Credit EDA & Credit Score Calculation with Python

Problem statement:

- To conduct a thorough exploratory data analysis (EDA) and deep analysis of a comprehensive dataset containing basic customer details and extensive credit-related information. The aim is to create new, informative features, calculate a hypothetical credit score, and uncover meaningful patterns, anomalies, and insights within the data. ### Suggestions for learners:

Exploratory Data Analysis (EDA):

- Perform a comprehensive EDA to understand the data's structure, characteristics, distributions, and relationships. Identify and address any missing values, mismatch data types, inconsistencies, or outliers.
- Utilize appropriate visualizations (e.g., histograms, scatter plots, box plots, correlation matrices) to uncover patterns and insights.

Feature Engineering:

- Create new features that can be leveraged for the calculation of credit scores based on domain knowledge and insights from EDA. Aggregate the data on the customer level if required

Hypothetical Credit Score Calculation:

- Develop a methodology to calculate a hypothetical credit score using relevant features(use a minimum of 5 maximum of 10 features).
- Clearly outline the developed methodology in the notebook, providing a detailed explanation of the reasoning behind it. (use inspiration from FICO scores and try to use relevant features you created)
- Explore various weighting schemes to assign scores.
- Provide a score for each individual customer

Analysis and Insights

- Add valuable insights from EDA and credit score calculation Can credit score and aggregated features be calculated at different time frames like the last 3 months/last 6 months (recency based metrics)

Data Description

Column Name	Description
ID	Represents a unique identification of an entry
Customer_ID	Represents a unique identification of a person
Month	Represents the month of the year
Name	Represents the name of a person
Age	Represents the age of the person
SSN	Represents the social security number of a person
Occupation	Represents the occupation of the person
Annual_Income	Represents the annual income of the person
Monthly_Inhand_Salary	Represents the monthly base salary of a person
Num_Bank_Accounts	Represents the number of bank accounts a person holds
Num_Credit_Card	Represents the number of other credit cards held by a person
Interest_Rate	Represents the interest rate on credit card
Num_of_Loan	Represents the number of loans taken from the bank
Type_of_Loan	Represents the types of loan taken by a person
Delay_from_due_date	Represents the average number of days delayed from the payment date
Num_of_Delayed_Payment	Represents the average number of payments delayed by a person
Changed_Credit_Limit	Represents the percentage change in credit card limit
Num_Credit_Inquiries	Represents the number of credit card inquiries
Credit_Mix	Represents the classification of the mix of credits
Outstanding_Debt	Represents the remaining debt to be paid (in USD)
Credit_Utilization_Ratio	Represents the utilization ratio of credit card
Credit_History_Age	Represents the age of credit history of the person
Payment_of_Min_Amount	Represents whether only the minimum amount was paid by the person
Total_EMI_per_month	Represents the monthly EMI payments (in USD)
Amount_invested_monthly	Represents the monthly amount invested by the customer (in USD)
Payment_Behaviour	Represents the payment behavior of the customer (in USD)
Monthly_Balance	Represents the monthly balance amount of the customer (in USD)

Colab Link :

https://colab.research.google.com/drive/1zDlNvaWmytj4PFwQwOkdYCqaU-d2l_5i?usp=sharing
(https://colab.research.google.com/drive/1zDlNvaWmytj4PFwQwOkdYCqaU-d2l_5i?usp=sharing)

In [9]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, c
all drive.mount("/content/drive", force_remount=True).
```

In [10]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy
import scipy.stats as stats
import warnings
warnings.filterwarnings("ignore")
```

In [11]:
```
df = pd.read_csv('/content/drive/MyDrive/fintech/Credit_score.csv')
```

In [12]:
```
df.head()
```

Out[12]:

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

5 rows × 27 columns

In [13]:
```
df.describe()
```

Out[13]:

	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Interest_Rate	Delay_
count	84998.000000	100000.000000	100000.00000	100000.000000	
mean	4194.170850	17.091280	22.47443	72.466040	
std	3183.686167	117.404834	129.05741	466.422621	
min	303.645417	-1.000000	0.00000	1.000000	
25%	1625.568229	3.000000	4.00000	8.000000	
50%	3093.745000	6.000000	5.00000	13.000000	
75%	5957.448333	7.000000	7.00000	20.000000	
max	15204.633330	1798.000000	1499.00000	5797.000000	

In [14]:
```
df1 = df.copy()
```

In [15]:
```
df1.shape
```

Out[15]:
```
(100000, 27)
```

In [16]:
```
df1.isna().sum()
```

Out[16]:
```
ID                              0
Customer_ID                     0
Month                           0
Name                         9985
Age                             0
SSN                             0
Occupation                      0
Annual_Income                   0
Monthly_Inhand_Salary       15002
Num_Bank_Accounts               0
Num_Credit_Card                 0
Interest_Rate                   0
Num_of_Loan                     0
Type_of_Loan                11408
Delay_from_due_date             0
Num_of_Delayed_Payment       7002
Changed_Credit_Limit            0
Num_Credit_Inquiries         1965
Credit_Mix                      0
Outstanding_Debt                0
Credit_Utilization_Ratio        0
Credit_History_Age           9030
Payment_of_Min_Amount           0
Total_EMI_per_month             0
Amount_invested_monthly      4479
Payment_Behaviour               0
Monthly_Balance              1200
dtype: int64
```

Treating outliers and missing columns

1) Name Column :

- Handled missing data by forward-filling within customer segments.

In [17]:
```
df1['Name'] = df1.groupby('Customer_ID')['Name'].fillna(method='ffill')
```

2) Age

- Eliminated redundant symbols within the column data.
- Addressed missing data points through forward and backward imputation for each customer group.
- Imposed an upper age limit of 95.

In [18]:
```
df1['Age'].nunique()
```

Out[18]:
```
1788
```

In [19]:
```
df1['Age']=df1['Age'].str.replace('-',"")
df1['Age']=df1['Age'].str.replace('_',"")
df1['Age'] = df1['Age'].astype('int')

df1['Age'].dtypes
```

Out[19]: dtype('int64')

In [20]:
```
df1['Age'].unique()
```

Out[20]: array([23, 500,   28, ..., 4808, 2263, 1342])

In [21]:
```
def Age(group):
    mode_age = group['Age'].mode()[0]
    group['Age'] = group['Age'].apply(lambda y: mode_age if y >= 95 else y)
    return group

# Apply the function to each group
df2 = df1.groupby('Customer_ID').apply(Age)
df2 = df2.reset_index(drop=True)


df1 =df2
df1['Age'].nunique()
```

Out[21]: 43

SSN Number

- Eliminated redundant symbols within the column data.
- Addressed missing data points through forward and backward imputation for each customer group.

In [22]:
```
# df1.groupby('Customer_ID')['SSN'].apply(lambda y : None if y == '#F%$D@*&
8' else y['SSN'] )
df1['SSN'] = df1['SSN'].replace("#F%$D@*&8", np.nan)
df1['SSN'].isna().sum()
def SSN(group):
    mode_ssn = group['SSN'].mode()[0]  # Calculate the mode of the 'SSN' co
lumn
    group['SSN'] = group['SSN'].apply(lambda y: mode_ssn if pd.isna(y) else
y)
    return group

# Apply the function to each group
df2 = df1.groupby('Customer_ID').apply(SSN)
df2 = df2.reset_index(drop=True)
df1 = df2
```

Occupation

- Eliminated redundant symbols within the column data.
- Addressed missing data points through forward and backward imputation for each customer group.

In [23]:
```
df1['Occupation'].replace('_______',"").unique()
```

Out[23]:
```
array(['Lawyer', 'Mechanic', '', 'Media_Manager', 'Doctor', 'Journalist',
       'Accountant', 'Manager', 'Entrepreneur', 'Scientist', 'Architect',
       'Teacher', 'Engineer', 'Writer', 'Developer', 'Musician'],
      dtype=object)
```

In [24]:
```
df1['Occupation'] = df1['Occupation'].replace('_______',"")
df1['Occupation'] = df1['Occupation'].replace("",np.nan)
df1['Occupation'] = df1.groupby('Customer_ID')['Occupation'].fillna(method
='ffill')
df1['Occupation'] = df1.groupby('Customer_ID')['Occupation'].fillna(method
='bfill')
```

Treating numeric columns

- Eliminated redundant symbols within the column data.
- Addressed missing data points through forward and backward imputation for each customer group.
- Performed mathematical corrections for neccessary columns
- Imposed upper limit to neccessary columns.

In [25]:
```
pd.set_option('display.float_format', lambda x: '%.6f' % x)
df1['Annual_Income'] = df1['Annual_Income'].str.replace('_',"").astype('flo
at')
```

In [26]:
```
df1['Monthly_Inhand_Salary'] = df1.groupby('Customer_ID')['Monthly_Inhand_S
alary'].fillna(method='ffill')
df1['Monthly_Inhand_Salary'] = df1.groupby('Customer_ID')['Monthly_Inhand_S
alary'].fillna(method='bfill')
```

In [27]:
```
columns = ['Num_Bank_Accounts','Num_Credit_Card']
for column in columns:

  df1[column] = df1[column].apply(lambda x: np.nan if x>10 else x)
  df1[column] = df1.groupby('Customer_ID')[column].fillna(method='ffill')

  df1[column] = df1.groupby('Customer_ID')[column].fillna(method='bfill')
  df1[column] = df1[column].astype('int')
```

In [28]:
```
df1['Num_Bank_Accounts'].unique()
```

Out[28]:
```
array([ 6,  1,  3,  7,  2,  5,  8,  4,  0, 10,  9, -1])
```

In [29]:
```
df1['Num_Bank_Accounts'] = df1['Num_Bank_Accounts'].apply(lambda x: -1*x if
x==-1 else x)
df1['Num_Credit_Card'] = df1['Num_Credit_Card'].apply(lambda x: -1*x if x==
-1 else x)
```

In [30]:
```
df1['Interest_Rate'].unique()
```

Out[30]:
```
array([  27,   17,    1, ..., 4892, 4378, 3808])
```

In [31]:
```
df1['Interest_Rate'] = df1['Interest_Rate'].apply(lambda x : np.nan if x>45
else x)
df1['Interest_Rate'] = df1.groupby('Customer_ID')['Interest_Rate'].fillna(m
ethod='ffill')
df1['Interest_Rate'] = df1.groupby('Customer_ID')['Interest_Rate'].fillna(m
ethod='bfill')
df1['Interest_Rate'].unique()
```

Out[31]:
```
array([27., 17.,  1.,  6., 16., 23.,  9., 11.,  2., 10., 30., 26.,  5.,
       18., 14.,  4., 24.,  8., 15., 21.,  7., 19., 31., 33., 34., 13.,
       20., 28., 32., 29., 12., 25.,  3., 22.])
```

In [32]:
```
df1['Num_of_Loan'] = df1['Num_of_Loan'].str.replace('_','')
df1['Num_of_Loan'] = df1['Num_of_Loan'].astype('int')
df1['Num_of_Loan'] = df1['Num_of_Loan'].apply(lambda x: np.nan if x>=23 or
x==-100 else x)
df1['Num_of_Loan'] = df1.groupby('Customer_ID')['Num_of_Loan'].fillna(metho
d='ffill')
df1['Num_of_Loan'] = df1.groupby('Customer_ID')['Num_of_Loan'].fillna(metho
d='bfill')
df1['Num_of_Loan'].unique()
```

Out[32]:
```
array([ 2.,  4.,  0.,  3.,  8.,  1.,  9.,  7.,  6.,  5., 17., 18., 19.])
```

In [33]:
```
df1['Num_of_Loan'] = df1['Num_of_Loan'].astype('int')
```

In [34]:
```
df1['Type_of_Loan'] = df1['Type_of_Loan'].fillna('Not Specified')
```

In [35]:
```
df1['Delay_from_due_date'].unique()
```

Out[35]:
```
array([62, 64, 67, 57,  8, 10,  3,  5, 14, 19,  9, 27, 29, 12, 16,  6, 24,
        0, -5, -4,  1, 15, 28, 23, 18, 13, 11, 25, 48, 47, 50, 46,  7,  2,
       -3,  4, 30, 17, 21, 20, 22, 35, 40, 31, 26, 59, 63, 58, 37, 42, 43,
       38, 55, 41, 36, 52, 53, 54, 49, -2, 44, 39, 61, 34, 33, -1, 45, 60,
       51, 66, 56, 32, 65])
```

In [36]:
```
df1['Delay_from_due_date'] = df1['Delay_from_due_date'].apply(lambda x: -1*
x if x<0 else x)
df1['Delay_from_due_date'].unique()
```

Out[36]:
```
array([62, 64, 67, 57,  8, 10,  3,  5, 14, 19,  9, 27, 29, 12, 16,  6, 24,
        0,  4,  1, 15, 28, 23, 18, 13, 11, 25, 48, 47, 50, 46,  7,  2, 30,
       17, 21, 20, 22, 35, 40, 31, 26, 59, 63, 58, 37, 42, 43, 38, 55, 41,
       36, 52, 53, 54, 49, 44, 39, 61, 34, 33, 45, 60, 51, 66, 56, 32, 6
5])
```

In [38]:
```
df1['Num_of_Delayed_Payment'] = df1['Num_of_Delayed_Payment'].str.replace
('_',"")
df1['Num_of_Delayed_Payment'] = df1['Num_of_Delayed_Payment'].str.replace
('-',"")
df1['Num_of_Delayed_Payment'] = df1['Num_of_Delayed_Payment'].astype('float
64')
df1['Num_of_Delayed_Payment'] = df1['Num_of_Delayed_Payment'].apply(lambda
x: np.nan if x>50 else x)
```

In [39]:
```
df1['Num_of_Delayed_Payment'] = df1.groupby('Customer_ID')['Num_of_Delayed_
Payment'].fillna(method='ffill')
df1['Num_of_Delayed_Payment'] = df1.groupby('Customer_ID')['Num_of_Delayed_
Payment'].fillna(method='bfill')
# pd.set_option('display.float_format', lambda x: '%.3f' % x)
df1['Num_of_Delayed_Payment'] = df1['Num_of_Delayed_Payment'].astype('int')
df1['Num_of_Delayed_Payment'].unique()
```

Out[39]:
```
array([25, 23, 28, 26, 16, 18, 19,  7,  9,  8, 12, 17, 15, 13, 10, 22, 20,
        2,  1,  5, 11, 14,  4,  3,  6, 21,  0, 24, 27, 46, 49, 47])
```

In [40]:
```
df1['Changed_Credit_Limit'] = df1['Changed_Credit_Limit'].replace('_',np.na
n)
df1['Changed_Credit_Limit'] = df1.groupby('Customer_ID')['Changed_Credit_Li
mit'].fillna(method='ffill')
df1['Changed_Credit_Limit'] = df1.groupby('Customer_ID')['Changed_Credit_Li
mit'].fillna(method='bfill')
```

In [41]:
```
df1['Num_Credit_Inquiries'] = df1['Num_Credit_Inquiries'].replace('.',"")
df1['Num_Credit_Inquiries'] = df1['Num_Credit_Inquiries'].astype('float')
```

In [42]:
```
df1['Num_Credit_Inquiries'] = df1['Num_Credit_Inquiries'].apply(lambda x: n
p.nan if x>15 else x)
df1['Num_Credit_Inquiries'] = df1.groupby('Customer_ID')['Num_Credit_Inquir
ies'].fillna(method='ffill')
df1['Num_Credit_Inquiries'] = df1.groupby('Customer_ID')['Num_Credit_Inquir
ies'].fillna(method='bfill')
df1['Num_Credit_Inquiries'] = df1['Num_Credit_Inquiries'].astype('int')
```

In [43]:
```
df1['Credit_Mix'] = df1['Credit_Mix'].replace('_',np.nan)

df1['Credit_Mix'] = df1.groupby('Customer_ID')['Credit_Mix'].fillna(method
='ffill')
df1['Credit_Mix'] = df1.groupby('Customer_ID')['Credit_Mix'].fillna(method
='bfill')
```

In [44]:
```
df1['Outstanding_Debt'] = df1['Outstanding_Debt'].str.replace('_',"")
df1['Outstanding_Debt'] = df1['Outstanding_Debt'].astype('float')
```

In [45]:
```
def convert_to_months(age_str):
    if pd.isna(age_str) or age_str == 'NA':
        return np.nan
    else:
        years, months = age_str.split(' and ')
        years = int(years.split()[0])
        months = int(months.split()[0])
        return years * 12 + months
# Apply conversion
df1['Credit_months'] = df1['Credit_History_Age'].apply(convert_to_months)
```

In [46]:
```
df1['Credit_months'] = df1.groupby('Customer_ID')['Credit_months'].fillna(m
ethod='ffill')
df1['Credit_months'] = df1.groupby('Customer_ID')['Credit_months'].fillna(m
ethod='bfill')
```

In [47]:
```
df1['Credit_months'] = df1['Credit_months'].astype('int')
```

In [48]:
```
df1['Credit_months'].isna().sum()
```
Out[48]: 0

In [49]:
```
def convert_to_years(age_str):
    if pd.isna(age_str) or age_str == 'NA':
        return np.nan
    else:
        years, months = age_str.split(' and ')
        years = int(years.split()[0])

        return years
# Apply conversion
df1['Credit_years'] = df1['Credit_History_Age'].apply(convert_to_years)
```

In [50]:
```
df1['Credit_years'] = df1.groupby('Customer_ID')['Credit_years'].fillna(method='ffill')
df1['Credit_years'] = df1.groupby('Customer_ID')['Credit_years'].fillna(method='bfill')
```

In [51]:
```
df1['Amount_invested_monthly'] = df1['Amount_invested_monthly'].str.replace('_',"")
df1['Amount_invested_monthly'] = df1.groupby('Customer_ID')['Amount_invested_monthly'].fillna(method='ffill')
df1['Amount_invested_monthly'] = df1.groupby('Customer_ID')['Amount_invested_monthly'].fillna(method='bfill')
df1['Amount_invested_monthly'] =df1['Amount_invested_monthly'].astype('float')
```

In [52]:
```
df1['Payment_Behaviour'] =df1['Payment_Behaviour'].replace('!@9#%8',np.nan)
df1['Payment_Behaviour'] = df1.groupby('Customer_ID')['Payment_Behaviour'].fillna(method='ffill')
df1['Payment_Behaviour'] = df1.groupby('Customer_ID')['Payment_Behaviour'].fillna(method='bfill')
```

In [53]:
```
df1['Payment_Behaviour'] = df1.groupby('Customer_ID')['Payment_Behaviour'].fillna(method='ffill')
df1['Payment_Behaviour'] = df1.groupby('Customer_ID')['Payment_Behaviour'].fillna(method='bfill')
```

In [54]:
```
df1['Monthly_Balance'].dtypes
```
Out[54]: dtype('O')

In [55]:
```
df1['Monthly_Balance'] = df1.groupby('Customer_ID')['Monthly_Balance'].fillna(method='ffill')
df1['Monthly_Balance'] = df1.groupby('Customer_ID')['Monthly_Balance'].fillna(method='bfill')
df1['Monthly_Balance'] = df1['Monthly_Balance'].replace('__-333333333333333333333333333__',np.nan)
df1['Monthly_Balance'] = df1['Monthly_Balance'].astype('float')
```

In [56]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 29 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                      98630 non-null   object 
 4   Age                       100000 non-null  int64  
 5   SSN                       100000 non-null  object 
 6   Occupation                100000 non-null  object 
 7   Annual_Income             100000 non-null  float64
 8   Monthly_Inhand_Salary     100000 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  float64
 12  Num_of_Loan               100000 non-null  int64  
 13  Type_of_Loan              100000 non-null  object 
 14  Delay_from_due_date       100000 non-null  int64  
 15  Num_of_Delayed_Payment    100000 non-null  int64  
 16  Changed_Credit_Limit      100000 non-null  object 
 17  Num_Credit_Inquiries      100000 non-null  int64  
 18  Credit_Mix                100000 non-null  object 
 19  Outstanding_Debt          100000 non-null  float64
 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   100000 non-null  float64
 25  Payment_Behaviour         100000 non-null  object 
 26  Monthly_Balance           99991 non-null   float64
 27  Credit_months             100000 non-null  int64  
 28  Credit_years              100000 non-null  float64
dtypes: float64(9), int64(8), object(12)
memory usage: 22.1+ MB
```

In [57]:
```
df1.head()
```

Out[57]:

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_
0	0x1628a	CUS_0x1000	January	Alistair Barrf	17	913-74-1218	Lawyer	30625.940000	
1	0x1628b	CUS_0x1000	February	Alistair Barrf	17	913-74-1218	Lawyer	30625.940000	
2	0x1628c	CUS_0x1000	March	Alistair Barrf	17	913-74-1218	Lawyer	30625.940000	
3	0x1628d	CUS_0x1000	April	Alistair Barrf	17	913-74-1218	Lawyer	30625.940000	
4	0x1628e	CUS_0x1000	May	Alistair Barrf	17	913-74-1218	Lawyer	30625.940000	

5 rows × 29 columns

In [58]:
```
df1['Changed_Credit_Limit'] = df1['Changed_Credit_Limit'].astype('float')
```

Downloading the Cleaned data

In [61]:
```
df1.to_csv('cleaned_credit_info.csv')
```

Importing the cleaned data

In [62]:
```
df1 = pd.read_csv('/content/cleaned_credit_info.csv')
```

In [63]:
```
df1.describe()
```

Out[63]:

	Unnamed: 0	Age	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Ac
count	100000.000000	100000.000000	100000.000000	100000.000000	100000.(
mean	49999.500000	33.311180	176415.701298	4198.771619	5.:
std	28867.657797	10.764783	1429618.051414	3187.494354	2.!
min	0.000000	14.000000	7005.930000	303.645417	0.(
25%	24999.750000	24.000000	19457.500000	1626.761667	3.(
50%	49999.500000	33.000000	37578.610000	3096.378333	5.(
75%	74999.250000	42.000000	72790.920000	5961.745000	7.(
max	99999.000000	56.000000	24198062.000000	15204.633330	10.(

In [64]:
```
df1.describe(include='object').T
```

Out[64]:

	count	unique	top	freq
ID	100000	100000	0x1628a	1
Customer_ID	100000	12500	CUS_0x1000	8
Month	100000	8	January	12500
Name	98630	10139	Langep	48
SSN	100000	12500	913-74-1218	8
Occupation	100000	15	Lawyer	7096
Type_of_Loan	100000	6260	Not Specified	12816
Credit_Mix	100000	3	Standard	45848
Credit_History_Age	90970	404	15 Years and 11 Months	446
Payment_of_Min_Amount	100000	3	Yes	52326
Payment_Behaviour	100000	6	Low_spent_Small_value_payments	27588

- There is a total of 12500 unique customers.
- The data is from January to August.
- Low_spent_Small_value_payments has high frequency 27588
- Standard has highest frequency from credit mix categories.

In [65]:
```
['Age', 'Annual_Income', 'Monthly_Inhand_Salary',
       'Num_Bank_Accounts', 'Num_Credit_Card', 'Interest_Rate', 'Num_of_Loa
n',
       'Delay_from_due_date', 'Num_of_Delayed_Payment', 'Changed_Credit_Lim
it',
       'Num_Credit_Inquiries', 'Outstanding_Debt', 'Credit_Utilization_Rati
o',
       'Total_EMI_per_month', 'Amount_invested_monthly', 'Monthly_Balance',
       'Credit_months', 'Credit_years']
```

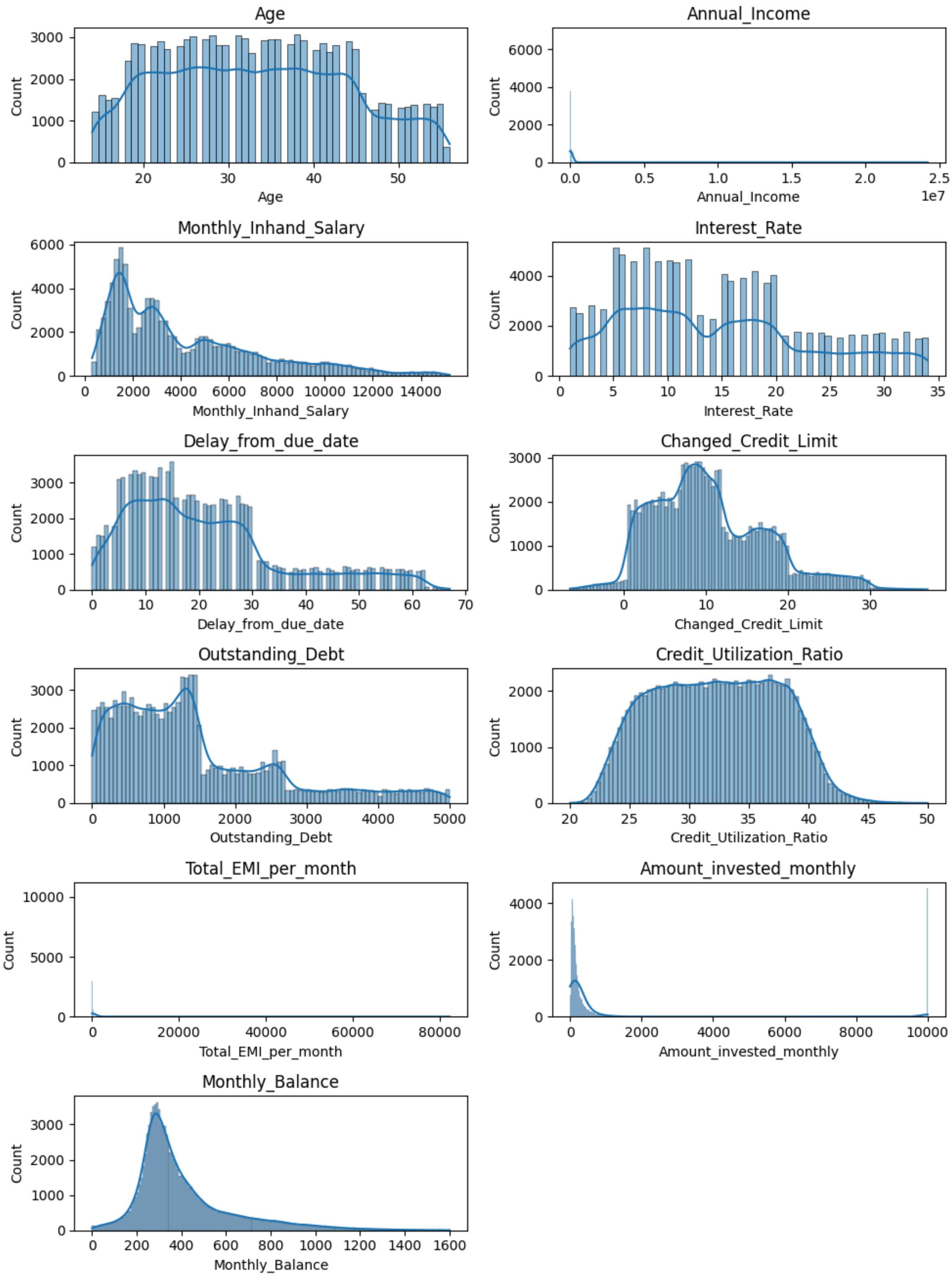
Out[65]:
```
['Age',
 'Annual_Income',
 'Monthly_Inhand_Salary',
 'Num_Bank_Accounts',
 'Num_Credit_Card',
 'Interest_Rate',
 'Num_of_Loan',
 'Delay_from_due_date',
 'Num_of_Delayed_Payment',
 'Changed_Credit_Limit',
 'Num_Credit_Inquiries',
 'Outstanding_Debt',
 'Credit_Utilization_Ratio',
 'Total_EMI_per_month',
 'Amount_invested_monthly',
 'Monthly_Balance',
 'Credit_months',
 'Credit_years']
```

In [66]:
```
df1['Customer_ID'].nunique()
```
Out[66]:
```
12500
```

In [67]:
```
df1[['Customer_ID','Month']][df1['Month']=='August'].count()
```
Out[67]:
```
Customer_ID    12500
Month          12500
dtype: int64
```

-

In [68]:
```
numericals_feature = ['Age', 'Annual_Income', 'Monthly_Inhand_Salary',
        'Interest_Rate',
       'Delay_from_due_date',  'Changed_Credit_Limit',
       'Outstanding_Debt', 'Credit_Utilization_Ratio',
       'Total_EMI_per_month', 'Amount_invested_monthly', 'Monthly_Balance',
      ]
plt.figure(figsize=(10,15))

for i in range(1, len(numericals_feature) + 1):
    plt.subplot(7, 2, i)
    sns.histplot(df1[numericals_feature[i-1]], kde=True)
    plt.title(numericals_feature[i-1])

plt.tight_layout()
plt.show()
```


Age
Annual_Income
Monthly_Inhand_Salary
Interest_Rate
Delay_from_due_date
Changed_Credit_Limit
Outstanding_Debt
Credit_Utilization_Ratio
Total_EMI_per_month
Amount_invested_monthly
Monthly_Balance
Count
1e7

Insights:

- The distribution of age is relatively uniform, with a slight peak around the mid-20s to early 30s.
- There is a noticeable drop in the number of individuals above the age of 50.
- fewer individuals earning very high monthly inhand salaries.
- The interest rate distribution is fairly uniform, with small peaks around 10-15% and another around 20-25%.
- The delay from the due date has a broad distribution with many individuals experiencing delays of up to 30 days.
- Most changes in credit limits are moderate, with few instances of very high adjustments.
- The distribution shows a high frequency of individuals with outstanding debt in the range of 0 to 2000 units.
- The majority of individuals maintain a credit utilization ratio within the 20% to 40% range, indicating good credit management practices.
- Monthly EMI payments are generally low, suggesting that most individuals do not have heavy debt burdens from EMIs.
- Most individuals invest small amounts monthly, indicating cautious or limited investment behavior.

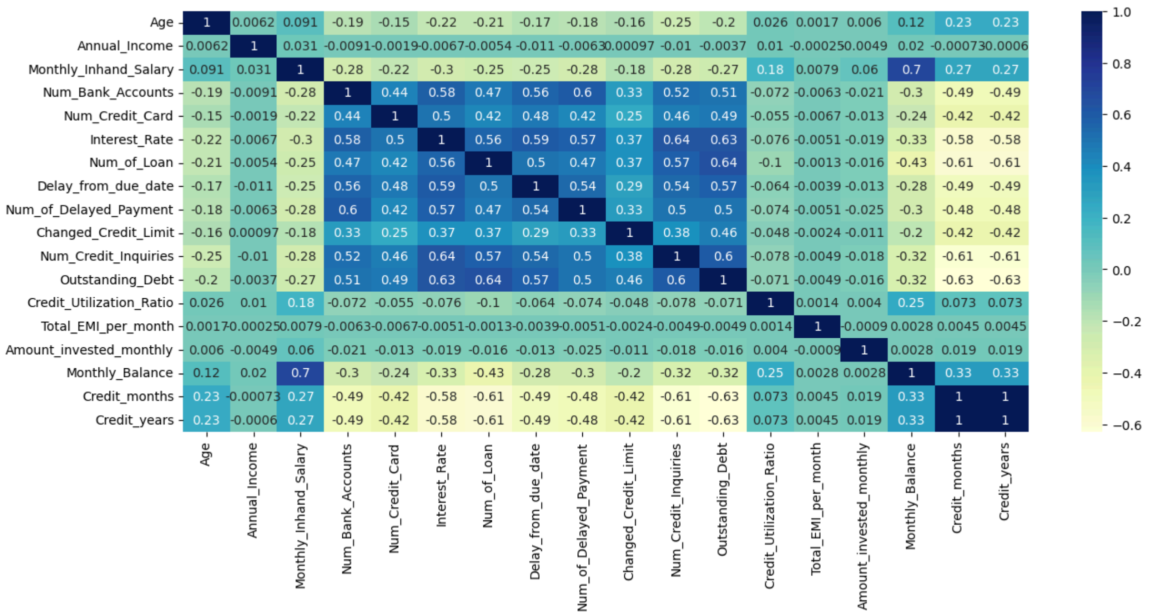
In [69]:
```
num = df1[['Age', 'Annual_Income', 'Monthly_Inhand_Salary',
       'Num_Bank_Accounts', 'Num_Credit_Card', 'Interest_Rate', 'Num_of_Loan',
       'Delay_from_due_date', 'Num_of_Delayed_Payment', 'Changed_Credit_Limit',
       'Num_Credit_Inquiries', 'Outstanding_Debt', 'Credit_Utilization_Ratio',
       'Total_EMI_per_month', 'Amount_invested_monthly', 'Monthly_Balance',
       'Credit_months', 'Credit_years']]

data = num.corr()
```

In [70]:
```
data
```

Out[70]:

	Age	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accc
Age	1.000000	0.006235	0.090623	-0.19
Annual_Income	0.006235	1.000000	0.030508	-0.00
Monthly_Inhand_Salary	0.090623	0.030508	1.000000	-0.28
Num_Bank_Accounts	-0.190335	-0.009087	-0.283243	1.00
Num_Credit_Card	-0.148567	-0.001941	-0.216958	0.44
Interest_Rate	-0.217531	-0.006702	-0.301906	0.58
Num_of_Loan	-0.213355	-0.005440	-0.254155	0.47
Delay_from_due_date	-0.173892	-0.010670	-0.249300	0.55
Num_of_Delayed_Payment	-0.183664	-0.006277	-0.284396	0.60
Changed_Credit_Limit	-0.156400	0.000974	-0.175135	0.33
Num_Credit_Inquiries	-0.252376	-0.010166	-0.281860	0.52
Outstanding_Debt	-0.202361	-0.003706	-0.269078	0.50
Credit_Utilization_Ratio	0.025523	0.010316	0.176081	-0.07
Total_EMI_per_month	0.001698	-0.000248	0.007949	-0.00
Amount_invested_monthly	0.005982	-0.004870	0.060218	-0.02
Monthly_Balance	0.117456	0.019595	0.702733	-0.29
Credit_months	0.234635	-0.000728	0.271516	-0.48
Credit_years	0.234569	-0.000602	0.271353	-0.48

In [71]:
```python
plt.figure(figsize=(15,6))
sns.heatmap(data, cmap="YlGnBu", annot=True)
plt.show()
```



Positive Correlations

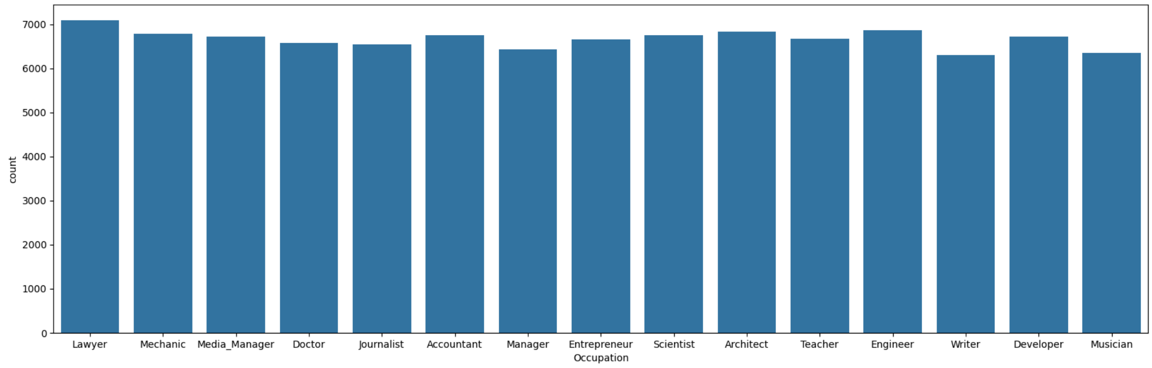
- Higher monthly in-hand salary is strongly associated with a higher monthly balance.
- More bank accounts and credit cards tend to be associated with more loans.
- Higher interest rates are associated with higher outstanding debt.
- A higher credit utilization ratio is somewhat associated with higher outstanding debt.

Negative Correlations

- Delays in payment are associated with lower monthly balances.
- A higher credit utilization ratio has a small positive relationship with monthly balance, which might indicate that those with higher utilization ratios maintain a slightly higher balance
- More delayed payments are linked to more loans and higher outstanding debt.

In [72]:
```
plt.figure(figsize=(20,6))
sns.countplot(x='Occupation',data=df1)
```

Out[72]: <Axes: xlabel='Occupation', ylabel='count'>

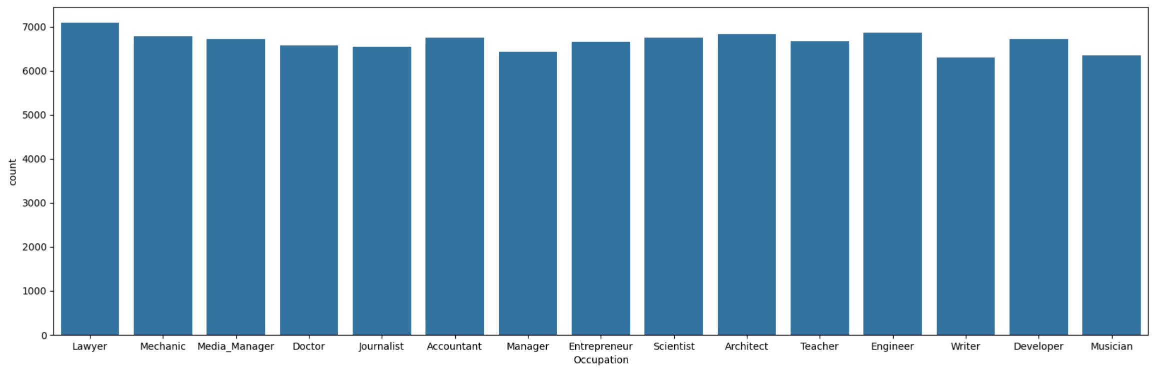


Insights

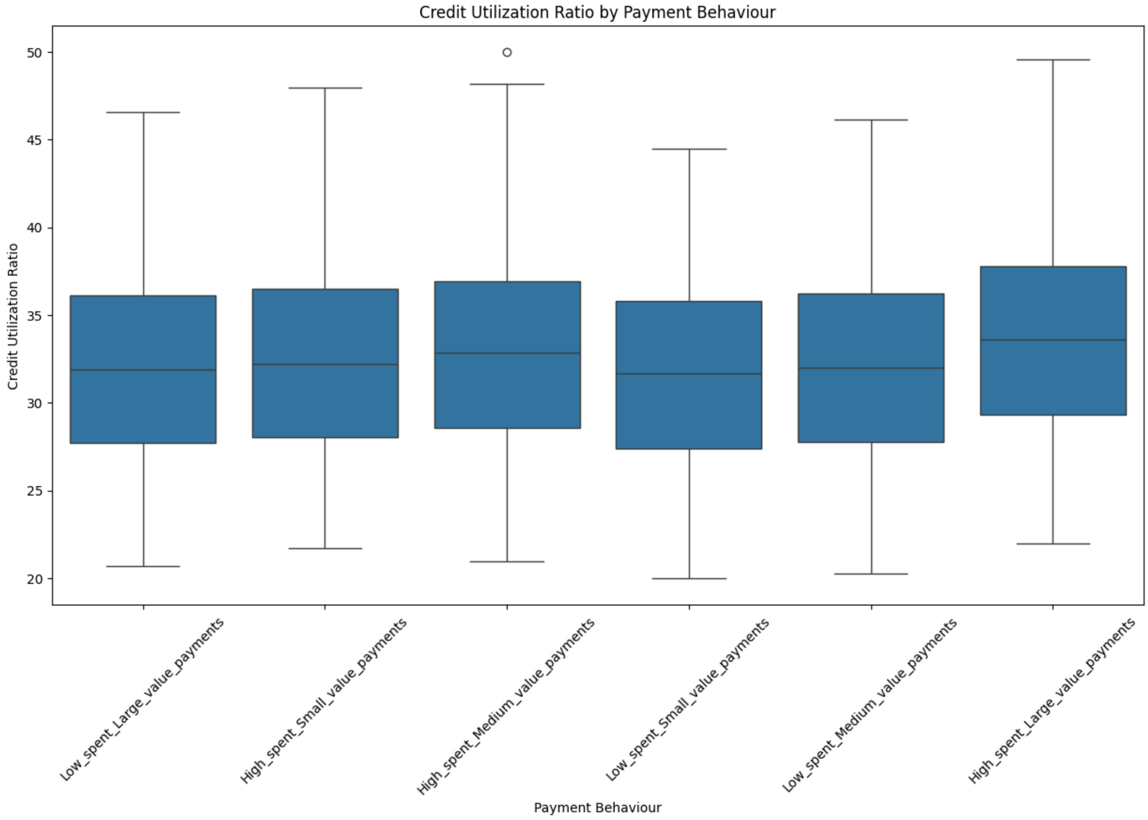
- The distribution is almost uniform across all the categories of occupation

In [73]:
```
plt.figure(figsize=(20,6))
sns.countplot(x='Occupation',data=df1)
```

Out[73]: <Axes: xlabel='Occupation', ylabel='count'>



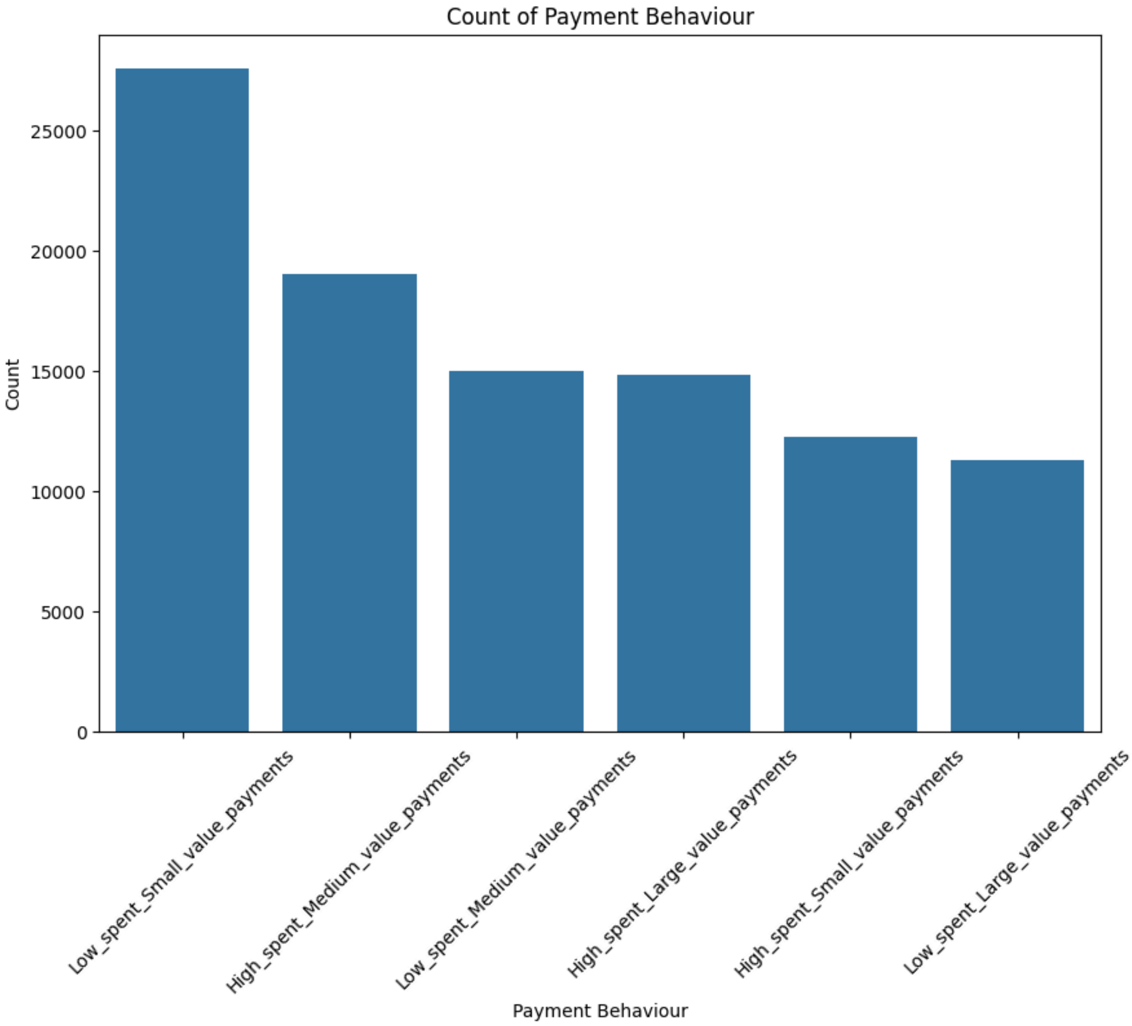
In [74]:
```
plt.figure(figsize=(15, 8))
sns.boxplot(x='Payment_Behaviour', y='Credit_Utilization_Ratio', data=df1)
plt.title('Credit Utilization Ratio by Payment Behaviour')
plt.xlabel('Payment Behaviour')
plt.ylabel('Credit Utilization Ratio')
plt.xticks(rotation=45)
plt.show()
```



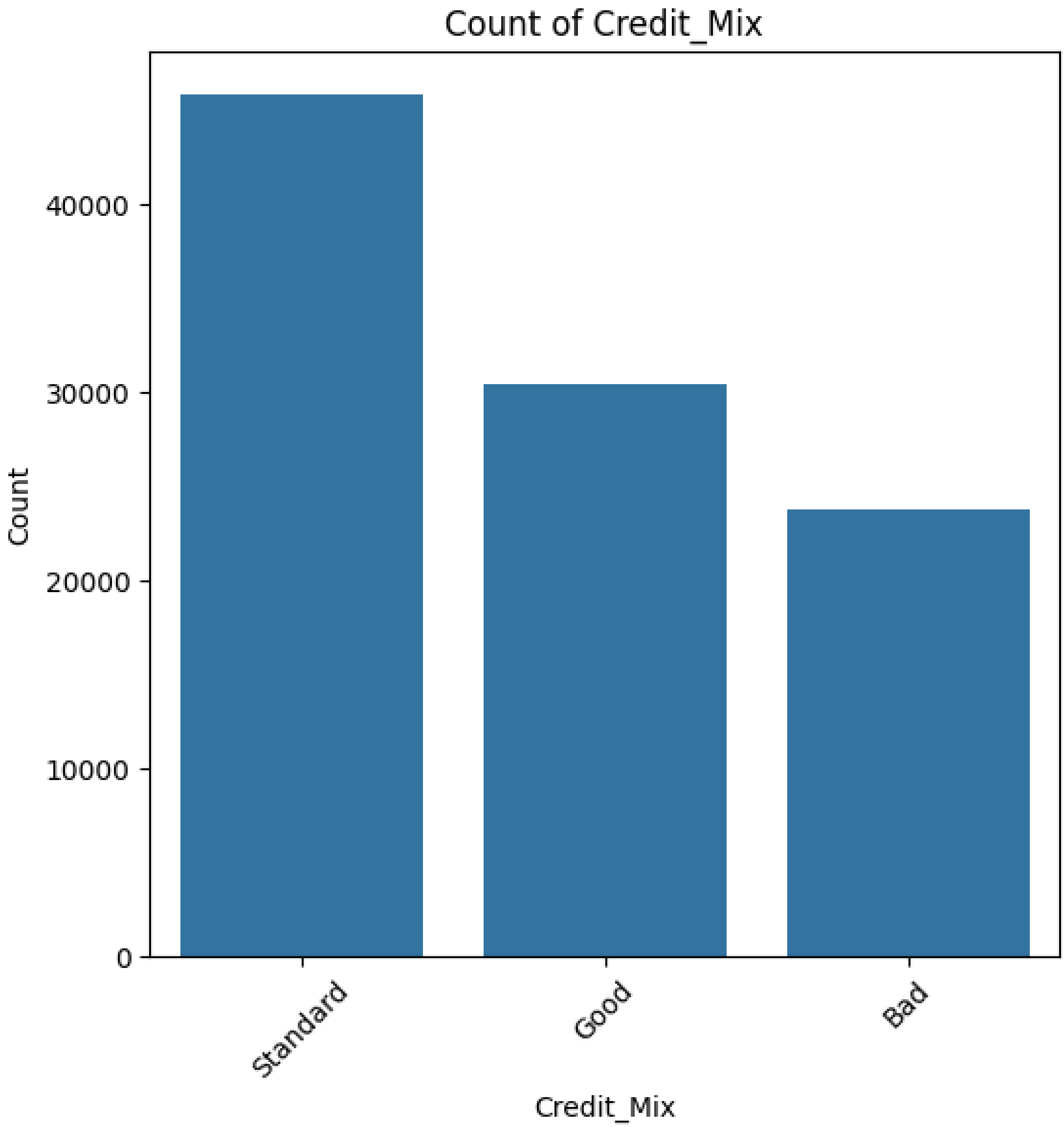
Insights

- All payment behavior categories exhibit similar median Credit Utilization Ratios, which appear to be around 30-35.

In [75]:
```
plt.figure(figsize=(10, 7))
sns.countplot(x='Payment_Behaviour', data=df1,order = df1['Payment_Behaviou
r'].value_counts().index)
plt.title('Count of Payment Behaviour')
plt.xlabel('Payment Behaviour')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```



In [76]:
```
plt.figure(figsize=(6, 6))
sns.countplot(x='Credit_Mix', data=df1,order = df1['Credit_Mix'].value_coun
ts().index)
plt.title('Count of Credit_Mix')
plt.xlabel('Credit_Mix')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```



- Low spent smaller values payments and standard credit mix have max frequencies

In [77]:
```
df1.groupby(['Credit_Mix'])['Num_Credit_Card'].value_counts().reset_index()
```

Out[77]:

	Credit_Mix	Num_Credit_Card	count
0	Bad	7	4057
1	Bad	8	4017
2	Bad	5	3997
3	Bad	6	3985
4	Bad	10	3864
5	Bad	9	3819
6	Bad	4	29
7	Good	5	6144
8	Good	4	6071
9	Good	3	5668
10	Good	7	4146
11	Good	6	3962
12	Good	1	2185
13	Good	2	2151
14	Good	8	43
15	Good	0	14
16	Standard	6	8982
17	Standard	7	8826
18	Standard	5	8763
19	Standard	4	8258
20	Standard	3	7897
21	Standard	10	1134
22	Standard	8	1012
23	Standard	9	934
24	Standard	2	42

In [78]:
```
df1['Credit_Utilization_Category'] = pd.cut(df1['Credit_Utilization_Rati
o'], bins=[0, 10, 30, 50, 70, 100], labels=['0-10%', '10-30%', '30-50%', '5
0-70%', '70-100%'])
credit_mix_vs_credit_utilization = pd.crosstab(df1['Credit_Mix'], df1['Cred
it_Utilization_Category'],normalize=True)
credit_mix_vs_credit_utilization*100
```

Out[78]:

Credit_Utilization_Category	10-30%	30-50%
Credit_Mix		
Bad	9.459000	14.309000
Good	9.958000	20.426000
Standard	16.945000	28.903000

- **Credit Utilization (10-30%):**
  - Bad credit mix: 9.459
  - Good credit mix: 9.958
  - Standard credit mix: 16.945

- **Credit Utilization (30-50%):**
  - Bad credit mix: 14.309
  - Good credit mix: 20.426
  - Standard credit mix: 28.903

In [79]:
```
df1['Payment_Behaviour'].unique()
```

Out[79]:
```
array(['Low_spent_Large_value_payments',
       'High_spent_Small_value_payments',
       'High_spent_Medium_value_payments',
       'Low_spent_Small_value_payments',
       'Low_spent_Medium_value_payments',
       'High_spent_Large_value_payments'], dtype=object)
```

Calculation Of Credit Score:

- 1. Payment History (35%):
  - Payment_of_Min_Amount
  - Num_of_Delayed_Payment
  - Delay_from_due_date
- 1. Accounts Owed (30%):
  - Outstanding_Debt
  - Credit_Utilization_Ratio
  - Total_EMI_per_month
- 1. Length of Credit History (15%)
  - Credit_History_Age_Months
- 1. Credit Mix (10%)
  - Credit_Mix
  - Num_Bank_Accounts
  - Num_Credit_Card
  - Num_of_Loan
- 1. New Credit (10%) -Num_Credit_Inquiries

Assigning Scaling points to categories

In [80]:
```
# Create a new column for Credit History Age in months
df1['Credit_History_Age_Months'] = (df1['Credit_years'] * 12) + df1['Credit_months']

# Map Payment_Behaviour to numerical scores
payment_behaviour_map = {
    'Low_spent_Large_value_payments': 1,
    'High_spent_Small_value_payments': 2,
    'High_spent_Medium_value_payments': 3,
    'Low_spent_Small_value_payments': 4,
    'Low_spent_Medium_value_payments': 5,
    'High_spent_Large_value_payments': 6
}
df1['Payment_Behaviour_Score'] = df1['Payment_Behaviour'].map(payment_behaviour_map)

# Define the scoring function for Credit Utilization Ratio
def credit_utilization_score(ratio):
    if ratio <= 0.10:
        return 1.0  # Highest points
    elif ratio <= 0.30:
        return 0.5  # Medium points
    else:
        return 0.0  # Lowest points
```

Aggregating Data on customer Level

In [81]:
```
# Aggregating the data for each customer
df_aggregated = df1.groupby('Customer_ID').agg({
    'Payment_of_Min_Amount': 'last',
    'Num_of_Delayed_Payment': 'sum',
    'Delay_from_due_date': 'sum',
    'Outstanding_Debt': 'mean',
    'Credit_Utilization_Ratio': 'mean',
    'Total_EMI_per_month': 'mean',
    'Credit_History_Age_Months': 'last',
    'Num_Credit_Inquiries': 'sum',
    'Num_Bank_Accounts': 'mean',
    'Num_Credit_Card': 'mean',
    'Num_of_Loan': 'mean',
    'Credit_Mix': 'last',
    'Payment_Behaviour_Score': 'last'
}).reset_index()




# Apply the scoring function
df_aggregated['Credit_Utilization_Ratio_Score'] = df_aggregated['Credit_Utilization_Ratio'].apply(credit_utilization_score)
```

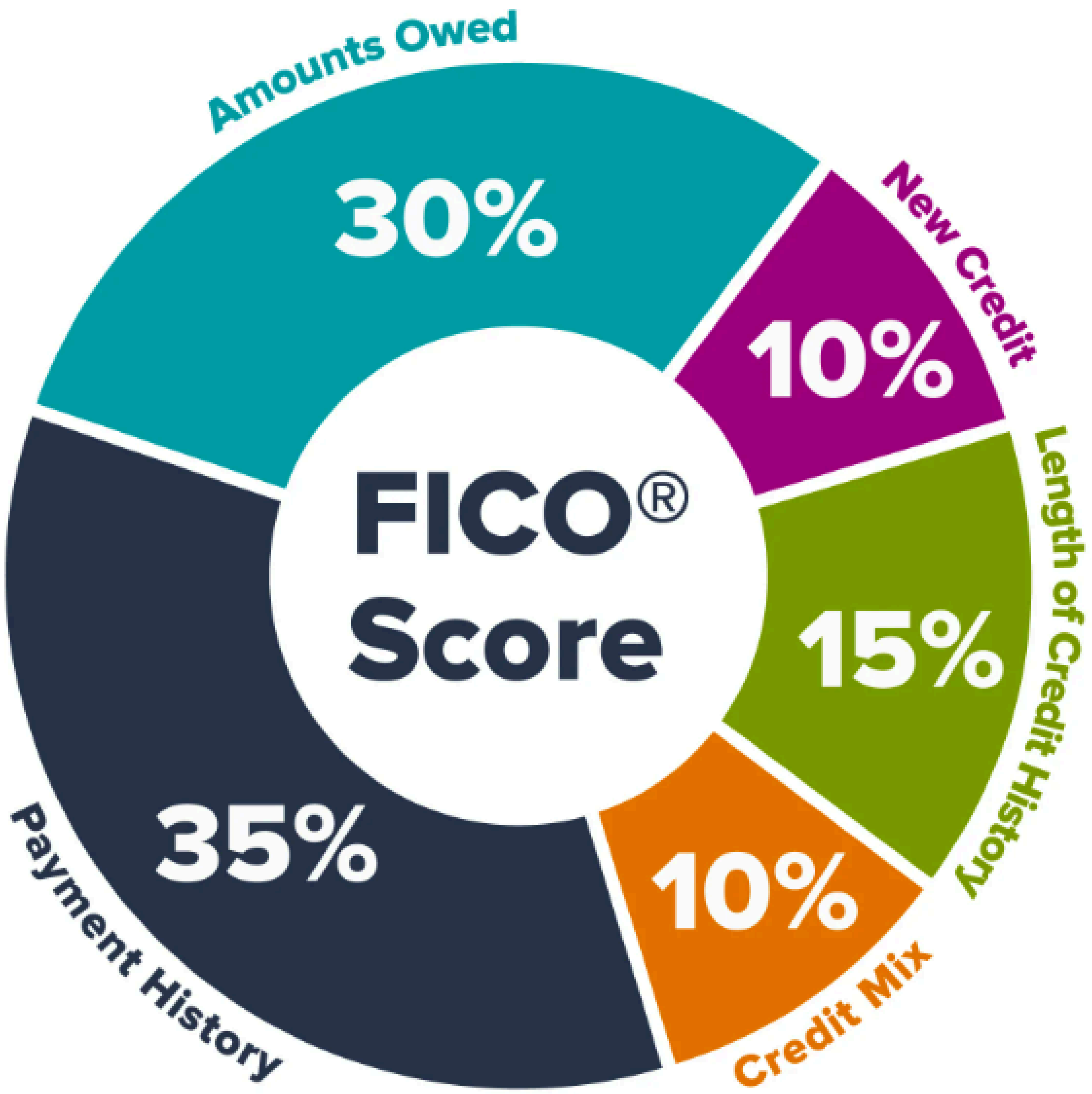
In [82]:
```
df_aggregated.head(5)
```

Out[82]:

	Customer_ID	Payment_of_Min_Amount	Num_of_Delayed_Payment	Delay_from_due_date	O
0	CUS_0x1000	Yes	200	498	
1	CUS_0x1009	Yes	141	58	
2	CUS_0x100b	No	59	108	
3	CUS_0x1011	Yes	114	218	
4	CUS_0x1013	No	68	100	

Creating new features by scaling the features

In [83]:
```
# Define the normalization functions for other factors
def min_max_scaling(column):
    return (column - column.min()) / (column.max() - column.min())

# Apply min-max scaling to the relevant columns
df_aggregated['Num_of_Delayed_Payment_scaled'] = min_max_scaling(df_aggrega
ted['Num_of_Delayed_Payment'])
df_aggregated['Delay_from_due_date_scaled'] = min_max_scaling(df_aggregated
['Delay_from_due_date'])
df_aggregated['Outstanding_Debt_scaled'] = min_max_scaling(df_aggregated['O
utstanding_Debt'])
df_aggregated['Total_EMI_per_month_scaled'] = min_max_scaling(df_aggregated
['Total_EMI_per_month'])
df_aggregated['Credit_History_Age_Months_scaled'] = min_max_scaling(df_aggr
egated['Credit_History_Age_Months'])
df_aggregated['Num_Credit_Inquiries_scaled'] = min_max_scaling(df_aggregate
d['Num_Credit_Inquiries'])
df_aggregated['Num_Bank_Accounts_scaled'] = min_max_scaling(df_aggregated
['Num_Bank_Accounts'])
df_aggregated['Num_Credit_Card_scaled'] = min_max_scaling(df_aggregated['Nu
m_Credit_Card'])
df_aggregated['Num_of_Loan_scaled'] = min_max_scaling(df_aggregated['Num_of
_Loan'])
df_aggregated['Payment_Behaviour_Score_scaled'] = min_max_scaling(df_aggreg
ated['Payment_Behaviour_Score'])
```



Applying factor-based normalization to credit score data.

In [84]:
```
# Define functions to normalize each factor
def normalize_payment_history(row):
    return (row['Payment_of_Min_Amount'] == 'Yes') * 0.7 + (1 - row['Num_of
_Delayed_Payment_scaled']) * 0.2 + (1 - row['Delay_from_due_date_scaled'])
* 0.1

def normalize_amounts_owed(row):
    return (1 - row['Outstanding_Debt_scaled']) * 0.5 + (row['Credit_Utiliz
ation_Ratio_Score']) * 0.3 + (1 - row['Total_EMI_per_month_scaled']) * 0.2

def normalize_length_of_credit_history(row):
    return row['Credit_History_Age_Months_scaled']

def normalize_new_credit(row):
    return (1 - row['Num_Credit_Inquiries_scaled'])

def normalize_credit_mix(row):
    credit_mix_score = 0
    if row['Credit_Mix'] == 'Good':
        credit_mix_score = 1
    elif row['Credit_Mix'] == 'Standard':
        credit_mix_score = 0.5
    elif row['Credit_Mix'] == 'Bad':
        credit_mix_score = 0
    return (row['Num_Bank_Accounts_scaled'] * 0.25 +
            row['Num_Credit_Card_scaled'] * 0.25 +
            row['Num_of_Loan_scaled'] * 0.25 +
            credit_mix_score * 0.25)

def normalize_payment_behaviour(row):
    return row['Payment_Behaviour_Score_scaled'] * 0.1

# Normalize each factor for all rows
df_aggregated['Payment_History_Score'] = df_aggregated.apply(normalize_paym
ent_history, axis=1)
df_aggregated['Amounts_Owed_Score'] = df_aggregated.apply(normalize_amounts
_owed, axis=1)
df_aggregated['Length_of_Credit_History_Score'] = df_aggregated.apply(norma
lize_length_of_credit_history, axis=1)
df_aggregated['New_Credit_Score'] = df_aggregated.apply(normalize_new_credi
t, axis=1)
df_aggregated['Credit_Mix_Score'] = df_aggregated.apply(normalize_credit_mi
x, axis=1)
df_aggregated['Payment_Behaviour_Score'] = df_aggregated.apply(normalize_pa
yment_behaviour, axis=1)

# Calculate the final credit score
df_aggregated['Credit_Score'] = (df_aggregated['Payment_History_Score'] *
0.35 +
                                 df_aggregated['Amounts_Owed_Score'] * 0.30
+
                                 df_aggregated['Length_of_Credit_History_Sc
ore'] * 0.15 +
                                 df_aggregated['New_Credit_Score'] * 0.10 +
                                 df_aggregated['Credit_Mix_Score'] * 0.10 +
                                 df_aggregated['Payment_Behaviour_Score'] *
0.05)  # Adjust weight if needed

df_aggregated['Credit_Score'] = 300 + (df_aggregated['Credit_Score'] * 550)
```

```
df_aggregated.to_csv('credit_scores_aggregated.csv', index=False)
```

factor wise score and credit score.

In [85]:
```
df_aggregated[['Customer_ID','Payment_History_Score','Amounts_Owed_Score','Length_of_Credit_History_Score','New_Credit_Score','Credit_Mix_Score','Credit_Score']]
```

Out[85]:

	Customer_ID	Payment_History_Score	Amounts_Owed_Score	Length_of_Credit_History_
0	CUS_0x1000	0.712008	0.543378	0.3
1	CUS_0x1009	0.854888	0.679023	0.9
2	CUS_0x100b	0.222732	0.596958	0.4
3	CUS_0x1011	0.848860	0.651865	0.4
4	CUS_0x1013	0.215782	0.534822	0.5
...	...	...	...	
12495	CUS_0xff3	0.215230	0.576840	0.5
12496	CUS_0xff4	0.882958	0.623470	0.5
12497	CUS_0xff6	0.268995	0.665334	0.7
12498	CUS_0xffc	0.805038	0.568134	0.3
12499	CUS_0xffd	0.876433	0.528541	0.5

12500 rows × 7 columns

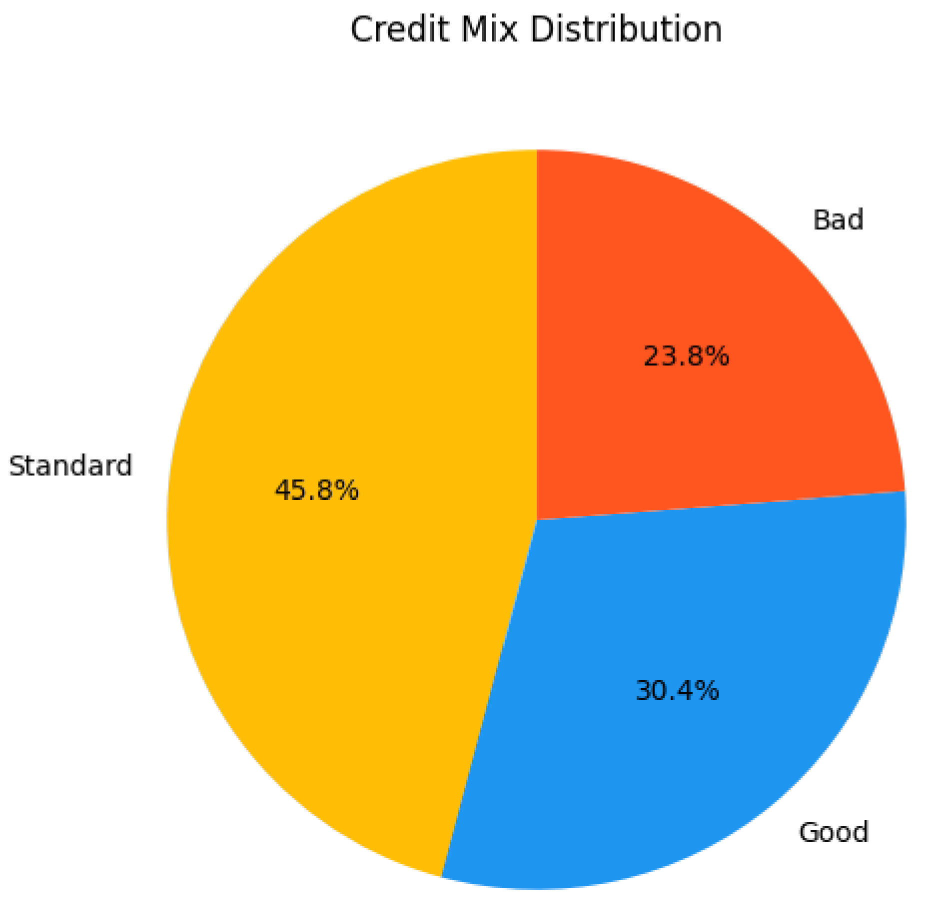
In [86]:
```
df_aggregated.head()
```

Out[86]:

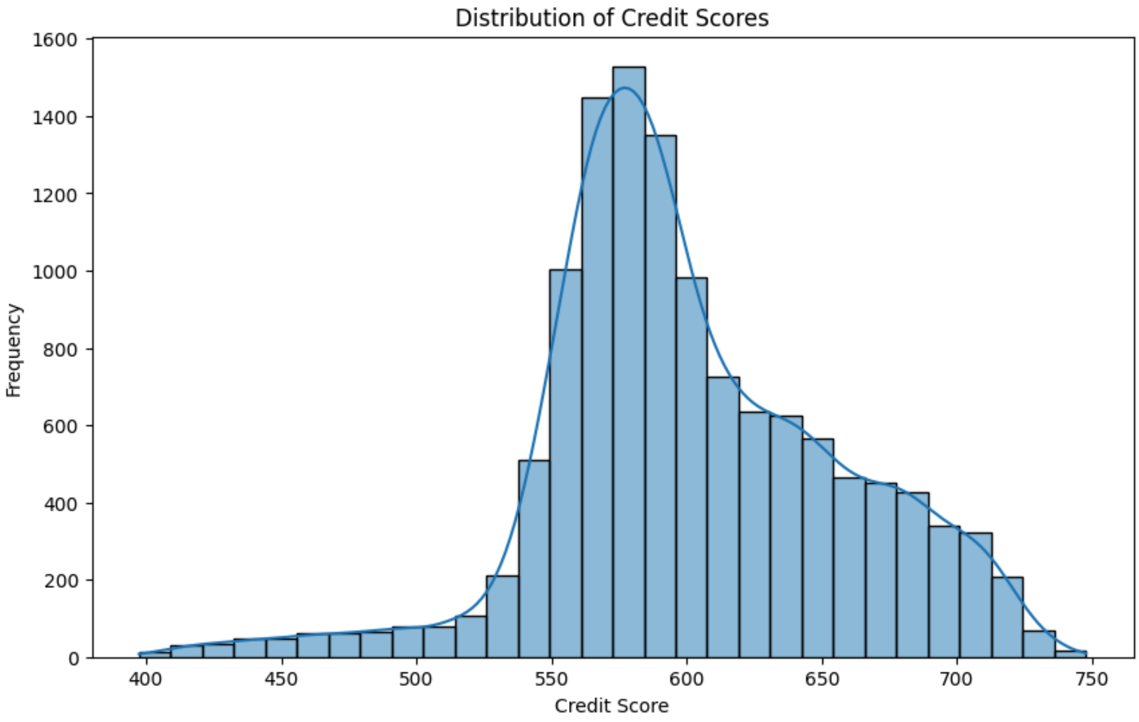
	Customer_ID	Payment_of_Min_Amount	Num_of_Delayed_Payment	Delay_from_due_date	O
0	CUS_0x1000	Yes	200	498	
1	CUS_0x1009	Yes	141	58	
2	CUS_0x100b	No	59	108	
3	CUS_0x1011	Yes	114	218	
4	CUS_0x1013	No	68	100	

5 rows × 31 columns

In [87]:
```
credit_mix_distribution = df_aggregated['Credit_Mix'].value_counts()
plt.figure(figsize=(8, 6))
credit_mix_distribution.plot.pie(autopct='%1.1f%%', startangle=90, colors=
['#FFC107', '#2196F3', '#FF5722'])
plt.title('Credit Mix Distribution')
plt.ylabel('')
plt.show()
```



In [88]:
```
plt.figure(figsize=(10, 6))
sns.histplot(df_aggregated['Credit_Score'], bins=30, kde=True)
plt.title('Distribution of Credit Scores')
plt.xlabel('Credit Score')
plt.ylabel('Frequency')
plt.show()
```



Final Insights:

- The highest frequency of credit scores is around 630-640, indicating that a significant portion of individuals fall within this range.
- The credit scores range from approximately 400 to 750, providing a broad perspective on the creditworthiness of individuals in the dataset.
- There are fewer individuals with scores above 700, indicating that only a small portion of the population has excellent credit.
- The central tendency of the credit scores is around 600-650, which can be considered the average credit score range for the population in this dataset

Recommndations:

- Provide credit utilization monitoring tools and alerts to help customers maintain their utilization ratios below 30%.
- Target segment (credit score > 700) with premium credit cards, wealth management, and high-interest savings accounts.
- Focus on customers with credit scores between 650-700 by offering balance transfer credit cards, personal loans, and home loan options to meet their financial needs and build loyalty.
- Run targeted marketing campaigns tailored to different customer segments to effectively reach and engage them. -Introduce payment reminders and flexible repayment options to help customers avoid payment delays and improve financial health.

In [ ]: