64

There are no null values

Number of Unique Values:  14950

Distribution of column:

0.000000        10613
49.574949           8
73.533361           8
22.960835           8
38.661127           8
                ...
36408.000000        1
23760.000000        1
24612.000000        1
24325.000000        1
58638.000000        1
Name: Total_EMI_per_month, Length: 14950, dtype: int64

-----------------------------------------------------

Cleaning steps

Existing Min, Max Values:
min        0.0
max    82331.0
Name: Total_EMI_per_month, dtype: float64

After Cleaning Min, Max Values:
min       0.000000
max    1779.103254
Name: Total_EMI_per_month, dtype: float64

No. of Unique values after Cleaning: 11890

No. of Null values after Cleaning: 0

-----------------------------------------------------

Total EMI per month Distribution
```

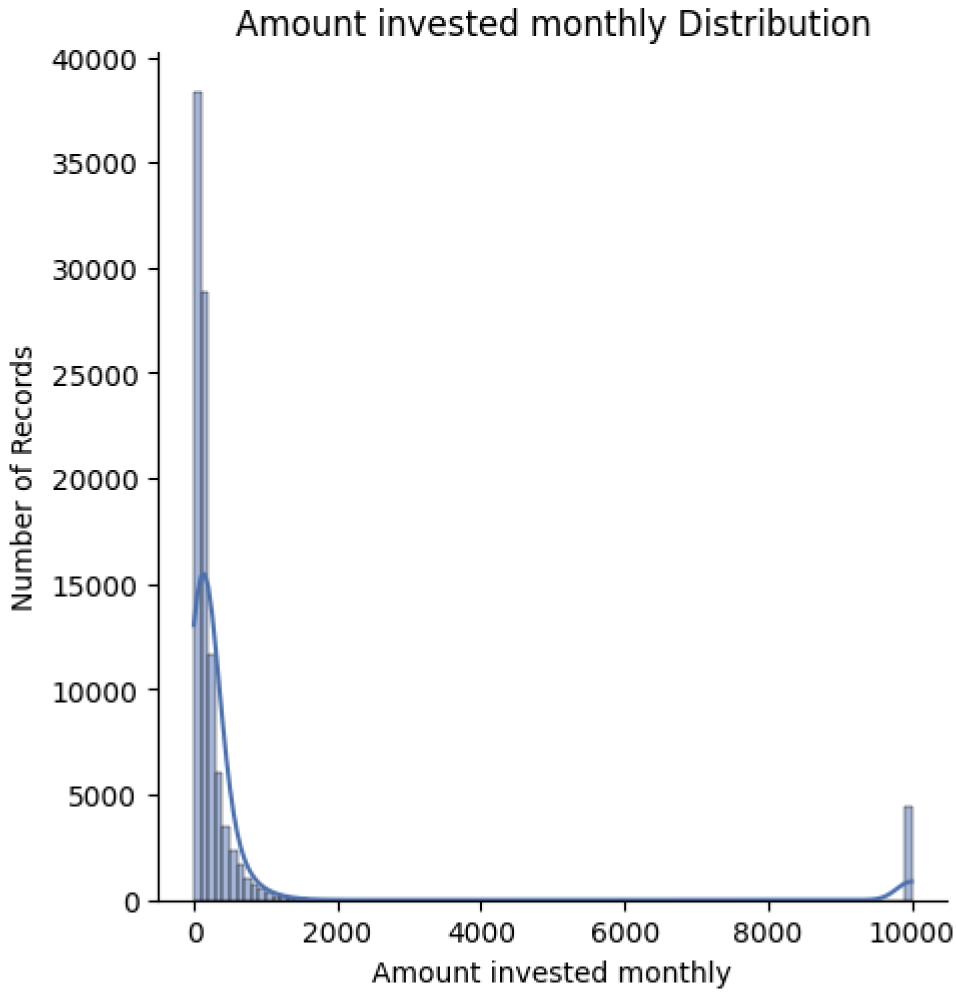


Amount Invested Monthly

Summary

In [48]:
```python
column_name = 'Amount_invested_monthly'
group_by = 'Customer_ID'
user_friendly_name = 'Amount invested monthly'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_numerical_field(df_train,group_by,column_name,datatype=float,strip='_')

#Plot Graph
plot_displot(df_train,column_name,user_friendly_name,bins=100)
```

```
Details of Amount_invested_monthly column

DataType:  object

There are  4479  null values

Number of Unique Values:  91049

Distribution of column:

__10000__            4305
0.0                   169
80.41529543900253       1
36.66235139442514       1
89.7384893604547        1
                     ...
36.541908593249026      1
93.45116318631192       1
140.80972223052834      1
38.73937670100975       1
167.1638651610451       1
Name: Amount_invested_monthly, Length: 91049, dtype: int64

-----------------------------------------------------

Cleaning steps

Trailing & leading _ are removed

Datatype of Amount_invested_monthly is changed to <class 'float'>

Existing Min, Max Values:
min        0.0
max    10000.0
Name: Amount_invested_monthly, dtype: float64

After Cleaning Min, Max Values:
min        0.0
max    10000.0
Name: Amount_invested_monthly, dtype: float64

No. of Unique values after Cleaning: 91049

No. of Null values after Cleaning: 0

-----------------------------------------------------

Amount invested monthly Distribution
```

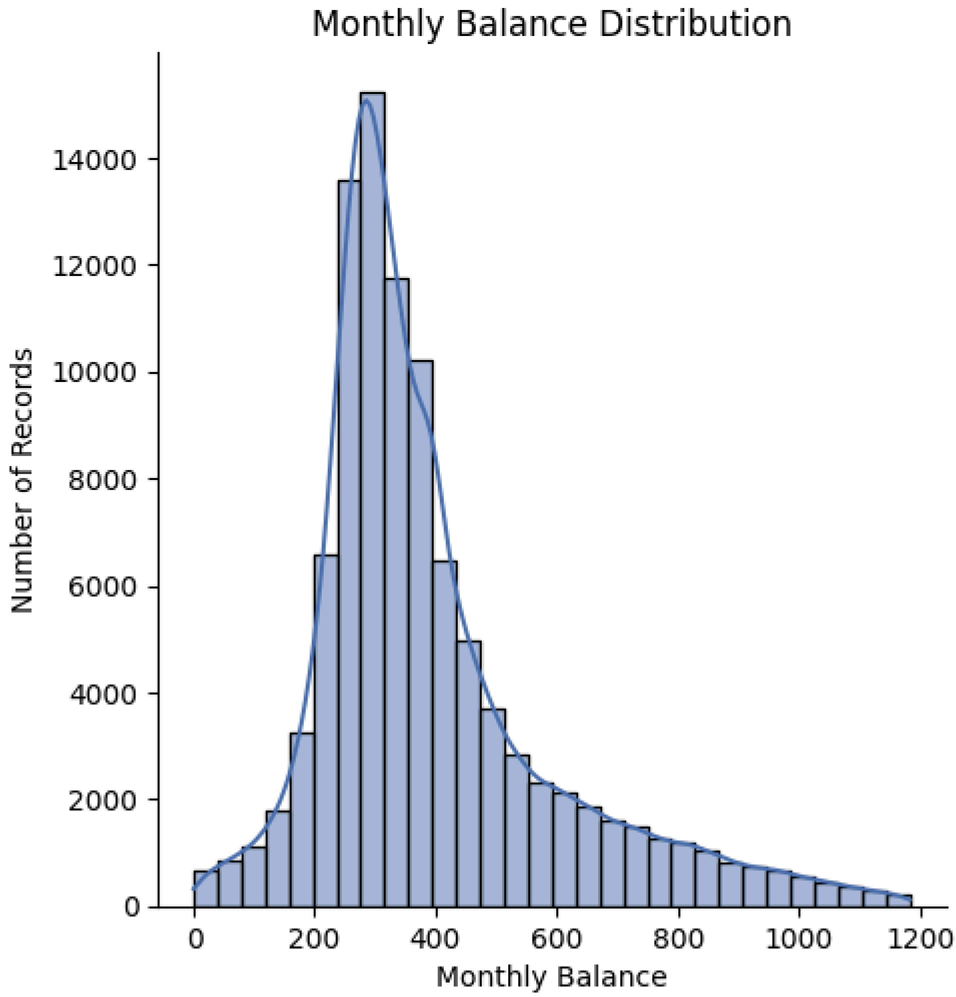


Monthly Balance

Summary

In [49]:
```
column_name = 'Monthly_Balance'
group_by = 'Customer_ID'
user_friendly_name = 'Monthly Balance'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
df_train[column_name].replace('',np.nan)
clean_numerical_field(df_train,group_by,column_name,strip='_',datatype=float,replace_

#Plot Graph
plot_displot(df_train,column_name,user_friendly_name,bins=30)
```

```
Details of Monthly_Balance column

DataType:  object

There are  1200  null values

Number of Unique Values:  98792

Distribution of column:

__-333333333333333333333333333__    9
312.49408867943663                  1
415.32532309844316                  1
252.08489793906085                  1
254.9709216273975                   1
                                   ..
366.2890379762706                   1
151.1882696261166                   1
306.75027851710234                  1
278.8720257394474                   1
393.6736955618808                   1
Name: Monthly_Balance, Length: 98792, dtype: int64

-----------------------------------------------------

Cleaning steps

Garbage value __-333333333333333333333333333__ is replaced with np.nan

Trailing & leading _ are removed

Datatype of Monthly_Balance is changed to <class 'float'>

Existing Min, Max Values:
min       0.007760
max    1602.040519
Name: Monthly_Balance, dtype: float64

After Cleaning Min, Max Values:
min       0.007760
max    1183.930696
Name: Monthly_Balance, dtype: float64

No. of Unique values after Cleaning: 96427

No. of Null values after Cleaning: 0

-----------------------------------------------------

Monthly Balance Distribution
```

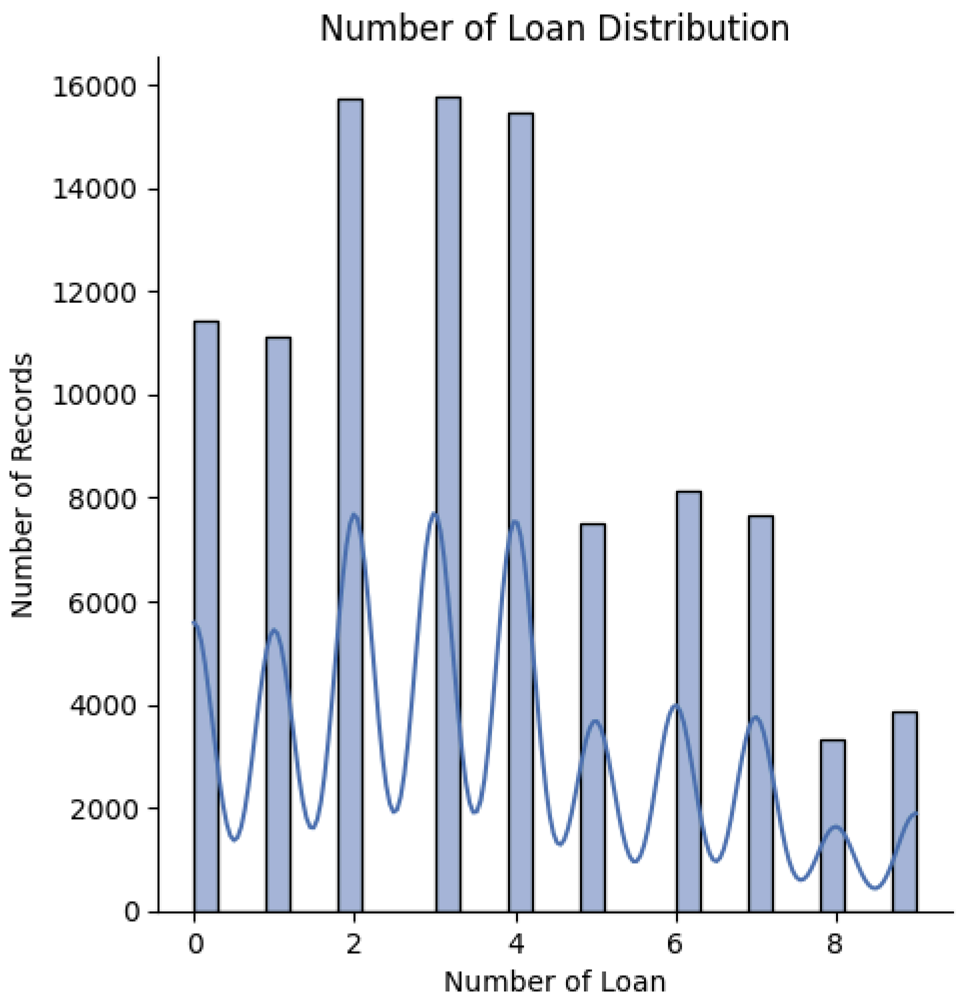


Number of Loan

Summary

In [50]:
```
column_name = 'Num_of_Loan'
group_by = 'Customer_ID'
user_friendly_name = 'Number of Loan'

#Get Details
get_column_details(df_train,column_name)

#Cleaning
clean_numerical_field(df_train,group_by,column_name,strip='_',datatype=float)

#Plot Graph
plot_displot(df_train,column_name,user_friendly_name,bins=30)
```

```
Details of Num_of_Loan column

DataType:  object

There are no null values

Number of Unique Values:  434

Distribution of column:

3        14386
2        14250
4        14016
0        10380
1        10083
         ...
1320_        1
103          1
1444         1
392          1
966          1
Name: Num_of_Loan, Length: 434, dtype: int64

-----------------------------------------------------

Cleaning steps

Trailing & leading _ are removed

Datatype of Num_of_Loan is changed to <class 'float'>

Existing Min, Max Values:
min    -100.0
max    1496.0
Name: Num_of_Loan, dtype: float64

After Cleaning Min, Max Values:
min    0.0
max    9.0
Name: Num_of_Loan, dtype: float64

No. of Unique values after Cleaning: 10

No. of Null values after Cleaning: 0

-----------------------------------------------------

Number of Loan Distribution
```



In [51]:
```
#Check if null values are present
df_train.isna().sum()
```

Out[51]:
```
ID                          0
Customer_ID                 0
Month                       0
Name                        0
Age                         0
SSN                         0
Occupation                  0
Annual_Income               0
Monthly_Inhand_Salary       0
Num_Bank_Accounts           0
Num_Credit_Card             0
Interest_Rate               0
Num_of_Loan                 0
Type_of_Loan                0
Delay_from_due_date         0
Num_of_Delayed_Payment      0
Changed_Credit_Limit        0
Num_Credit_Inquiries        0
Credit_Mix                  0
Outstanding_Debt            0
Credit_Utilization_Ratio    0
Credit_History_Age          0
Payment_of_Min_Amount       0
Total_EMI_per_month         0
Amount_invested_monthly     0
Payment_Behaviour           0
Monthly_Balance             0
Credit_Score                0
dtype: int64
```

5. Data Transformation

In [52]:
```
#Drop columns
print("Size of Dataset before dropping columns : ",df_train.shape)
drop_columns = ['ID','Customer_ID','Name','SSN']
df_train.drop(drop_columns,axis=1,inplace=True)
print("Size of Dataset after dropping columns : ",df_train.shape)
```

```
Size of Dataset before dropping columns :  (100000, 28)
Size of Dataset after dropping columns :  (100000, 24)
```

In [53]:
```
#Label Encoding
from sklearn.preprocessing import LabelEncoder

categorical_columns = ['Occupation','Type_of_Loan','Credit_Mix','Payment_of_Min_Amoun
# Initialize the LabelEncoder
label_encoder = LabelEncoder()

# Loop through each column and apply label encoding
for column in categorical_columns:
    df_train[column] = label_encoder.fit_transform(df_train[column])
```

In [54]:
```
df_train.head()
```

Out[54]:

	Month	Age	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_C
0	1	23.0	12	19114.12	1824.843333	3.0	
1	2	23.0	12	19114.12	1824.843333	3.0	
2	3	23.0	12	19114.12	1824.843333	3.0	
3	4	23.0	12	19114.12	1824.843333	3.0	
4	5	23.0	12	19114.12	1824.843333	3.0	

5 rows × 24 columns

In [55]:
```
#Spli Input & Output Data
X = df_train.drop('Credit_Score',axis=1)
y = df_train['Credit_Score']
print(X.shape)
print(y.shape)
```

```
(100000, 23)
(100000,)
```

In [56]:
```
#Normalize Data
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X = scaler.fit_transform(X)
```

6. Model Building

Approach 1

In [57]:
```
#Split Data
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(80000, 23)
(20000, 23)
(80000,)
(20000,)
```

In [58]:
```
#Method to evaluate the performance of the model
def evaluate_model(y_test,y_pred):
    print("Classification Report")
    print(classification_report(y_test, y_pred))

    print("\n---------------------------------------------\n")
    # Compute confusion matrix
    cm = confusion_matrix(y_test, y_pred)

    # Create a heatmap of the confusion matrix using Seaborn
    sns.heatmap(cm, annot=True, cmap='Greens',fmt='.0f')

    plt.xlabel('Predicted Labels')
    plt.ylabel('True Labels')
    plt.title('Confusion Matrix')

    plt.show()
```

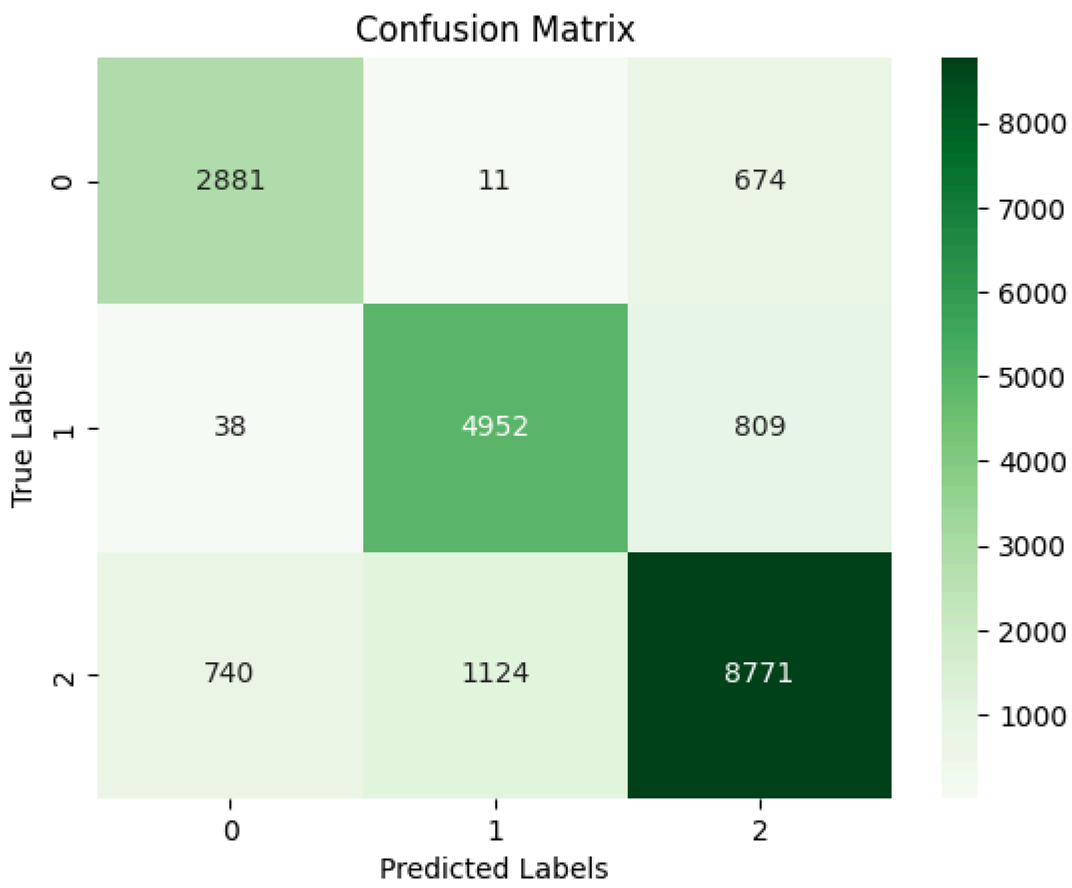
In [59]:

```
# List of classifiers to test
classifiers = [
    ('Decision Tree', DecisionTreeClassifier()),
    ('Random Forest', RandomForestClassifier()),
    ('KNN', KNeighborsClassifier(n_neighbors=5)),
    ('Gaussion NB',GaussianNB()),
    ('XGB',xgb.XGBClassifier())
]

# Iterate over each classifier and evaluate performance
for clf_name, clf in classifiers:
    # Perform cross-validation
    scores = cross_val_score(clf, X_train, y_train, cv=5, scoring='accuracy')

    # Calculate average performance metrics
    avg_accuracy = scores.mean()
    avg_precision = cross_val_score(clf, X_train, y_train, cv=5, scoring='precision_m
    avg_recall = cross_val_score(clf, X_train, y_train, cv=5, scoring='recall_macro')

    # Print the performance metrics
    print(f'Classifier: {clf_name}')
    print(f'Average Accuracy: {avg_accuracy:.4f}')
    print(f'Average Precision: {avg_precision:.4f}')
    print(f'Average Recall: {avg_recall:.4f}')
    print('-----------------------')
```

```
Classifier: Decision Tree
Average Accuracy: 0.7225
Average Precision: 0.7047
Average Recall: 0.7055
-----------------------
Classifier: Random Forest
Average Accuracy: 0.8157
Average Precision: 0.8049
Average Recall: 0.8098
-----------------------
Classifier: KNN
Average Accuracy: 0.7030
Average Precision: 0.6757
Average Recall: 0.6851
-----------------------
Classifier: Gaussion NB
Average Accuracy: 0.6394
Average Precision: 0.6328
Average Recall: 0.6882
-----------------------
Classifier: XGB
Average Accuracy: 0.7713
Average Precision: 0.7561
Average Recall: 0.7607
-----------------------
```

In [60]:
```
# Creating the Random Forest classifier
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)

# Training the classifier
rf_classifier.fit(X_train, y_train)

# Making predictions on the test set
y_pred = rf_classifier.predict(X_test)

# Evaluating the model
evaluate_model(y_test, y_pred)
```

```
Classification Report
              precision    recall  f1-score   support

           0       0.79      0.81      0.80      3566
           1       0.81      0.85      0.83      5799
           2       0.86      0.82      0.84     10635

    accuracy                           0.83     20000
   macro avg       0.82      0.83      0.82     20000
weighted avg       0.83      0.83      0.83     20000


---------------------------------------------
```



Approach 2

In [61]:
```
#Handle Imbalance Data
from imblearn.over_sampling import SMOTE

smote = SMOTE()
X_sm, y_sm = smote.fit_resample(X, y)

y_sm.value_counts()
```

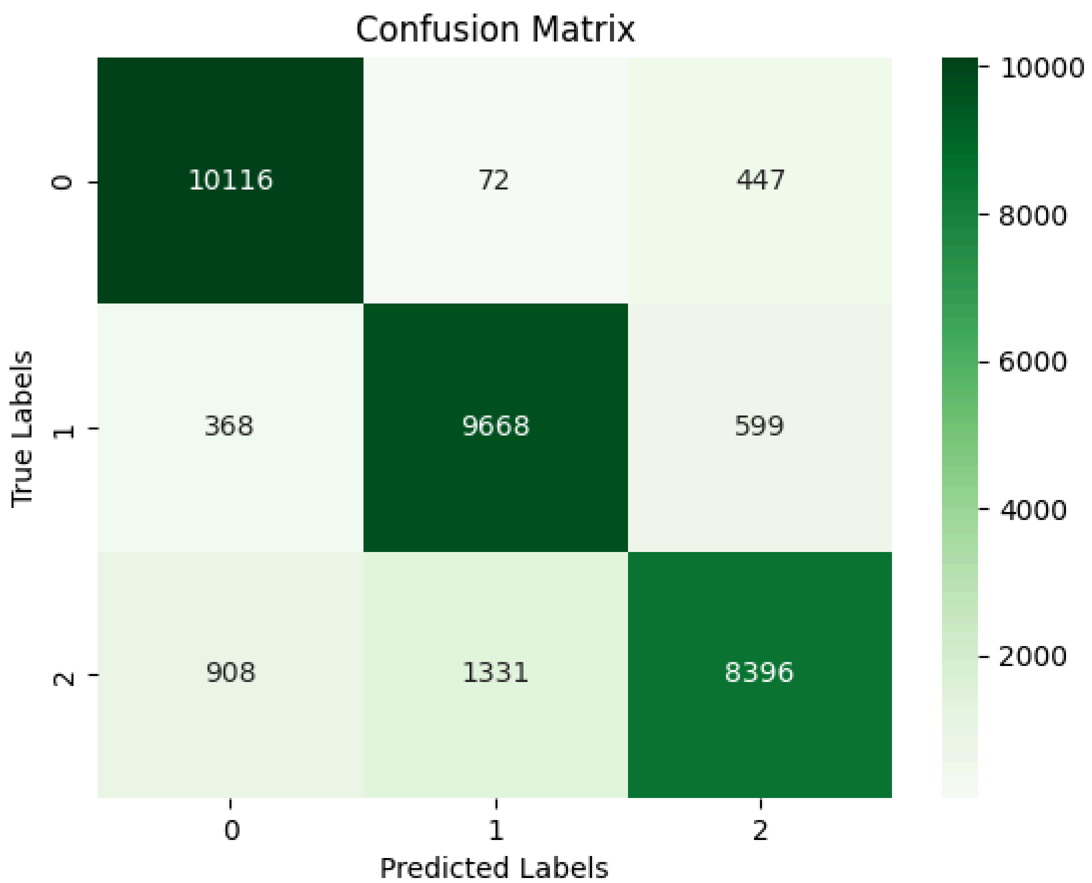
Out[61]:
```
0    53174
2    53174
1    53174
Name: Credit_Score, dtype: int64
```

In [62]:
```
#Split data
X_train, X_test, y_train, y_test = train_test_split(X_sm, y_sm, test_size=0.2, random

print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(127617, 23)
(31905, 23)
(127617,)
(31905,)
```

In [63]:
```
# Creating the Random Forest classifier
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)

# Training the classifier
rf_classifier.fit(X_train, y_train)

# Making predictions on the test set
y_pred = rf_classifier.predict(X_test)

# Evaluating the model
evaluate_model(y_test, y_pred)
```

```
Classification Report
              precision    recall  f1-score   support

           0       0.89      0.95      0.92     10635
           1       0.87      0.91      0.89     10635
           2       0.89      0.79      0.84     10635

    accuracy                           0.88     31905
   macro avg       0.88      0.88      0.88     31905
weighted avg       0.88      0.88      0.88     31905


---------------------------------------------
```



Insights:

Credit Score Classification project can provide several valuable insights for financial institutions or banks:

Risk Assessment: By accurately classifying credit scores, banks can better assess the creditworthiness of individuals applying for loans or credit cards. Insights from the project can help banks identify high-risk borrowers and make more informed lending decisions to minimize the risk of defaults.

Customer Segmentation: Analysis of credit score patterns and trends can enable banks to segment their customer base effectively. Understanding the credit profiles of different demographic groups or customer segments can help banks tailor their products and services to meet the specific needs of each segment.

Product Development: Insights from the project can inform the development of new financial products and services designed to meet the needs of customers with varying credit scores. Banks can use this information to create innovative lending products or personalized financial solutions tailored to different credit profiles.

Marketing Strategies: Understanding the factors influencing credit scores can help banks develop targeted marketing strategies to attract customers with specific credit profiles. Insights from the project can guide banks in identifying the most effective channels and messaging to reach their target audience.

Regulatory Compliance: Compliance with regulatory requirements is essential for banks operating in the financial industry. Insights from the project can help banks ensure compliance with regulations related to responsible lending practices and consumer protection.

Overall, the Credit Score Classification project can provide valuable insights for financial institutions, enabling them to improve risk management, enhance customer segmentation, develop innovative products and services, refine marketing strategies, and ensure regulatory compliance. These insights can ultimately lead to more efficient operations and better outcomes for both banks and their customers.

*********** End of Project *******************

In [ ]:

```

```