🏧💸Credit EDA & Credit Score Calculation 💳💯

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.

Libraries📄

In [163…
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Importing Dataset📩

In [164…
```
data = pd.read_csv("/content/drive/MyDrive/Datasets/Credit_score (1).csv")
data.shape
```

Out[164…
```
(100000, 27)
```

In [165…
```
df = data.copy()
df.head(2)
```

Out[165…

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	...	Num_Credit_Inquiries	Credit_Mix	Outstanding_Debt	Cr
0	0x1602	CUS_0xd40	January	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843333	3	...	4.0	_	809.98	
1	0x1603	CUS_0xd40	February	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	NaN	3	...	4.0	Good	809.98	

2 rows × 27 columns

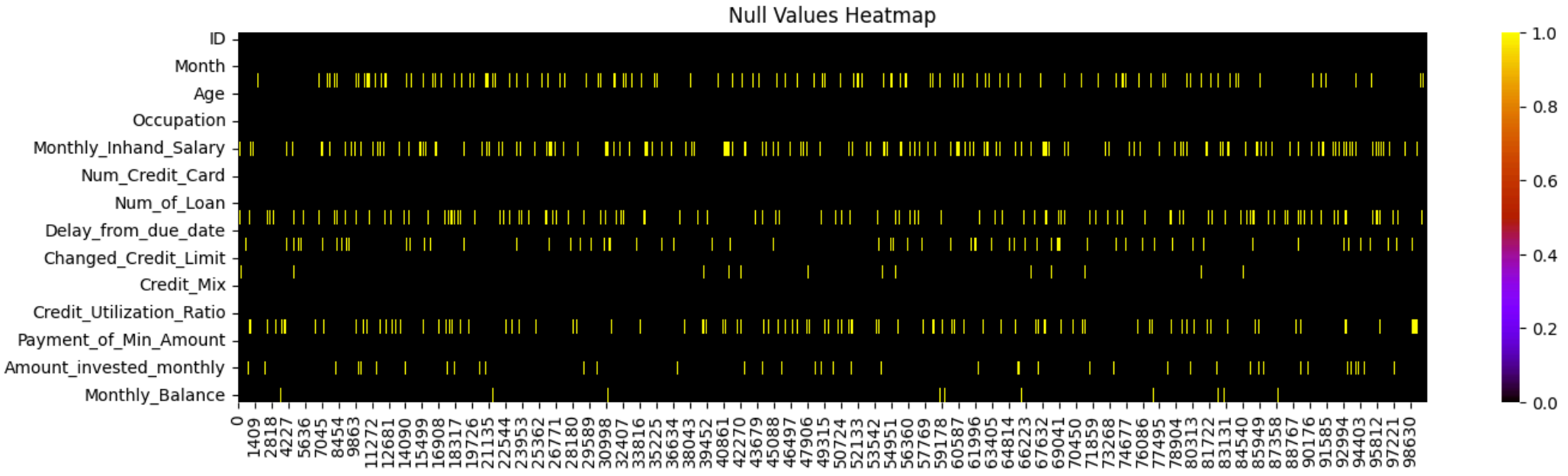
EDA 📊

In [166…
```
df.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
```

In [167…

```
# Null value heatmap:
plt.figure(figsize = (16,4))
sns.heatmap(df.isnull().T, cmap='gnuplot')
plt.title('Null Values Heatmap')
plt.show()
```



Name

In [168…

```
#3Name - filling with ffill and bfill
df['Name'] = df.groupby('Customer_ID')['Name'].transform(lambda x: x.fillna(method='ffill').fillna(method='bfill'))
df["Name"].isna().sum()
```

Out[168…

```
0
```

Age

In [169…

```
# 4.Age
# Remove non-numeric characters from the 'Age' column
df['Age'] = df['Age'].str.replace(r'\D', '', regex=True)
df["Age"].dtype
```

Out[169…

```
dtype('O')
```

In [170…

```
# Convert the cleaned 'Age' column to numeric values
df['Age'] = pd.to_numeric(df['Age'], errors='coerce')
df["Age"].dtype
```

Out[170…

```
dtype('int64')
```

In [171…

```
df["Age"].isna().sum()
```

Out[171…

```
0
```

In [172…

```
#Checking the abnormal age
df[(df["Age"] <= 0) | (df["Age"] > 100)]
```

Out[172…

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	...	Num_Credit_Inquiries	Credit_Mix	Outstandin
2	0x1604	CUS_0xd40	March	Aaron Maashoh	500	821-00-0265	Scientist	19114.12	NaN	3	...	4.0	Good	
56	0x1656	CUS_0x5407	January	Annk	7580	500-92-6408	Media_Manager	34081.38_	NaN	8	...	5.0	Standard	
113	0x16ab	CUS_0xff4	February	Poornimaf	500	655-05-7666	Entrepreneur	25546.26	NaN	8	...	NaN	Standard	
122	0x16b8	CUS_0x33d2	March	Chalmersa	181	965-46-2491	Scientist	31993.78	2942.148333	6	...	1.0	Standard	
219	0x1749	CUS_0x3edc	April	Williamso	995	663-16-3845	Accountant	43070.24	3622.186667	3	...	4.0	Standard	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
99913	0x25f6f	CUS_0x1619	February	Phil Wahbao	2263	683-59-7399	Media_Manager	20059.98	1523.665000	8	...	3.0	Good	
99937	0x25f93	CUS_0xad4f	February	Sabina Zawadzkig	500	226-45-0652	_____	22620.79	1722.065833	7	...	2.0	Standard	
99950	0x25fa4	CUS_0x51b3	July	Ryana	1342	837-85-9800	Media_Manager	59146.36	4908.863333	3	...	5.0	_	
99963	0x25fb9	CUS_0x372c	April	Lucia Mutikanik	500	340-85-7301	Lawyer	42903.79	NaN	0	...	1.0	Good	
99972	0x25fc6	CUS_0xf16	May	Maria Sheahanb	1753	868-70-2218	Media_Manager	16680.35	1528.029167	1	...	8.0	Good	

2776 rows × 27 columns

In [173…
```
# Replace invalid age values with NaN
df.loc[(df["Age"] <= 0) | (df["Age"] > 100), 'Age'] = np.nan
df["Age"].isna().sum()
```

Out[173… 2776

In [174…
```
# filling null values
df['Age'] = df.groupby('Customer_ID')['Age'].transform(lambda x: x.fillna(method='ffill').fillna(method='bfill'))
df["Age"].isna().sum()
```

Out[174… 0

SSN

In [175…
```
# 5.ssn -Replace special character with NaN
df['SSN'] = df['SSN'].replace("#F%$D@*&8", np.nan)
```

In [176…
```
# checking no of NaN values
df["SSN"].value_counts(dropna = False)
```

Out[176…

SSN	count
NaN	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

12501 rows × 1 columns

dtype: int64

In [177…
```
# filling with ffill and bfill
df['SSN'] = df.groupby('Customer_ID')['SSN'].ffill().bfill()
```

In [178…
```
df["SSN"].isna().sum()
```

Out[178… 0

Occupation

In [179…
```
# 6.Occupation
df["Occupation"].isna().sum()
```

Out[179… 0

In [180…
```
# replacing the spl characters with nan
df["Occupation"].replace("_______", np.nan)
df["Occupation"].isna().sum()
```

Out[180…
```
0
```

In [181…
```
# filling nan values with ffill and bfill
df["Occupation"] = df.groupby("Customer_ID")["Occupation"].ffill().bfill()
df["Occupation"].isna().sum()
```

Out[181…
```
0
```

Annual Income

In [182…
```
#7 Annual_Income
df["Annual_Income"].isna().sum()
```

Out[182…
```
0
```

In [183…
```
# treating the non numerical values
df['Annual_Income'] = df['Annual_Income'].str.replace(r'\D', '', regex=True)
df["Annual_Income"].dtype
```

Out[183…
```
dtype('O')
```

In [184…
```
#converting to Numeric
df['Annual_Income'] = pd.to_numeric(df['Annual_Income'], errors='coerce')
df["Annual_Income"].dtype
```

Out[184…
```
dtype('int64')
```

In [185…
```
# filling null values
df["Annual_Income"] = df.groupby("Customer_ID")["Annual_Income"].ffill().bfill()
df["Annual_Income"].isna().sum()
```

Out[185…
```
0
```

Monthly_Inhand_Salary

In [186…
```
# 8.Monthly_Inhand_Salary
df["Monthly_Inhand_Salary"].isna().sum()
```

Out[186…
```
15002
```

In [187…
```
#converting to numeric
df['Monthly_Inhand_Salary'] = pd.to_numeric(df['Monthly_Inhand_Salary'], errors='coerce')
#filling with ffill and bfill
df["Monthly_Inhand_Salary"] = df.groupby("Customer_ID")["Monthly_Inhand_Salary"].ffill().bfill()
df["Monthly_Inhand_Salary"].isna().sum()
```

Out[187…
```
0
```

creating fillmode - function

In [188…
```
# fillmode- function
def fill_mode(series):
    mode_value = series.mode()
    if not mode_value.empty:
        return mode_value[0]  # Use the first mode if there are multiple modes
    else:
        return np.nan
```

Num_of_Bank_Accounts

In [189…
```
#9.Num_Bank_Accounts - replacing negative with 0
df["Num_Bank_Accounts"].replace(-1,0)
```

Out[189…

	Num_Bank_Accounts
0	3
1	3
2	3
3	3
4	3
...	...
99995	4
99996	4
99997	4
99998	4
99999	4

100000 rows × 1 columns

dtype: int64

In [190…
```
# creating a new column and filling with mode
df["num_bank_accounts"] = df.groupby("Customer_ID")["Num_Bank_Accounts"].transform(fill_mode)
df["num_bank_accounts"].isna().sum()
```

Out[190…
```
0
```

Num_Credit_Card

In [191…
```
#10 Num_Credit_Card
df["Num_Credit_Card"].isna().sum()
```

Out[191… 0

In [192…
```
# creating a new column and filling with mode
df["num_credit_card"] = df.groupby("Customer_ID")["Num_Credit_Card"].transform(fill_mode)
df["num_credit_card"].isna().sum()
```

Out[192… 0

Interest_Rate

In [193…
```
#11.Interest_Rate
df["Interest_Rate"].isna().sum()
```

Out[193… 0

In [194…
```
df["Interest_Rate"].value_counts()
```

Out[194…

Interest_Rate	count
8	5012
5	4979
6	4721
12	4540
10	4540
...	...
4995	1
1899	1
2120	1
5762	1
5729	1

1750 rows × 1 columns

dtype: int64

In [195…
```
# creating a new column and filling with mode
df["interest_rate"] = df.groupby("Customer_ID")["Interest_Rate"].transform(fill_mode)
df["interest_rate"].min(), df["interest_rate"].max()
```

Out[195… (1, 34)

Num_of_Loan

In [196…
```
# 12.Num_of_Loan
df["Num_of_Loan"].isna().sum()
```

Out[196… 0

In [197…
```
df["Num_of_Loan"].value_counts()
```

Out[197…

Num_of_Loan	count
3	14386
2	14250
4	14016
0	10380
1	10083
...	...
1320_	1
103	1
1444	1
392	1
966	1

434 rows × 1 columns

dtype: int64

In [198…
```
# treating the non-numeric values
df["Num_of_Loan"] = df["Num_of_Loan"].str.replace(r'\D', '', regex=True)
```

In [199…
```
# converting it to numeric
df["Num_of_Loan"] = pd.to_numeric(df["Num_of_Loan"], errors = "coerce")
```

In [200…
```
df["Num_of_Loan"].dtype
```

Out[200… dtype('int64')

In [201…
```
# replacing negative values with 0
df["Num_of_Loan"].replace(-100,0,inplace =True)
```

In [202…
```
# creating a new column and filling it with mode
df["num_of_loan"] = df.groupby("Customer_ID")["Num_of_Loan"].transform(fill_mode)
df["num_of_loan"].isna().sum()
```

Out[202… 0

Type_of_Loan

In [203…
```
# 13 Type_of_Loan
df["Type_of_Loan"].isna().sum()
```

Out[203… 11408

In [204…
```
# filling the blanks with "no loan status"
df["Type_of_Loan"] = df["Type_of_Loan"].fillna("No Loan Status")
df["Type_of_Loan"].isna().sum()
```

Out[204… 0

Delay_from_due_date

In [205…
```
#14. Delay_from_due_date
# Replace values which are less than 0 with 0
df['Delay_from_due_date'] = df['Delay_from_due_date'].apply(lambda x: 0 if x < 0 else x)
```

In [206…
```
df["Delay_from_due_date"].isna().sum()
```

Out[206… 0

In [207…
```
df["Delay_from_due_date"].value_counts(dropna = False)
```

Out[207…

Delay_from_due_date	count
15	3596
13	3424
8	3324
14	3313
10	3281
...	...
63	69
64	64
65	56
66	32
67	22

68 rows × 1 columns

dtype: int64

In [208…
```
# creating a column and filling with mode
df["delay_from_due_date"] = df.groupby("Customer_ID")["Delay_from_due_date"].transform(fill_mode)
```

Num_of_Delayed_Payment

In [209…
```
# 15 Num_of_Delayed_Payment
df["Num_of_Delayed_Payment"].isna().sum()
```

Out[209… 7002

In [210…
```
# treating non-numeric values
df['Num_of_Delayed_Payment'] = df['Num_of_Delayed_Payment'].str.replace(r'\D', '', regex=True)
```

In [211…
```
df["Num_of_Delayed_Payment"].dtype
```

Out[211… dtype('O')

In [212…
```
# converting it to numeric
df['Num_of_Delayed_Payment'] = pd.to_numeric(df['Num_of_Delayed_Payment'], errors='coerce')
df["Num_of_Delayed_Payment"].dtype
```

Out[212… dtype('float64')

In [213…
```
# applying 0 to negative values
df["Num_of_Delayed_Payment"] = df['Num_of_Delayed_Payment'].apply(lambda x: 0 if x < 0 else x)
```

In [214…
```
df["Num_of_Delayed_Payment"].isna().sum()
```

Out[214… 7002

In [215…
```
# creating a new column and filling with mode
df["num_of_delayed_payment"] = df.groupby("Customer_ID")["Num_of_Delayed_Payment"].transform(fill_mode)
df["num_of_delayed_payment"].isna().sum()
```

Out[215… 0

In [216…
```
df["num_of_delayed_payment"].min(),df["num_of_delayed_payment"].max()
```

Out[216… (0.0, 28.0)

Changed_credit_Limit

In [217…
```
# 16  Changed_Credit_Limit- cleaning
pattern = r'_'
df["Changed_Credit_Limit"] = df['Changed_Credit_Limit'].replace(to_replace = pattern, value = np.nan, regex = True)
```

In [218…
```
# convert to numerical
df["Changed_Credit_Limit"] = pd.to_numeric(df["Changed_Credit_Limit"], errors = "coerce")
```

In [219…
```
# no of null values
df["Changed_Credit_Limit"].isna().sum()
```

Out[219… 2091

In [220…
```
# filling ffill and bfill
df["Changed_Credit_Limit"] = df.groupby("Customer_ID")["Changed_Credit_Limit"].ffill().bfill()
```

In [221…
```
# recheck for nulls
df["Changed_Credit_Limit"].isna().sum()
```

Out[221… 0

In [222…
```
#checking min, max values
df["Changed_Credit_Limit"].min(), df["Changed_Credit_Limit"].max()
```

Out[222… (-6.49, 36.97)

Num_credit_Inquiries

In [223…
```
#  17  Num_Credit_Inquiries
df["Num_Credit_Inquiries"].isna().sum()
```

Out[223… 1965

In [224…
```
# creating a new column and filling the null with mode
df["num_credit_inquiries"] = df.groupby("Customer_ID")["Num_Credit_Inquiries"].transform(fill_mode)
df["num_credit_inquiries"].isna().sum()
```

Out[224… 0

In [225…
```
#checking min, max values
df["num_credit_inquiries"].min(), df["num_credit_inquiries"].max()
```

Out[225… (0.0, 17.0)

Credit_Mix

In [226…
```
#  18  Credit_Mix
df["Credit_Mix"].isna().sum()
```

Out[226… 0

In [227…
```
# Cleaning
pattern = r'_'
df["Credit_Mix"] = df['Credit_Mix'].replace(to_replace = pattern, value = np.nan, regex = True)
```

In [228…
```
# filling ffill and bfill
df["Credit_Mix"] = df.groupby("Customer_ID")["Credit_Mix"].ffill().bfill()
```

In [229…
```
df["Credit_Mix"].value_counts(dropna = False)
```

Out[229…

Credit_Mix	count
Standard	45848
Good	30384
Bad	23768

dtype: int64

Outstanding_Debt

In [230…
```
# 19  Outstanding_Debt
df["Outstanding_Debt"].isna().sum()
```

Out[230… 0

In [231…
```
# Cleaning
pattern = r'_'
df["Outstanding_Debt"] = df['Outstanding_Debt'].replace(to_replace = pattern, value = np.nan, regex = True)
```

In [232…
```
df["Outstanding_Debt"].dtype
```

Out[232… dtype('O')

In [233…
```
#Convert it to numeric
df["Outstanding_Debt"] = pd.to_numeric(df["Outstanding_Debt"], errors = "coerce")
df["Outstanding_Debt"].dtype
```

Out[233… dtype('float64')

In [234…
```
# filling with ffill and bfill
df["Outstanding_Debt"] = df.groupby("Customer_ID")["Outstanding_Debt"].ffill().bfill()
```

In [235…
```
#  20  Credit_Utilization_Ratio - cleaning is not required
df["Credit_Utilization_Ratio"].isna().sum()
```

Out[235… 0

Credit_History_Age

In [236…
```
# 21  Credit_History_Age
df["Credit_History_Age"].isna().sum()
```

Out[236… 9030

In [237…
```
# Check the datatype
df['Credit_History_Age'].dtype
```

Out[237… dtype('O')

In [238…
```
# Check for nulls
df['Credit_History_Age'].isna().sum()
```

Out[238… 9030

In [239…
```
# Created a column by splitting the elements
df['Credit_History_Age_list'] = df['Credit_History_Age'].str.split()
```

In [240…
```
df['Credit_History_Age_list'].head()
```

Out[240…

	Credit_History_Age_list
0	[22, Years, and, 1, Months]
1	NaN
2	[22, Years, and, 3, Months]
3	[22, Years, and, 4, Months]
4	[22, Years, and, 5, Months]

dtype: object

In [241…
```
# Define a function to extract the year
def split_CRA(lst):
  #if type(lst) == float:
  if isinstance(lst, float):
    return 0
  else:
    return int(lst[0])
```

In [242…
```
# Apply the function
df['Credit_History_Age_all'] = df['Credit_History_Age_list'].apply(split_CRA)
```

In [243…
```
# Apply the function
df['credit_History_Age'] = df.groupby('Customer_ID')['Credit_History_Age_all'].transform(lambda series: series.max())
```

In [244…
```
#df.drop(columns=['Credit_History_Age', 'Credit_History_Age_list', 'Credit_History_Age_all'], inplace=True)
```

Payment_of_Min_Amount

In [245…
```
# 22  Payment_of_Min_Amount
df["Payment_of_Min_Amount"].value_counts()
```

Out[245…

Payment_of_Min_Amount	count
Yes	52326
No	35667
NM	12007

dtype: int64

In [246…
```
# converting Nm to No
df["Payment_of_Min_Amount"] = df["Payment_of_Min_Amount"].replace("NM", "No")
```

In [247…
```
df["Payment_of_Min_Amount"].value_counts()
```

Out[247…

Payment_of_Min_Amount	count
Yes	52326
No	47674

dtype: int64

Total_EMI_per_month

In [248…
```
# 23 Total_EMI_per_month - cleaning is required
df["Total_EMI_per_month"].isna().sum()
```

Out[248… 0

In [249…
```
# 24  Amount_invested_monthly
df["Amount_invested_monthly"].isna().sum()
```

Out[249… 4479

In [250…
```
df["Amount_invested_monthly"].dtype
```

Out[250… dtype('O')

In [251…
```
# cleaning str values
df["Amount_invested_monthly"] = df["Amount_invested_monthly"].str.replace(r'\D', '', regex=True)
```

In [252…
```
# converting it to numerical value
df["Amount_invested_monthly"] = pd.to_numeric(df["Amount_invested_monthly"], errors = "coerce")
df["Amount_invested_monthly"].dtype
```

Out[252… dtype('float64')

In [253…
```
df["Amount_invested_monthly"].isna().sum()
```

Out[253… 4479

In [254…
```
# replacing nan with 0
df["Amount_invested_monthly"] = df["Amount_invested_monthly"].replace(np.nan,0)
```

In [255…
```
df["Amount_invested_monthly"].isna().sum()
```

Out[255… 0

Payment_Behaviour

In [256…
```
#  25  Payment_Behaviour
df["Payment_Behaviour"].isna().sum()
```

Out[256… 0

In [257…
```
# replacing the spl characters with nan
df["Payment_Behaviour"] = df['Payment_Behaviour'].replace("!@9#%8", np.nan)
```

In [258…
```
df["Payment_Behaviour"].value_counts(dropna = False)
```

Out[258…

Payment_Behaviour	count
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
NaN	7600

dtype: int64

In [259…
```
# filling with ffill and bfill
df["Payment_Behaviour"] = df.groupby('Customer_ID')['Payment_Behaviour'].ffill().bfill()
```

Monthly_Balance

In [260…
```
# 26 Monthly_Balance
df["Monthly_Balance"].isna().sum()
```

Out[260… 1200

In [261…
```
df["Monthly_Balance"].dtype
```

Out[261… dtype('O')

In [262…
```
# treating the spl characters
df["Monthly_Balance"] = df["Monthly_Balance"].str.replace(r'\D', '', regex=True)
#replacing with nan
df["Monthly_Balance"] = df["Monthly_Balance"].replace(np.nan,0)
```

In [263…
```
df["Monthly_Balance"].dtype
```

Out[263… dtype('O')

In [264…
```
#converting into numeric
df["Monthly_Balance"] = pd.to_numeric(df["Monthly_Balance"], errors = "coerce")
df["Monthly_Balance"].dtype
```

Out[264… dtype('float64')

Dropping the extra Columns

In [265…
```
df.drop(columns=["Num_Bank_Accounts","Num_Credit_Card","Interest_Rate","Num_of_Loan","Delay_from_due_date",
                 "Num_of_Delayed_Payment","Num_Credit_Inquiries","Credit_History_Age","Credit_History_Age_list","Credit_History_Age_all"], inplace = True)
```

In [266…
```
df.head(2)
```

Out[266…

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Salary	Type_of_Loan	...	Payment_Behaviour	Monthly_Balance	num_bank_a
0	0x1602	CUS_0xd40	January	Aaron Maashoh	23.0	821-00-0265	Scientist	1911412	1824.843333	Auto Loan, Credit-Builder Loan, Personal Loan,...	...	High_spent_Small_value_payments	3.124941e+09	
1	0x1603	CUS_0xd40	February	Aaron Maashoh	23.0	821-00-0265	Scientist	1911412	1824.843333	Auto Loan, Credit-Builder Loan, Personal Loan,...	...	Low_spent_Large_value_payments	2.846292e+09	

2 rows × 27 columns

In [267…
```
df.shape
```

Out[267… (100000, 27)

In [268…
```
df.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                      100000 non-null  object
 4   Age                       100000 non-null  float64
 5   SSN                       100000 non-null  object
 6   Occupation                100000 non-null  object
 7   Annual_Income             100000 non-null  int64
 8   Monthly_Inhand_Salary     100000 non-null  float64
 9   Type_of_Loan              100000 non-null  object
 10  Changed_Credit_Limit      100000 non-null  float64
 11  Credit_Mix                100000 non-null  object
 12  Outstanding_Debt          100000 non-null  float64
 13  Credit_Utilization_Ratio  100000 non-null  float64
 14  Payment_of_Min_Amount     100000 non-null  object
 15  Total_EMI_per_month       100000 non-null  float64
 16  Amount_invested_monthly   100000 non-null  float64
 17  Payment_Behaviour         100000 non-null  object
 18  Monthly_Balance           100000 non-null  float64
 19  num_bank_accounts         100000 non-null  int64
 20  num_credit_card           100000 non-null  int64
 21  interest_rate             100000 non-null  int64
 22  num_of_loan               100000 non-null  int64
 23  delay_from_due_date       100000 non-null  int64
 24  num_of_delayed_payment    100000 non-null  float64
 25  num_credit_inquiries      100000 non-null  float64
 26  credit_History_Age        100000 non-null  int64
dtypes: float64(10), int64(7), object(10)
memory usage: 20.6+ MB
```

Feature Engineering

cleaned and arranged Data

In [269…
```
#deep copy
processed_df = df.copy()
```

In [270…
```
processed_df.shape
```

Out[270… (100000, 27)

In [271…
```
# Renaming the newly created column
names_d = {"num_bank_accounts" : "Num_Bank_Accounts",
           "num_credit_card" : "Num_Credit_Card",
           "interest_rate" : "Interest_Rate",
           "num_of_loan" : "Num_of_Loan",
           "delay_from_due_date" : "Delay_from_due_date",
           "num_of_delayed_payment" : "Num_of_Delayed_Payment",
           "num_credit_inquiries" : "Num_Credit_Inquiries",
           "credit_History_Age" : "Credit_History_Age"}

processed_df = processed_df.rename(columns = names_d)
```

In [272…
```
processed_df.head(2)
```

Out[272…

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Salary	Type_of_Loan	...	Payment_Behaviour	Monthly_Balance	Num_Bank_A
0	0x1602	CUS_0xd40	January	Aaron Maashoh	23.0	821-00-0265	Scientist	1911412	1824.843333	Auto Loan, Credit-Builder Loan, Personal Loan,...	...	High_spent_Small_value_payments	3.124941e+09	
1	0x1603	CUS_0xd40	February	Aaron Maashoh	23.0	821-00-0265	Scientist	1911412	1824.843333	Auto Loan, Credit-Builder Loan, Personal Loan,...	...	Low_spent_Large_value_payments	2.846292e+09	

2 rows × 27 columns

In [273…
```
# Changing the order of the column
ordered_column = [
    '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'
]

df_cleaned = processed_df.reindex(columns=ordered_column)
```

In [274…
```
df_cleaned.head()
```

Out[274…

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	...	Num_Credit_Inquiries	Credit_Mix	Outstanding_Debt	Cr
0	0x1602	CUS_0xd40	January	Aaron Maashoh	23.0	821-00-0265	Scientist	1911412	1824.843333	3	...	4.0	Good	809.98	
1	0x1603	CUS_0xd40	February	Aaron Maashoh	23.0	821-00-0265	Scientist	1911412	1824.843333	3	...	4.0	Good	809.98	
2	0x1604	CUS_0xd40	March	Aaron Maashoh	23.0	821-00-0265	Scientist	1911412	1824.843333	3	...	4.0	Good	809.98	
3	0x1605	CUS_0xd40	April	Aaron Maashoh	23.0	821-00-0265	Scientist	1911412	1824.843333	3	...	4.0	Good	809.98	
4	0x1606	CUS_0xd40	May	Aaron Maashoh	23.0	821-00-0265	Scientist	1911412	1824.843333	3	...	4.0	Good	809.98	

5 rows × 27 columns

Treating Month

In [275…
```
# Convert month names to month numbers and replace in the same column
df_cleaned['Month_num'] = pd.to_datetime(df_cleaned['Month'], format='%B').dt.month
```

Treating Credit_Mix

In [276…
```
df_cleaned['Credit_Mix'].unique()
```

Out[276…
```
array(['Good', 'Standard', 'Bad'], dtype=object)
```

In [277…
```
# Define a function for assigning numbers for Credit_Mix
def credit_mix(elem):
  if elem == "Good":
    return 2
  elif elem == "Standard":
    return 1
  else:
    return 0
```

In [278…
```
# Apply the function using transform
df_cleaned['Credit_Mix_eq_no'] = df_cleaned['Credit_Mix'].transform(credit_mix)
```

Treating Payment_of_min_amount

In [279…
```
df_cleaned['Payment_of_Min_Amount'].unique()
```

Out[279…
```
array(['No', 'Yes'], dtype=object)
```

In [280…
```
# Define a function for assigning numbers for Payment_of_Min_Amount
def Payment_of_Min_Amount(elem):
  if elem == 'Yes':
    return 1
  else:
    return 0
```

In [281…
```
# Apply the function using transform
df_cleaned['Payment_of_Min_Amount_eq_no'] = df_cleaned['Payment_of_Min_Amount'].transform(Payment_of_Min_Amount)
```

Treating Payment_Behaviour

In [282…
```
# Define mapping
payment_behaviour_mapping = {
    'High_spent_Small_value_payments': 4,
    'High_spent_Medium_value_payments': 5,
    'High_spent_Large_value_payments': 6,
    'Low_spent_Small_value_payments': 1,
    'Low_spent_Medium_value_payments': 2,
    'Low_spent_Large_value_payments': 3
}
# Apply mapping
df_cleaned['Payment_Behaviour_Num'] = df_cleaned['Payment_Behaviour'].map(payment_behaviour_mapping)
```

Observation

- High Spending, Small Payments: Indicates a potential financial risk if this pattern persists, suggesting possible issues in covering expenses.
- High Spending, Medium Payments: Shows higher risk, as the payment size may not be sufficient for the high spending level.
- High Spending, Large Payments: Suggests more financial responsibility but still signals a potential risk due to high expenditures.
- Low Spending, Small Payments: Reflects low financial risk, with minimal spending and payments.
- Low Spending, Medium Payments: Indicates moderate risk with payments that exceed the spending amount.
- Low Spending, Large Payments: Suggests underutilization of credit or conservative financial behavior.

Downloading the cleaned file

In [283…
```
# Download the cleaned file
df_cleaned.to_csv('Credit_score_cleaned', sep=",",index=False)
```

In [284…
```
df_cleaned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 31 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                          100000 non-null  object
 4   Age                           100000 non-null  float64
 5   SSN                           100000 non-null  object
 6   Occupation                    100000 non-null  object
 7   Annual_Income                 100000 non-null  int64
 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  int64
 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  float64
 16  Changed_Credit_Limit          100000 non-null  float64
 17  Num_Credit_Inquiries          100000 non-null  float64
 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            100000 non-null  int64
 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               100000 non-null  float64
 27  Month_num                     100000 non-null  int32
 28  Credit_Mix_eq_no              100000 non-null  int64
 29  Payment_of_Min_Amount_eq_no   100000 non-null  int64
 30  Payment_Behaviour_Num         100000 non-null  int64
dtypes: float64(10), int32(1), int64(10), object(10)
memory usage: 23.3+ MB
```

In [285…
```
df_cleaned.head(2)
```

Out[285…

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	...	Credit_History_Age	Payment_of_Min_Amount	Total_EMI
0	0x1602	CUS_0xd40	January	Aaron Maashoh	23.0	821-00-0265	Scientist	1911412	1824.843333	3	...	22	No	
1	0x1603	CUS_0xd40	February	Aaron Maashoh	23.0	821-00-0265	Scientist	1911412	1824.843333	3	...	22	No	

2 rows × 31 columns

In [286…
```
# Columns that are in int and float datatype
for i, elem in (enumerate(df_cleaned.columns)):
  if df_cleaned[elem].dtypes != 'object':
    print(f"{i+1}. {elem}: {df_cleaned[elem].nunique(), df_cleaned[elem].dtypes}")
```

```
5. Age: (46, dtype('float64'))
8. Annual_Income: (13701, dtype('int64'))
9. Monthly_Inhand_Salary: (13235, dtype('float64'))
10. Num_Bank_Accounts: (12, dtype('int64'))
11. Num_Credit_Card: (12, dtype('int64'))
12. Interest_Rate: (34, dtype('int64'))
13. Num_of_Loan: (10, dtype('int64'))
15. Delay_from_due_date: (63, dtype('int64'))
16. Num_of_Delayed_Payment: (29, dtype('float64'))
17. Changed_Credit_Limit: (3634, dtype('float64'))
18. Num_Credit_Inquiries: (18, dtype('float64'))
20. Outstanding_Debt: (12203, dtype('float64'))
21. Credit_Utilization_Ratio: (99998, dtype('float64'))
22. Credit_History_Age: (34, dtype('int64'))
24. Total_EMI_per_month: (14950, dtype('float64'))
25. Amount_invested_monthly: (91048, dtype('float64'))
27. Monthly_Balance: (97123, dtype('float64'))
28. Month_num: (8, dtype('int32'))
29. Credit_Mix_eq_no: (3, dtype('int64'))
30. Payment_of_Min_Amount_eq_no: (2, dtype('int64'))
31. Payment_Behaviour_Num: (6, dtype('int64'))
```

In [287…
```
# Columns that are in object datatype
for i, elem in (enumerate(df_cleaned.columns)):
  if df_cleaned[elem].dtypes == 'O':
    print(f"{i+1}. {elem}: {df_cleaned[elem].nunique(), df_cleaned[elem].dtypes}")
```

```
1. ID: (100000, dtype('O'))
2. Customer_ID: (12500, dtype('O'))
3. Month: (8, dtype('O'))
4. Name: (10139, dtype('O'))
6. SSN: (12500, dtype('O'))
7. Occupation: (16, dtype('O'))
14. Type_of_Loan: (6261, dtype('O'))
19. Credit_Mix: (3, dtype('O'))
23. Payment_of_Min_Amount: (2, dtype('O'))
26. Payment_Behaviour: (6, dtype('O'))
```

Aggregate data at customer level

In [288…
```
# Creating a dictionary for aggregation at Customer_ID level
agg_dict = {
    'ID': 'first',
     # Grouped by on Customer_ID so not included
    'Name': 'first',
    'Age': 'first',
    'SSN': 'first',
    'Occupation': 'first',
    'Annual_Income': 'first',
    'Monthly_Inhand_Salary': 'first',
    'Num_Bank_Accounts': 'first',
    'Num_Credit_Card': 'first',
```

```
    'Interest_Rate': 'first',
    'Num_of_Loan': 'first',
    'Type_of_Loan': 'first',
    'Delay_from_due_date': 'mean',
    'Num_of_Delayed_Payment': 'first',
    'Changed_Credit_Limit': 'mean',
    'Num_Credit_Inquiries': 'first',
    'Credit_Mix': 'first',
    'Outstanding_Debt': 'first',
    'Credit_Utilization_Ratio': 'mean',
    'Credit_History_Age': 'first',
    'Payment_of_Min_Amount': 'first',
    'Total_EMI_per_month': 'first',
    'Amount_invested_monthly': 'mean',
    # Payment_Behaviour not included
    'Monthly_Balance': 'mean',
    'Credit_Mix_eq_no': 'first',
    'Payment_of_Min_Amount_eq_no': 'first',
    'Payment_Behaviour_Num': 'mean'
}
df_aggregated = df_cleaned.groupby('Customer_ID').agg(agg_dict).reset_index()
```

In [289…

```
df_aggregated.head()
```

Out[289…

	Customer_ID	ID	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	...	Outstanding_Debt	Credit_Utilization_Ratio
0	CUS_0x1000	0x1628a	Alistair Barrf	17.0	913-74-1218	Lawyer	3062594	2706.161667	6	5	...	1562.91	33.477546
1	CUS_0x1009	0x66a2	Arunah	25.0	063-67-6938	Mechanic	5231268	4250.390000	6	5	...	202.68	29.839984
2	CUS_0x100b	0x1ef6	Shirboni	18.0	238-62-0395	Media_Manager	11378139	9549.782500	1	4	...	1030.20	34.841449
3	CUS_0x1011	0x17646	Schneyerh	43.0	793-05-8223	Doctor	5891847	5208.872500	3	3	...	473.14	27.655897
4	CUS_0x1013	0x243ea	Cameront	43.0	930-49-9615	Mechanic	9862098	7962.415000	3	3	...	1233.51	31.933940

5 rows × 28 columns

In [290…

```
# Download the cleaned file
df_aggregated.to_csv('Credit_score_cleaned_aggregated', sep=",",index=False)
```

In [291…

```
df_aggregated.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12500 entries, 0 to 12499
Data columns (total 28 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   Customer_ID                 12500 non-null  object
 1   ID                          12500 non-null  object
 2   Name                        12500 non-null  object
 3   Age                         12500 non-null  float64
 4   SSN                         12500 non-null  object
 5   Occupation                  12500 non-null  object
 6   Annual_Income               12500 non-null  int64
 7   Monthly_Inhand_Salary       12500 non-null  float64
 8   Num_Bank_Accounts           12500 non-null  int64
 9   Num_Credit_Card             12500 non-null  int64
 10  Interest_Rate               12500 non-null  int64
 11  Num_of_Loan                 12500 non-null  int64
 12  Type_of_Loan                12500 non-null  object
 13  Delay_from_due_date         12500 non-null  float64
 14  Num_of_Delayed_Payment      12500 non-null  float64
 15  Changed_Credit_Limit        12500 non-null  float64
 16  Num_Credit_Inquiries        12500 non-null  float64
 17  Credit_Mix                  12500 non-null  object
 18  Outstanding_Debt            12500 non-null  float64
 19  Credit_Utilization_Ratio    12500 non-null  float64
 20  Credit_History_Age          12500 non-null  int64
 21  Payment_of_Min_Amount       12500 non-null  object
 22  Total_EMI_per_month         12500 non-null  float64
 23  Amount_invested_monthly     12500 non-null  float64
 24  Monthly_Balance             12500 non-null  float64
 25  Credit_Mix_eq_no            12500 non-null  int64
 26  Payment_of_Min_Amount_eq_no 12500 non-null  int64
 27  Payment_Behaviour_Num       12500 non-null  float64
dtypes: float64(12), int64(8), object(8)
memory usage: 2.7+ MB
```

In [292…

```
# Columns that are in int and float datatype
for i, elem in (enumerate(df_aggregated.columns)):
  if df_aggregated[elem].dtypes != 'object':
    print(f"{i+1}. {elem}: {df_aggregated[elem].nunique(), df_aggregated[elem].dtypes}")
```

```
4. Age: (44, dtype('float64'))
7. Annual_Income: (12489, dtype('int64'))
8. Monthly_Inhand_Salary: (12489, dtype('float64'))
9. Num_Bank_Accounts: (12, dtype('int64'))
10. Num_Credit_Card: (12, dtype('int64'))
11. Interest_Rate: (34, dtype('int64'))
12. Num_of_Loan: (10, dtype('int64'))
14. Delay_from_due_date: (63, dtype('float64'))
15. Num_of_Delayed_Payment: (29, dtype('float64'))
16. Changed_Credit_Limit: (4796, dtype('float64'))
17. Num_Credit_Inquiries: (18, dtype('float64'))
19. Outstanding_Debt: (12203, dtype('float64'))
20. Credit_Utilization_Ratio: (12500, dtype('float64'))
21. Credit_History_Age: (34, dtype('int64'))
23. Total_EMI_per_month: (11114, dtype('float64'))
24. Amount_invested_monthly: (12500, dtype('float64'))
25. Monthly_Balance: (12282, dtype('float64'))
26. Credit_Mix_eq_no: (3, dtype('int64'))
27. Payment_of_Min_Amount_eq_no: (2, dtype('int64'))
28. Payment_Behaviour_Num: (41, dtype('float64'))
```

In [293…

```python
# Columns that are in object datatype
for i, elem in (enumerate(df_aggregated.columns)):
  if df_aggregated[elem].dtypes == 'O':
    print(f"{i+1}. {elem}: {df_aggregated[elem].nunique(), df_aggregated[elem].dtypes}")
```

```
1. Customer_ID: (12500, dtype('O'))
2. ID: (12500, dtype('O'))
3. Name: (10139, dtype('O'))
5. SSN: (12500, dtype('O'))
6. Occupation: (16, dtype('O'))
13. Type_of_Loan: (6261, dtype('O'))
18. Credit_Mix: (3, dtype('O'))
22. Payment_of_Min_Amount: (2, dtype('O'))
```

In [294…

```python
# Display the range of attributes
print("Range of attributes:")
print("-" * 20)
df_aggregated.describe(include='all').T
```

```
Range of attributes:
--------------------
```

Out[294…

	count	unique	top	freq	mean	std	min	25%	50%	7
Customer_ID	12500	12500	CUS_0x1000	1	NaN	NaN	NaN	NaN	NaN	N
ID	12500	12500	0x1628a	1	NaN	NaN	NaN	NaN	NaN	N
Name	12500	10139	Jessicad	6	NaN	NaN	NaN	NaN	NaN	N
Age	12500.0	NaN	NaN	NaN	33.02992	10.770496	14.0	24.0	33.0	4
SSN	12500	12500	913-74-1218	1	NaN	NaN	NaN	NaN	NaN	N
Occupation	12500	16	_____	827	NaN	NaN	NaN	NaN	NaN	N
Annual_Income	12500.0	NaN	NaN	NaN	8284401795642.241211	261644154591651.09375	7908.0	1814001.75	3803281.0	8048646
Monthly_Inhand_Salary	12500.0	NaN	NaN	NaN	4208.493531	3194.903138	303.645417	1628.941875	3103.639167	5971.357
Num_Bank_Accounts	12500.0	NaN	NaN	NaN	5.36752	2.593412	-1.0	3.0	5.0	
Num_Credit_Card	12500.0	NaN	NaN	NaN	5.53272	2.067576	0.0	4.0	5.0	
Interest_Rate	12500.0	NaN	NaN	NaN	14.53208	8.741636	1.0	7.0	13.0	2
Num_of_Loan	12500.0	NaN	NaN	NaN	3.53288	2.446442	0.0	2.0	3.0	
Type_of_Loan	12500	6261	No Loan Status	1426	NaN	NaN	NaN	NaN	NaN	N
Delay_from_due_date	12500.0	NaN	NaN	NaN	21.05056	14.761702	0.0	10.0	18.0	2
Num_of_Delayed_Payment	12500.0	NaN	NaN	NaN	13.26664	6.195202	0.0	9.0	14.0	1
Changed_Credit_Limit	12500.0	NaN	NaN	NaN	10.389303	6.544067	-1.07	5.45	9.365	14.65
Num_Credit_Inquiries	12500.0	NaN	NaN	NaN	5.67776	3.827382	0.0	3.0	5.0	
Credit_Mix	12500	3	Standard	5731	NaN	NaN	NaN	NaN	NaN	N
Outstanding_Debt	12500.0	NaN	NaN	NaN	1426.220376	1155.169458	0.23	566.0725	1166.155	1945.9
Credit_Utilization_Ratio	12500.0	NaN	NaN	NaN	32.285173	2.060556	25.476634	30.854492	32.24183	33.600
Credit_History_Age	12500.0	NaN	NaN	NaN	18.23592	8.313547	0.0	12.0	18.0	2
Payment_of_Min_Amount	12500	2	Yes	6524	NaN	NaN	NaN	NaN	NaN	N
Total_EMI_per_month	12500.0	NaN	NaN	NaN	1303.78104	8118.261086	0.0	29.128806	66.372879	149.904
Amount_invested_monthly	12500.0	NaN	NaN	NaN	3255901368.34274	1010890082.809271	545741601.0	2531526584.96875	3189429980.5625	3915380590.03
Monthly_Balance	12500.0	NaN	NaN	NaN	3000000000003405774848.0	1117676131978666452189184.0	0.0	2557436098.84375	3100875599.6875	4076286420.156
Credit_Mix_eq_no	12500.0	NaN	NaN	NaN	1.06616	0.73293	0.0	1.0	1.0	
Payment_of_Min_Amount_eq_no	12500.0	NaN	NaN	NaN	0.52192	0.499539	0.0	0.0	1.0	
Payment_Behaviour_Num	12500.0	NaN	NaN	NaN	3.24603	0.965455	1.0	2.5	3.25	

In [295…

```python
# Display the statistical summary
print("statistical summary:")
print("-" * 20)
df_aggregated.describe().T
```

```
statistical summary:
--------------------
```

Out[295...

	count	mean	std	min	25%	50%	75%	max
Age	12500.0	3.302992e+01	1.077050e+01	1.400000e+01	2.400000e+01	3.300000e+01	4.100000e+01	9.500000e+01
Annual_Income	12500.0	8.284402e+12	2.616442e+14	7.908000e+03	1.814002e+06	3.803281e+06	8.048647e+06	1.335812e+16
Monthly_Inhand_Salary	12500.0	4.208494e+03	3.194903e+03	3.036454e+02	1.628942e+03	3.103639e+03	5.971358e+03	1.520463e+04
Num_Bank_Accounts	12500.0	5.367520e+00	2.593412e+00	-1.000000e+00	3.000000e+00	5.000000e+00	7.000000e+00	1.000000e+01
Num_Credit_Card	12500.0	5.532720e+00	2.067576e+00	0.000000e+00	4.000000e+00	5.000000e+00	7.000000e+00	1.100000e+01
Interest_Rate	12500.0	1.453208e+01	8.741636e+00	1.000000e+00	7.000000e+00	1.300000e+01	2.000000e+01	3.400000e+01
Num_of_Loan	12500.0	3.532880e+00	2.446442e+00	0.000000e+00	2.000000e+00	3.000000e+00	5.000000e+00	9.000000e+00
Delay_from_due_date	12500.0	2.105056e+01	1.476170e+01	0.000000e+00	1.000000e+01	1.800000e+01	2.800000e+01	6.200000e+01
Num_of_Delayed_Payment	12500.0	1.326664e+01	6.195202e+00	0.000000e+00	9.000000e+00	1.400000e+01	1.800000e+01	2.800000e+01
Changed_Credit_Limit	12500.0	1.038930e+01	6.544067e+00	-1.070000e+00	5.450000e+00	9.365000e+00	1.465625e+01	3.139500e+01
Num_Credit_Inquiries	12500.0	5.677760e+00	3.827382e+00	0.000000e+00	3.000000e+00	5.000000e+00	8.000000e+00	1.700000e+01
Outstanding_Debt	12500.0	1.426220e+03	1.155169e+03	2.300000e-01	5.660725e+02	1.166155e+03	1.945963e+03	4.998070e+03
Credit_Utilization_Ratio	12500.0	3.228517e+01	2.060556e+00	2.547663e+01	3.085449e+01	3.224183e+01	3.360017e+01	4.239530e+01
Credit_History_Age	12500.0	1.823592e+01	8.313547e+00	0.000000e+00	1.200000e+01	1.800000e+01	2.500000e+01	3.300000e+01
Total_EMI_per_month	12500.0	1.303781e+03	8.118261e+03	0.000000e+00	2.912881e+01	6.637288e+01	1.499045e+02	8.212200e+04
Amount_invested_monthly	12500.0	3.255901e+09	1.010890e+09	5.457416e+08	2.531527e+09	3.189430e+09	3.915381e+09	7.613436e+09
Monthly_Balance	12500.0	3.000000e+22	1.117676e+24	0.000000e+00	2.557436e+09	3.100876e+09	4.076286e+09	4.166667e+25
Credit_Mix_eq_no	12500.0	1.066160e+00	7.329296e-01	0.000000e+00	1.000000e+00	1.000000e+00	2.000000e+00	2.000000e+00
Payment_of_Min_Amount_eq_no	12500.0	5.219200e-01	4.995393e-01	0.000000e+00	0.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00
Payment_Behaviour_Num	12500.0	3.246030e+00	9.654546e-01	1.000000e+00	2.500000e+00	3.250000e+00	4.000000e+00	6.000000e+00

Exploratory Data Analysis 🧐

Univariate Analysis

In [296...

```
blue_palette = ['#00008B', '#0000FF', '#1E90FF', '#4169E1', '#4682B4', '#87CEEB', '#00BFFF', '#00CED1', '#ADD8E6', '#B0E0E6']
```

In [297...

```
columns = ['Occupation', 'Credit_Mix', 'Payment_of_Min_Amount']

for elem in columns:
  print(f"Column Name: {elem}")
  print(data[elem].value_counts())
  print()
  print(round(((data[elem].value_counts(normalize=True)) * 100),2))
  print("_" * 35)
  print()
```

```
Column Name: Occupation
Occupation
_______          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: count, dtype: int64

Occupation
_______          7.06
Lawyer           6.58
Architect        6.36
Engineer         6.35
Scientist        6.30
Mechanic         6.29
Accountant       6.27
Developer        6.24
Media_Manager    6.23
Teacher          6.22
Entrepreneur     6.17
Doctor           6.09
Journalist       6.08
Manager          5.97
Musician         5.91
Writer           5.88
Name: proportion, dtype: float64
_____________________________________

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

Credit_Mix
Standard    36.48
Good        24.34
_           20.20
Bad         18.99
Name: proportion, dtype: float64
_____________________________________

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

Payment_of_Min_Amount
Yes    52.33
No     35.67
NM     12.01
Name: proportion, dtype: float64
_____________________________________
```

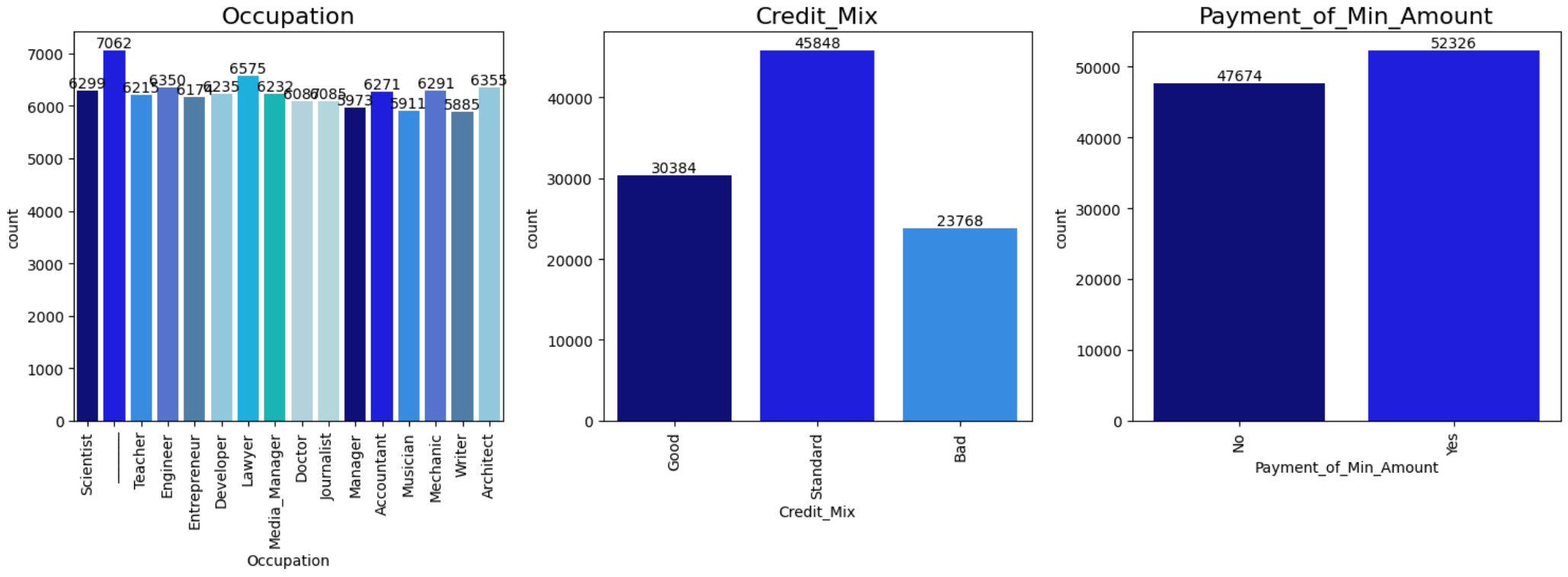
In [298…

```python
# Count Plots for Categorical features
columns = ['Occupation', 'Credit_Mix', 'Payment_of_Min_Amount']

plt.figure(figsize=(15,6))
for i, elem in enumerate(columns):
  plt.subplot(1,len(columns),i+1)
  label = sns.countplot(data = df, x = elem, palette = blue_palette)
  for i in label.containers:
    label.bar_label(i)

  plt.xticks(rotation = 90)
  plt.ylabel('count')
  plt.title(elem, fontsize=16)

plt.suptitle("Count Plots for Categorical features", fontsize = 18)
plt.tight_layout()
plt.show()
```



Observation

- **Occupation:** The data shows an even distribution of individuals in high-education or professional roles such as Scientists, Engineers, and Lawyers, indicating a strong representation of people with specialized skills.
- **Credit Mix:** The majority of individuals have a "Standard" credit mix, accounting for over a third of the dataset, while "Good" and "Bad" credit mixes are less common, suggesting a generally positive credit behavior.
- **Payment of Minimum Amount:** More than half of the population (52.33%) consistently pays the minimum amount on their debts, which might indicate careful debt management.

In [300…
```python
# Creating numerical_df
numerical_df = df_aggregated[['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', 'Credit_History_Age',
                              'Total_EMI_per_month', 'Amount_invested_monthly', 'Monthly_Balance']]
```

In [301…
```python
# Skewness Coefficient
numerical_df
print("Skewness Coefficient")
print("-" * 20)
print(numerical_df.skew().round(4))
```

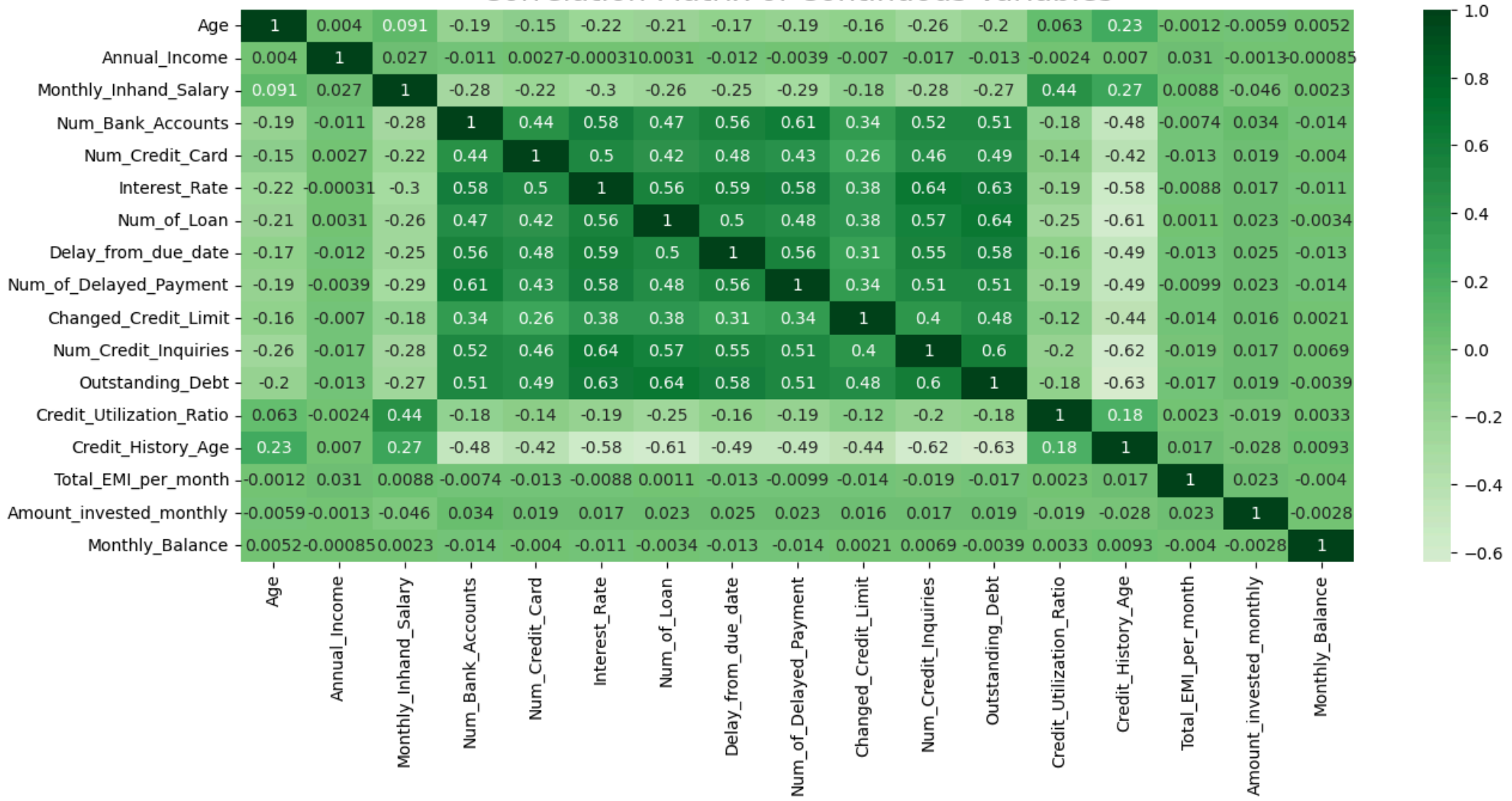
```
Skewness Coefficient
--------------------
Age                        0.1686
Annual_Income             35.1829
Monthly_Inhand_Salary      1.1276
Num_Bank_Accounts         -0.1906
Num_Credit_Card            0.2259
Interest_Rate              0.4963
Num_of_Loan                0.4457
Delay_from_due_date        0.9860
Num_of_Delayed_Payment    -0.2234
Changed_Credit_Limit       0.7189
Num_Credit_Inquiries       0.4162
Outstanding_Debt           1.2077
Credit_Utilization_Ratio   0.2752
Credit_History_Age        -0.0490
Total_EMI_per_month        7.4034
Amount_invested_monthly    0.3646
Monthly_Balance           37.2320
dtype: float64
```

Observation

- Annual_Income (35.18) and Monthly_Balance (37.23) show very high positive skewness, indicating the presence of a few individuals with extremely high values.
- Total_EMI_per_month (7.40) also displays significant positive skewness, highlighting outliers with higher EMIs.
- Monthly_Inhand_Salary (1.13) and Outstanding_Debt (1.21) show moderate positive skewness.
- Num_Bank_Accounts and Num_of_Delayed_Payment have slight negative skewness, suggesting most individuals have fewer bank accounts or delayed payments than average.

Bivariate Analysis 📊

In [302…
```python
# Correlation Matrix of Continuous Variables
plt.figure(figsize=(15, 6))
sns.heatmap(numerical_df.corr(), annot=True, cmap='Greens',center=0)
plt.title('Correlation Matrix of Continuous Variables', fontsize = 18)
plt.show()
```

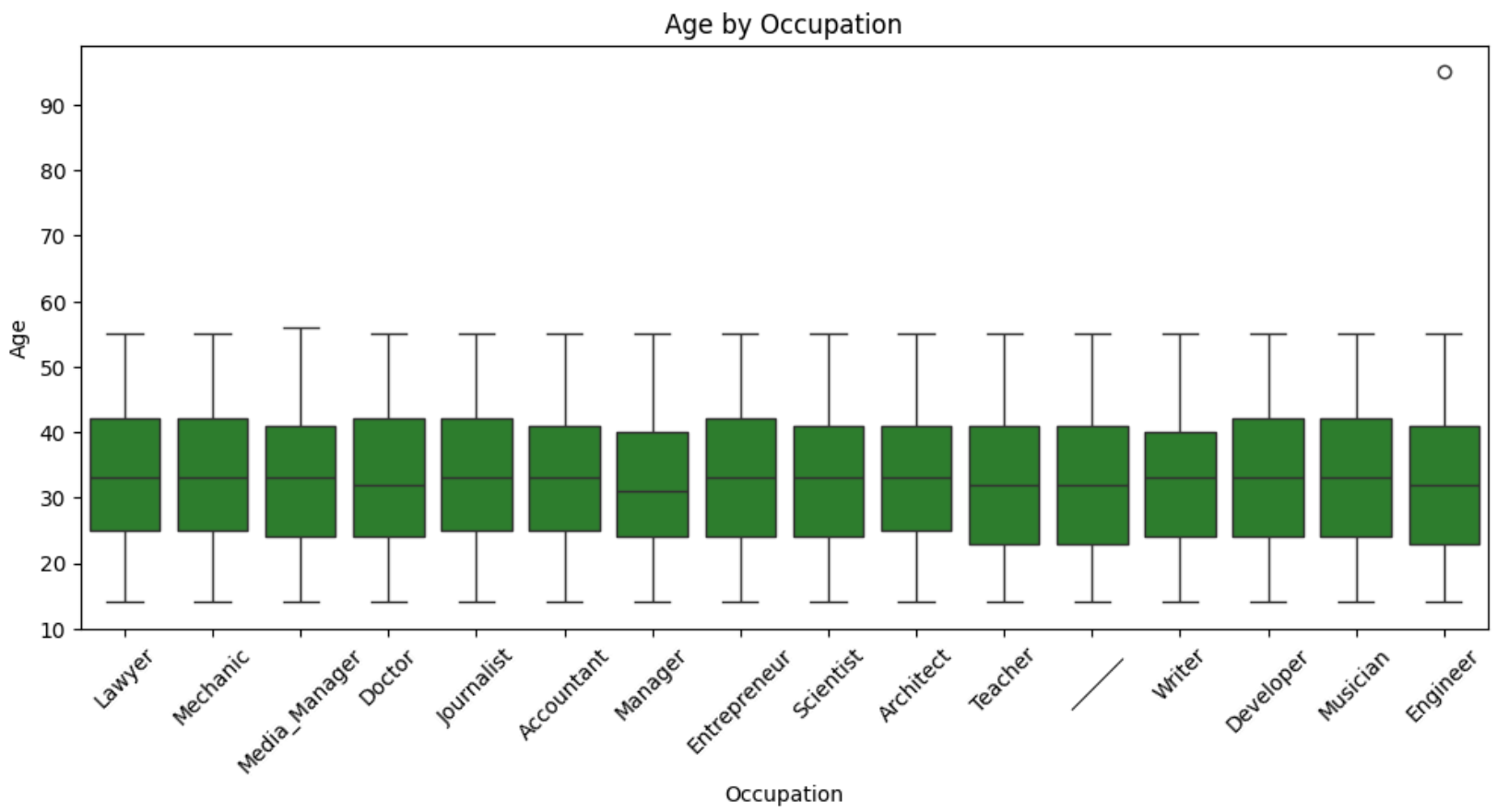


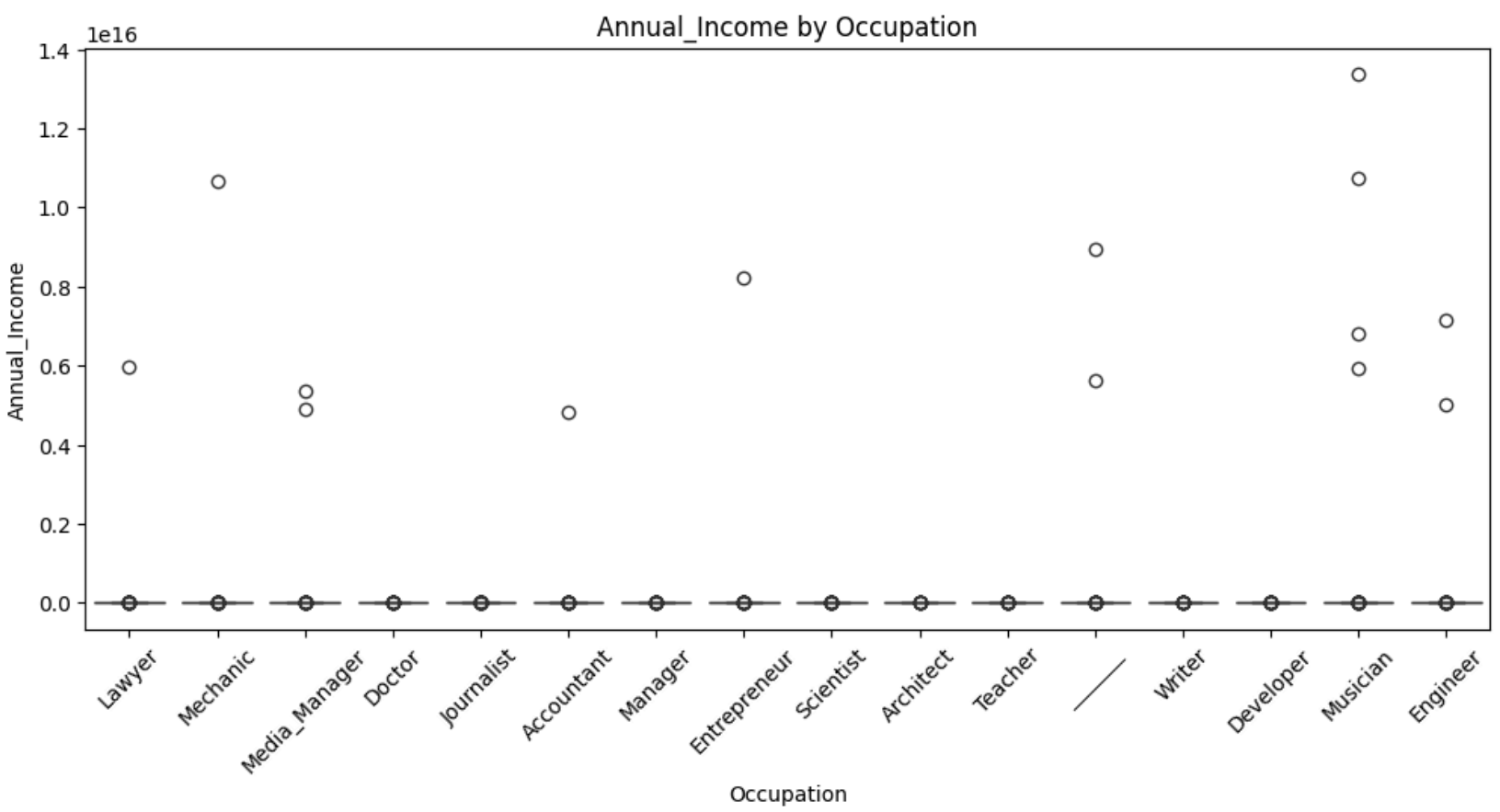
Observation

- Credit Utilization & Credit Cards: There is a strong positive correlation (0.56) between the number of credit cards and credit utilization.
- Debt & Delayed Payments: Outstanding debt and the number of delayed payments show a moderately strong correlation (0.58).
- Loans & Interest Rates: A strong correlation (0.56) exists between interest rates and the number of loans.
- Age & Credit History: Age and credit history are positively correlated (0.23), meaning older individuals tend to have longer credit histories.

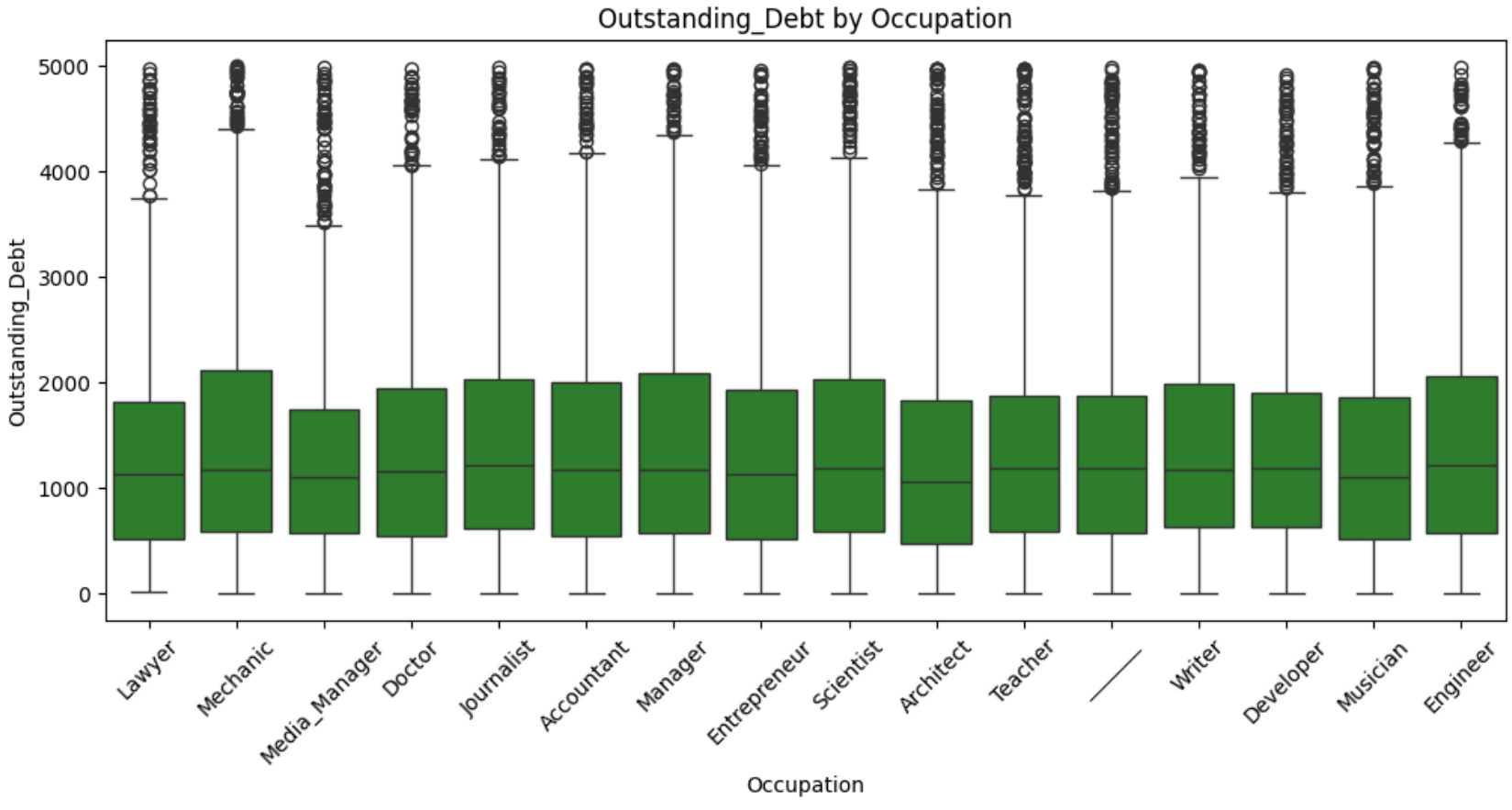
In [303…

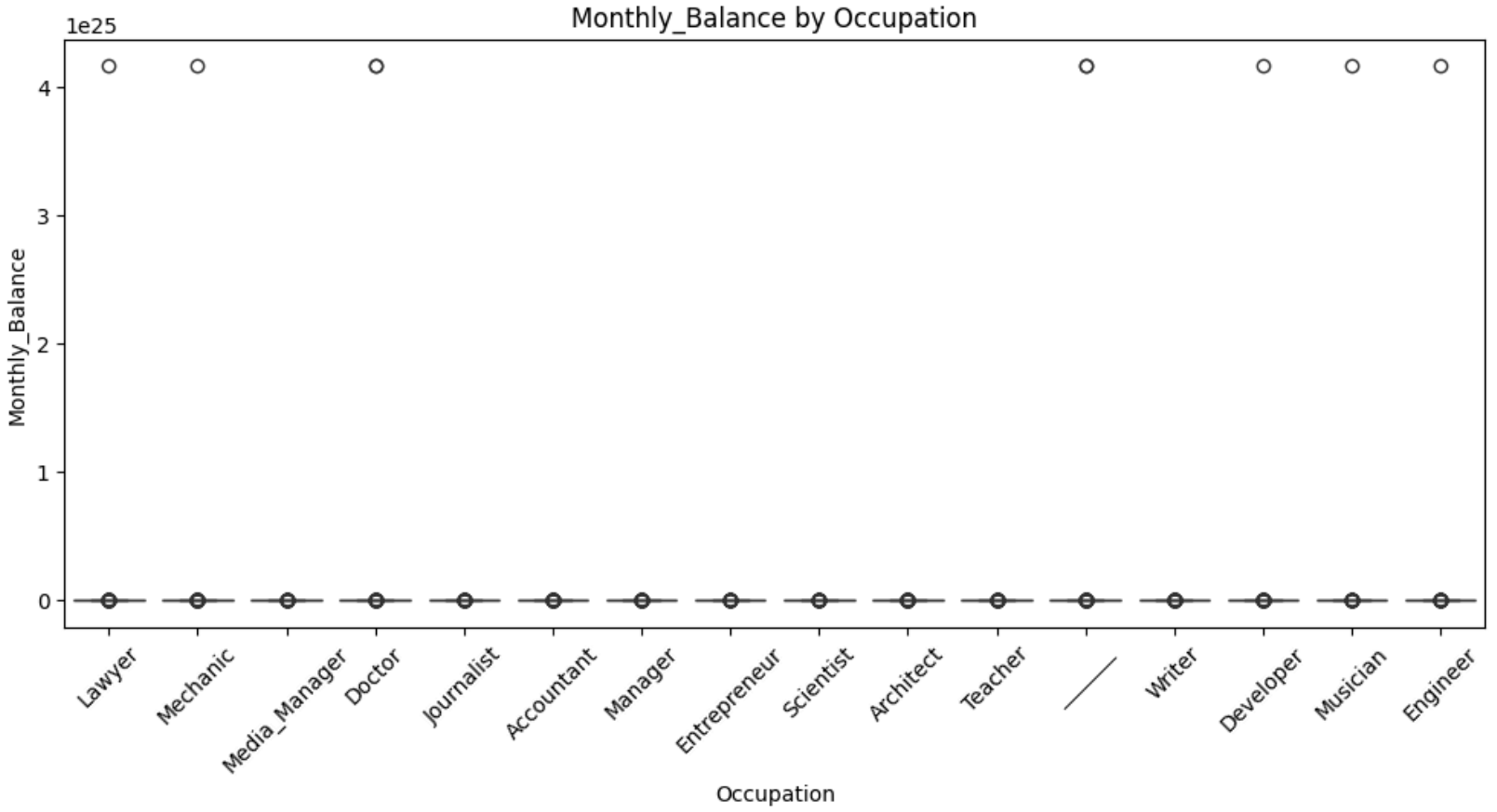
```
# Categorical vs. Numerical
palette = ['#228B22']
for column in ['Occupation', 'Credit_Mix', 'Payment_of_Min_Amount']:
    for i, num_column in enumerate(['Age', 'Annual_Income', 'Monthly_Inhand_Salary', 'Outstanding_Debt', 'Monthly_Balance']):
        plt.figure(figsize=(12, 5))
        sns.boxplot(x=df_aggregated[column], y=df_aggregated[num_column], palette=palette)
        plt.title(f'{num_column} by {column}')
        plt.xticks(rotation=45)
        plt.show()
```

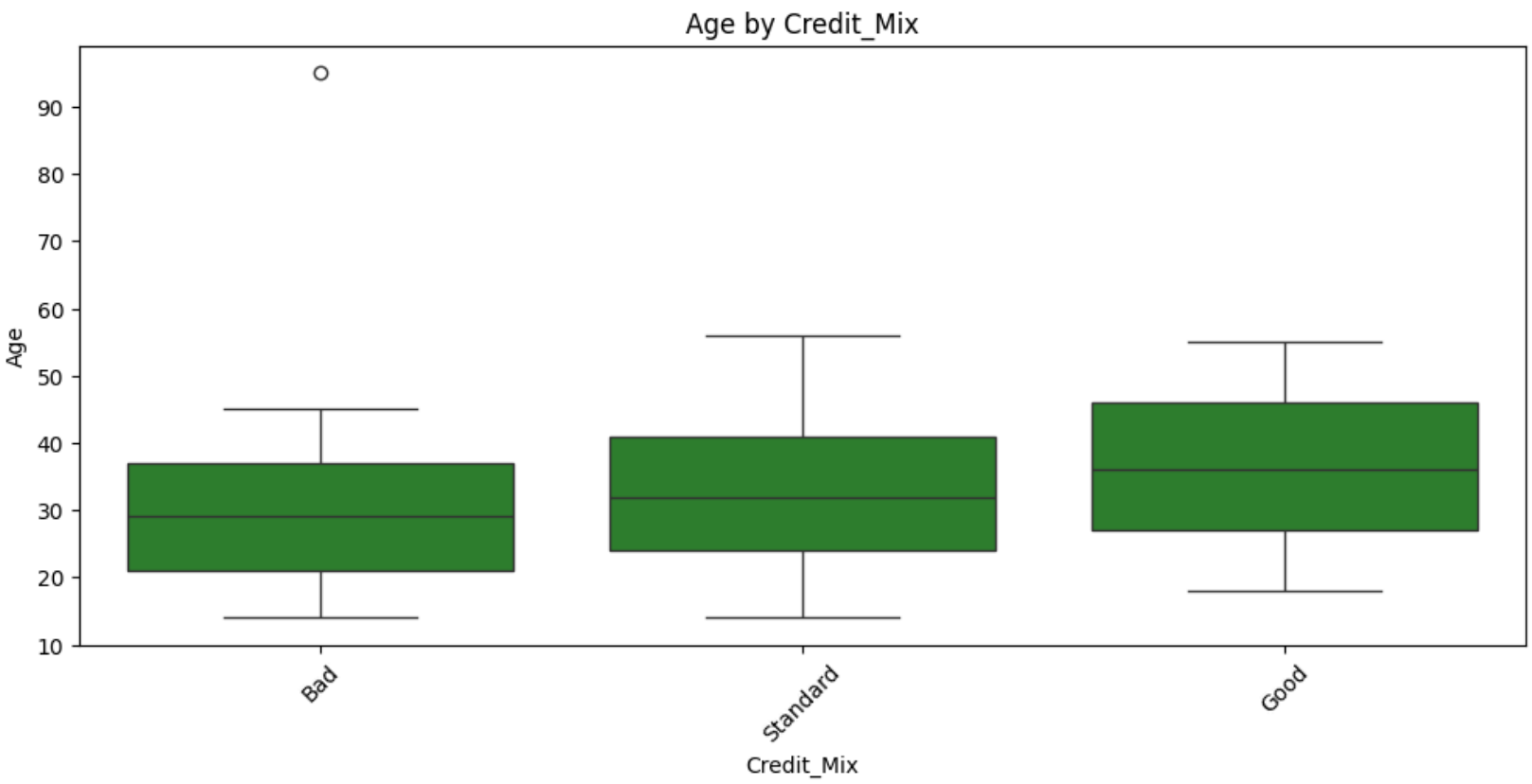


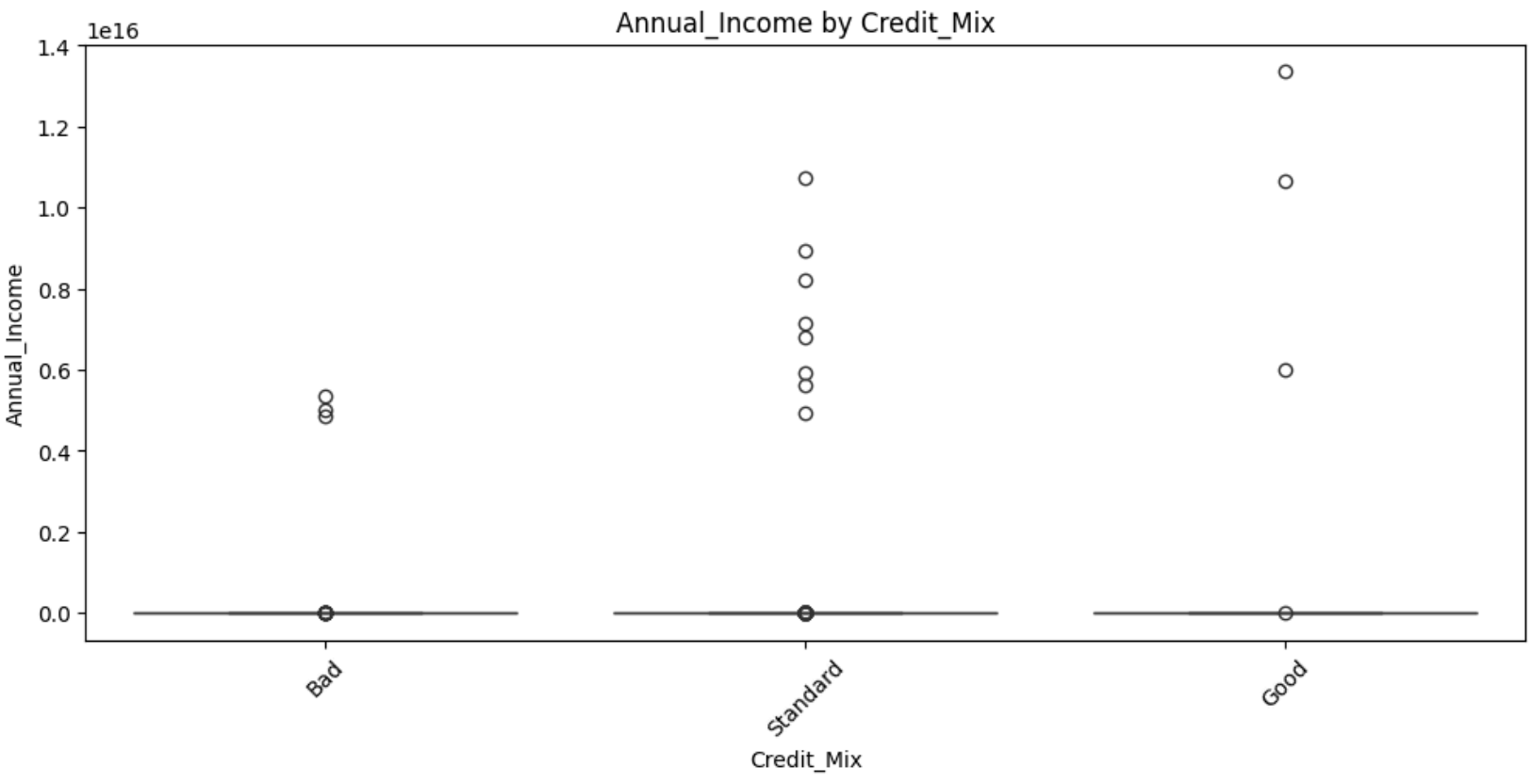

Annual_Income by Occupation
1e16
Annual_Income
Occupation
Lawyer
Mechanic
Media_Manager
Doctor
Journalist
Accountant
Manager
Entrepreneur
Scientist
Architect
Teacher
Writer
Developer
Musician
Engineer


Monthly_Inhand_Salary by Occupation
Monthly_Inhand_Salary
Occupation
Lawyer
Mechanic
Media_Manager
Doctor
Journalist
Accountant
Manager
Entrepreneur
Scientist
Architect
Teacher
Writer
Developer
Musician
Engineer

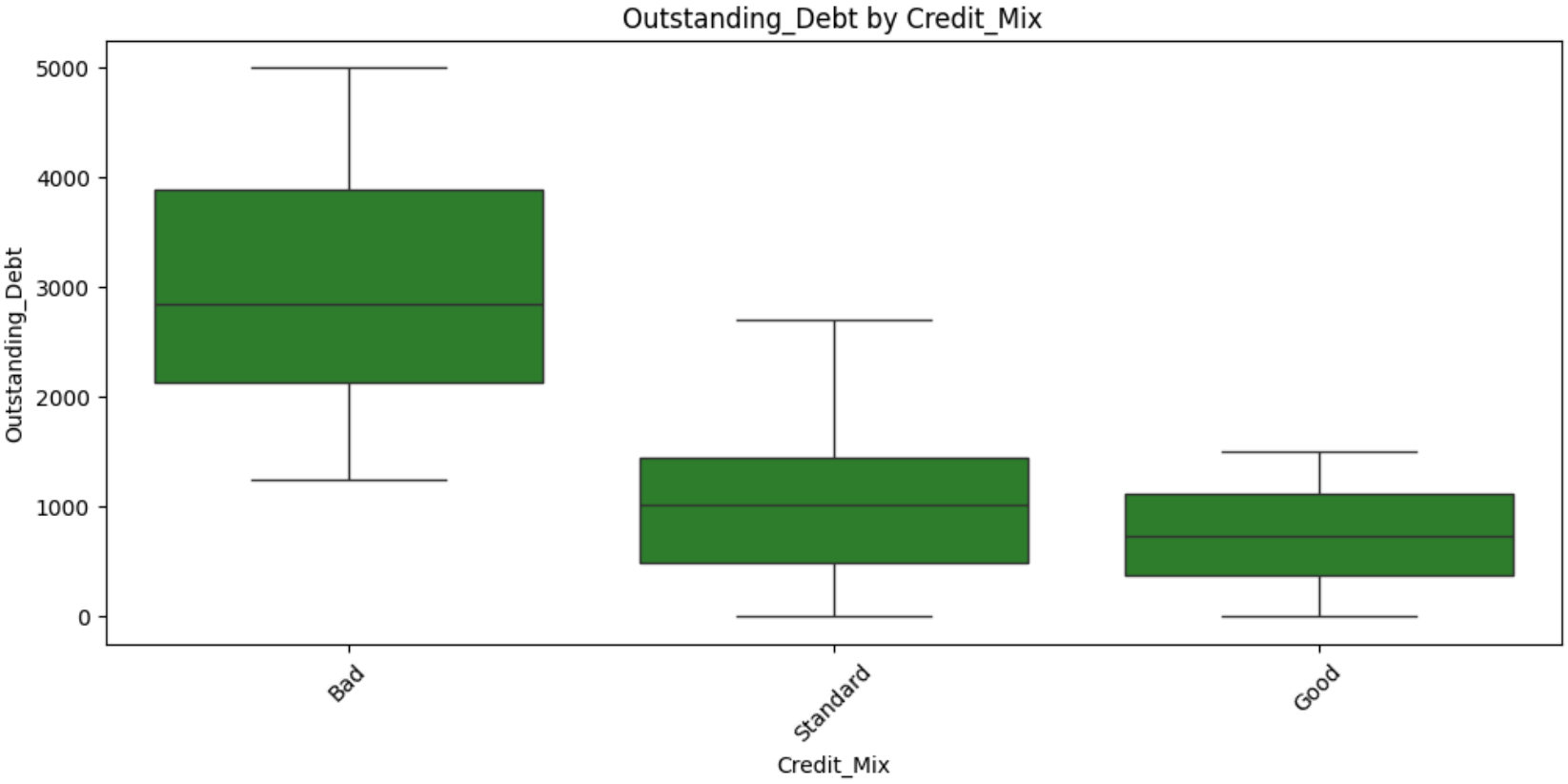

Outstanding_Debt by Occupation
Outstanding_Debt
Occupation
Lawyer
Mechanic
Media_Manager
Doctor
Journalist
Accountant
Manager
Entrepreneur
Scientist
Architect
Teacher
Writer
Developer
Musician
Engineer

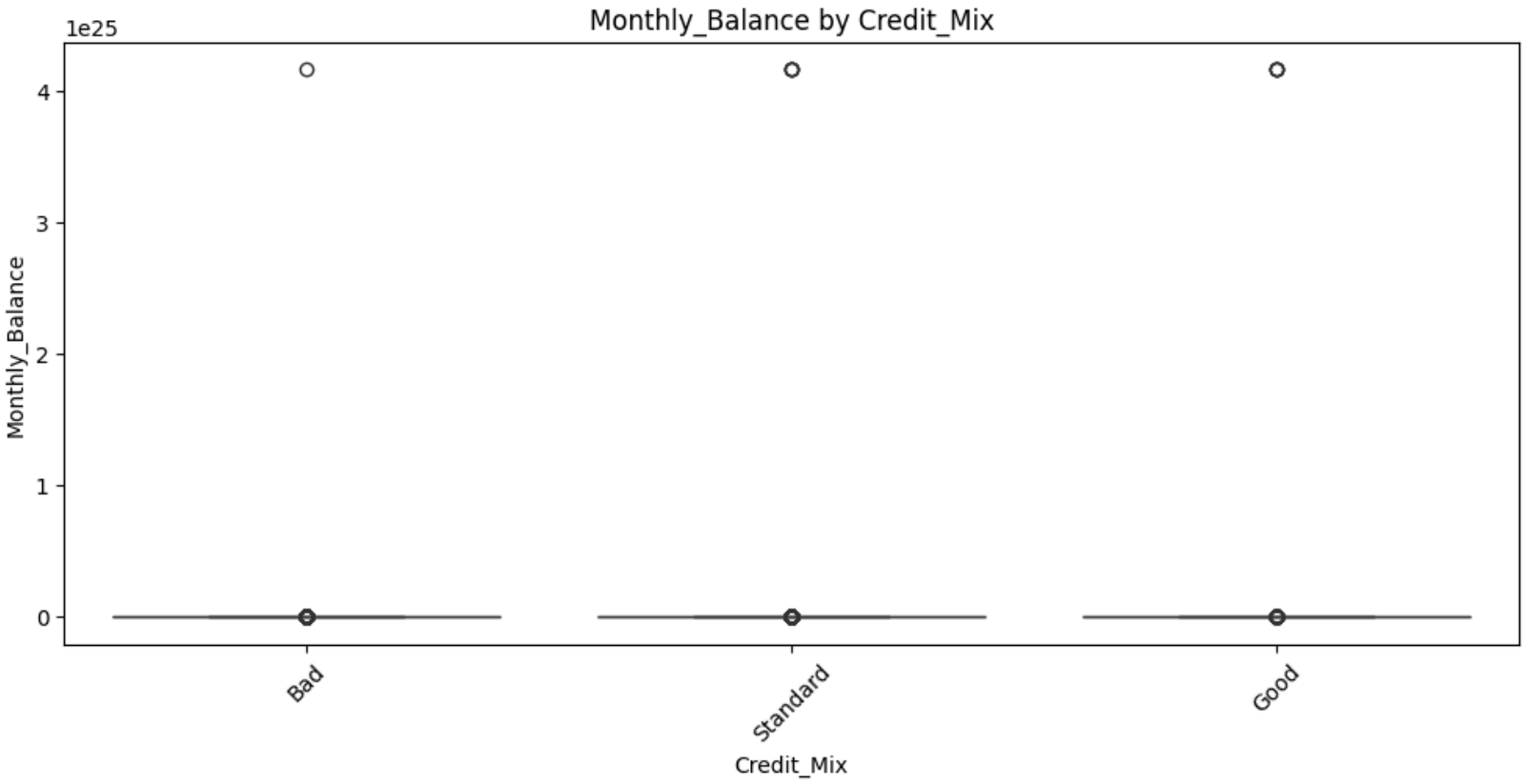

Monthly_Balance by Occupation
1e25
Monthly_Balance
0
1
2
3
4
Lawyer
Mechanic
Media_Manager
Doctor
Journalist
Accountant
Manager
Entrepreneur
Scientist
Architect
Teacher
Writer
Developer
Musician
Engineer
Occupation

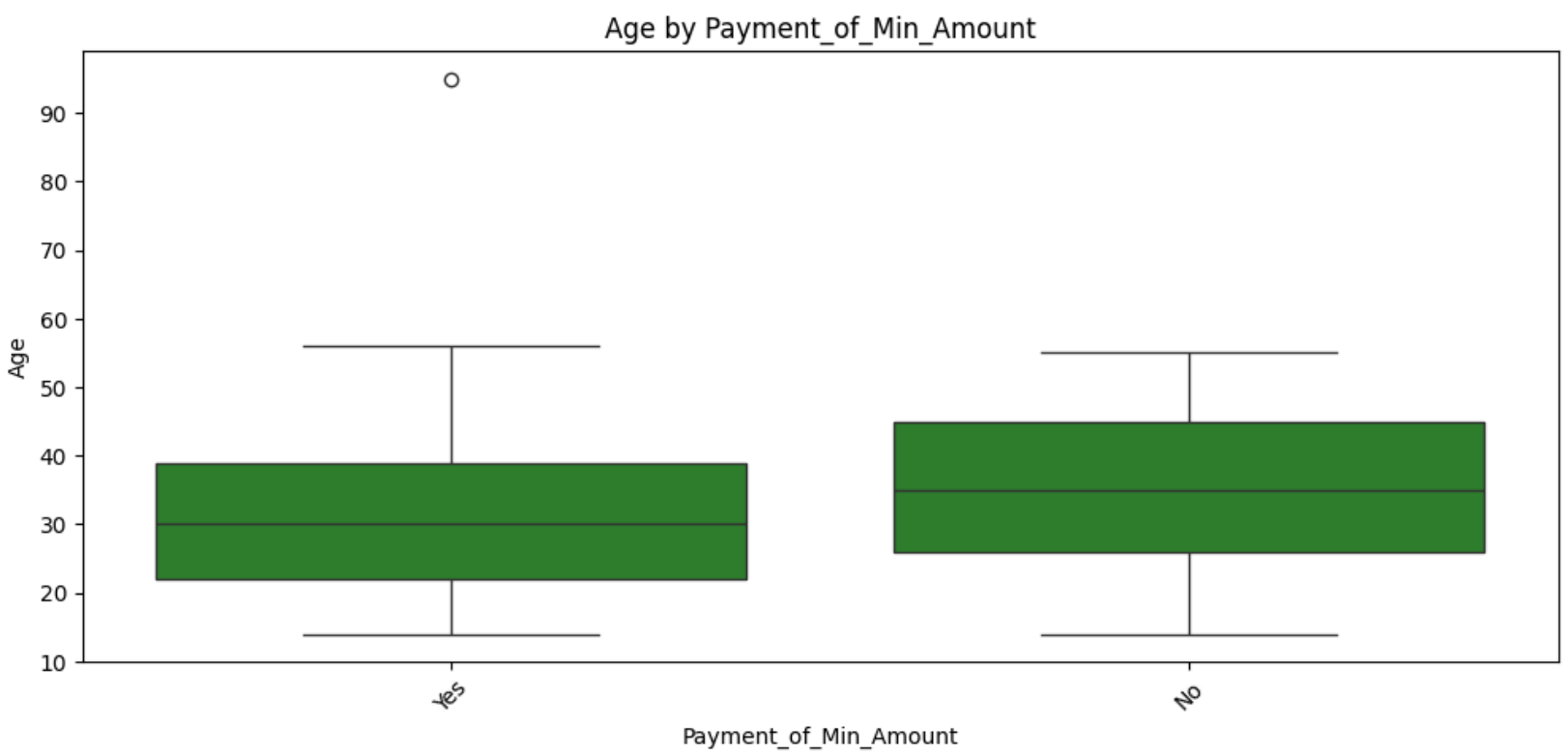

Age by Credit_Mix
Age
10
20
30
40
50
60
70
80
90
Bad
Standard
Good
Credit_Mix

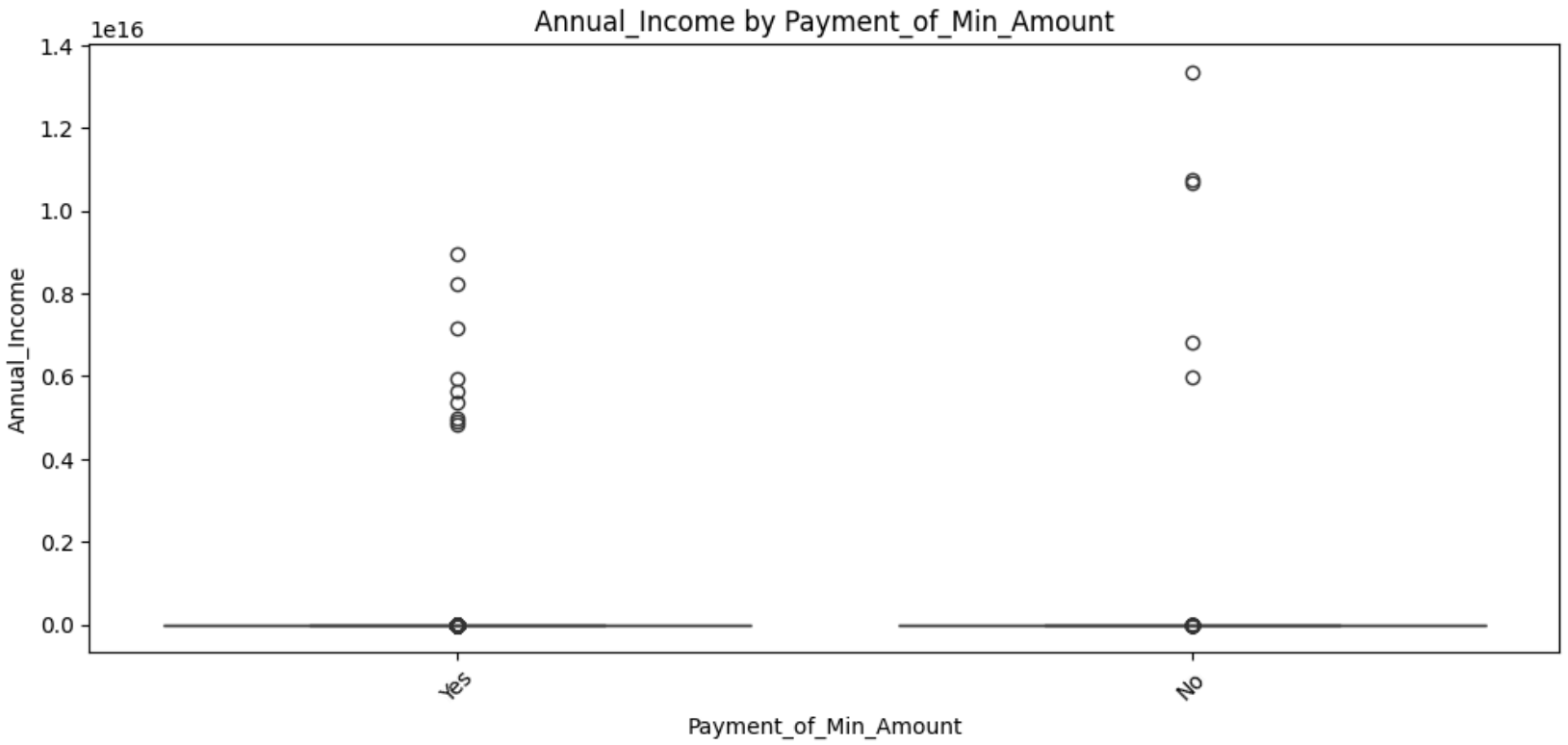

Annual_Income by Credit_Mix
1e16
Annual_Income
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
Bad
Standard
Good
Credit_Mix

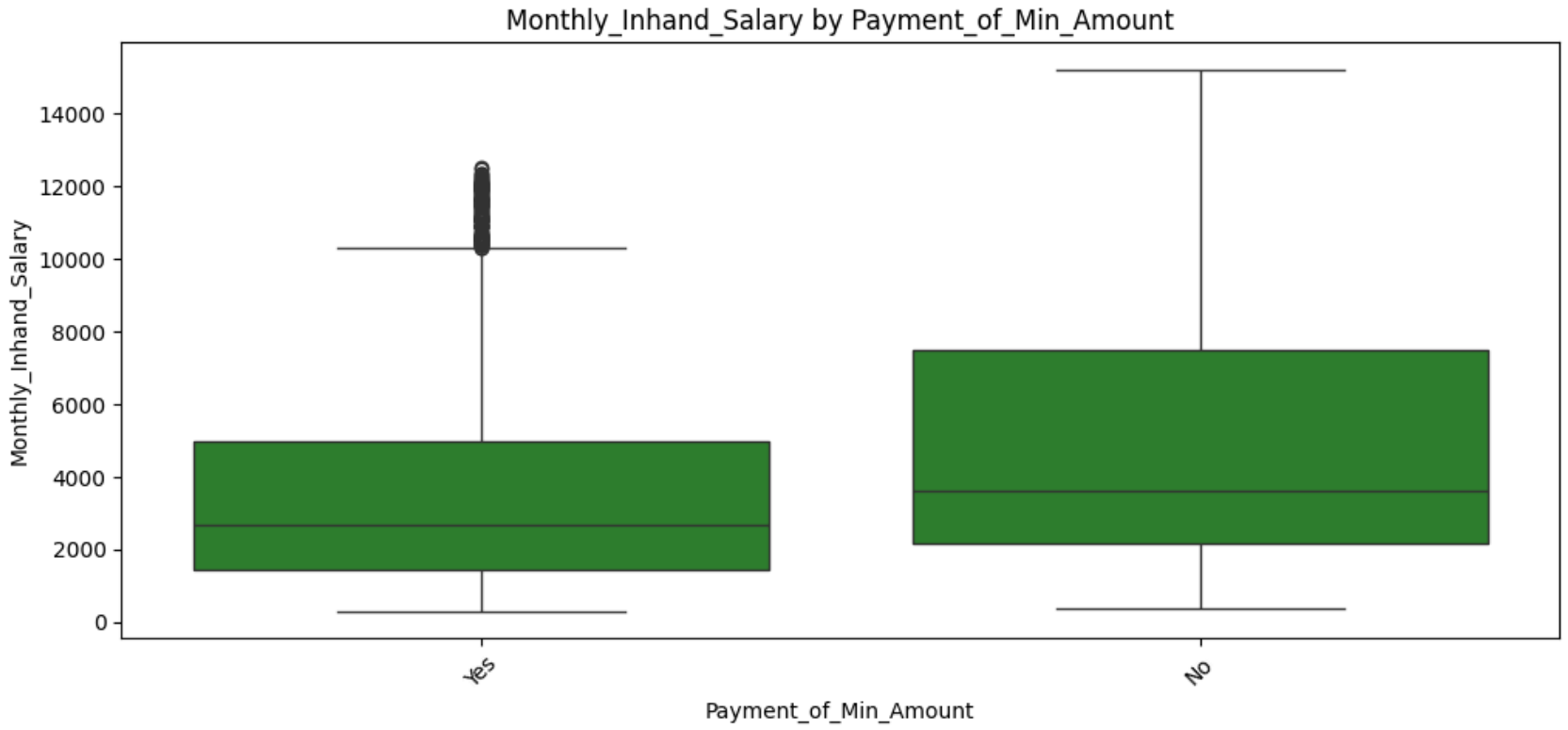

Monthly_Inhand_Salary by Credit_Mix
Monthly_Inhand_Salary
0
2000
4000
6000
8000
10000
12000
14000
Bad
Standard
Good
Credit_Mix

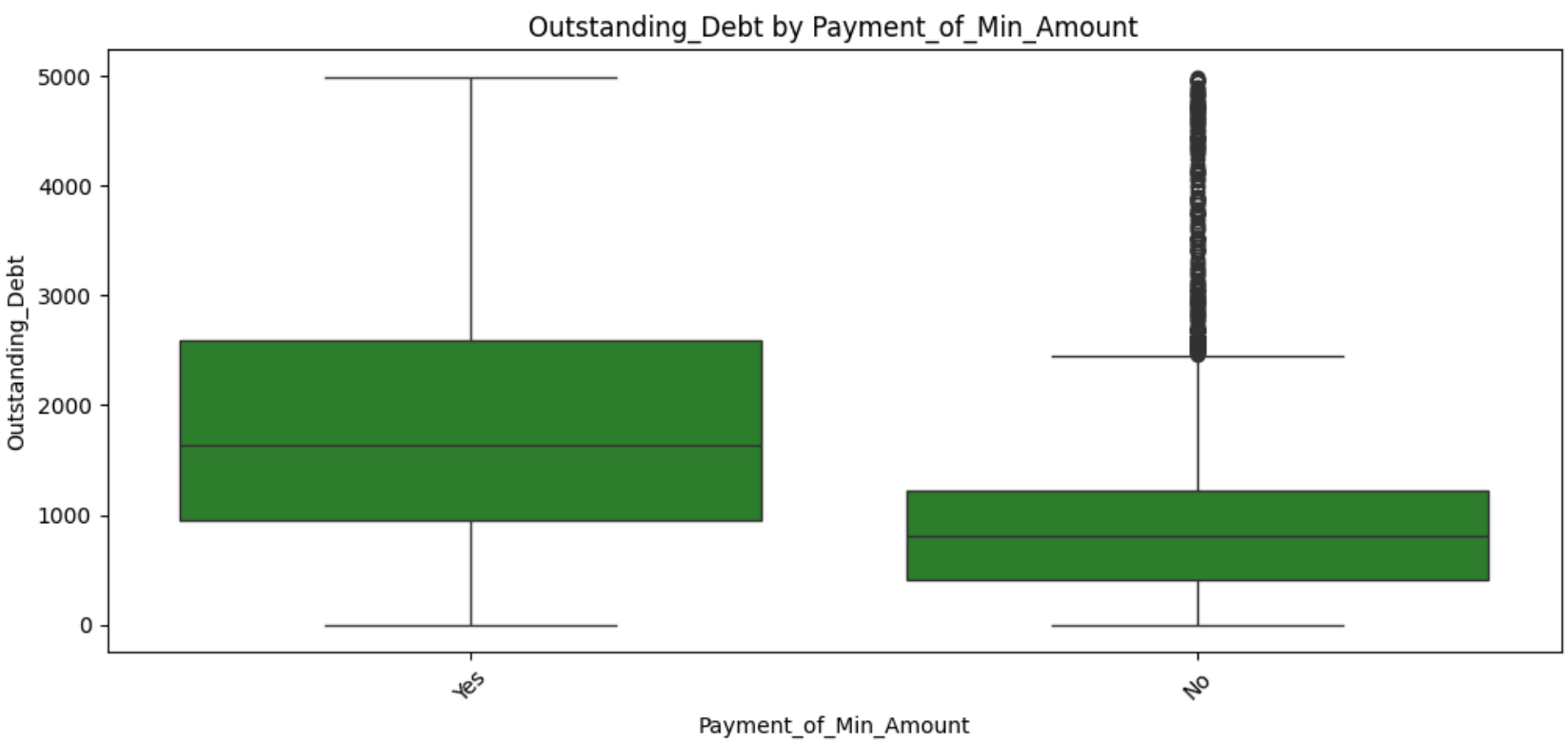

Outstanding_Debt by Credit_Mix
Outstanding_Debt
0
1000
2000
3000
4000
5000
Bad
Standard
Good
Credit_Mix

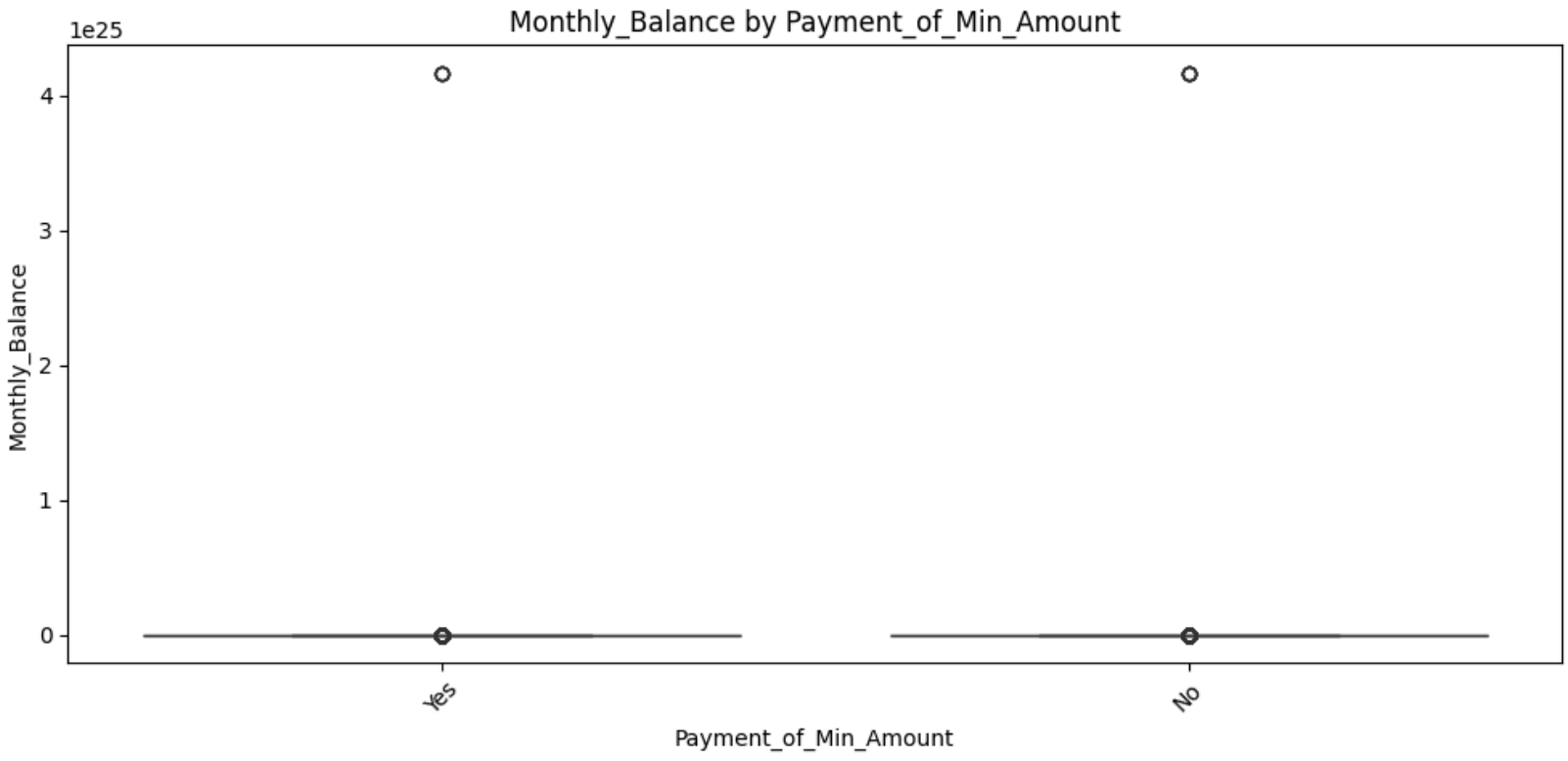

Monthly_Balance by Credit_Mix
1e25
Monthly_Balance
0
1
2
3
4
Bad
Standard
Good
Credit_Mix


Age by Payment_of_Min_Amount
Age
90
80
70
60
50
40
30
20
10
Yes
No
Payment_of_Min_Amount


Annual_Income by Payment_of_Min_Amount
1e16
Annual_Income
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Yes
No
Payment_of_Min_Amount


Monthly_Inhand_Salary by Payment_of_Min_Amount
Monthly_Inhand_Salary
14000
12000
10000
8000
6000
4000
2000
0
Yes
No
Payment_of_Min_Amount





In [304…

```
# Median values for Credit_Mix
print("Median values for Credit_Mix:")
print("-" * 30)
for elem in (['Age', 'Monthly_Inhand_Salary', 'Outstanding_Debt', 'Monthly_Balance']):
  print(f"Column Name: {elem}")
  print(df_aggregated.groupby('Credit_Mix')[elem].median())
  print()
  print("-" * 50)
```

```
Median values for Credit_Mix:
------------------------------
Column Name: Age
Credit_Mix
Bad         29.0
Good        36.0
Standard    32.0
Name: Age, dtype: float64

--------------------------------------------------
Column Name: Monthly_Inhand_Salary
Credit_Mix
Bad         1879.709167
Good        4509.357500
Standard    2927.622500
Name: Monthly_Inhand_Salary, dtype: float64

--------------------------------------------------
Column Name: Outstanding_Debt
Credit_Mix
Bad         2849.38
Good         732.22
Standard    1019.44
Name: Outstanding_Debt, dtype: float64

--------------------------------------------------
Column Name: Monthly_Balance
Credit_Mix
Bad         2.559598e+09
Good        3.693380e+09
Standard    3.143079e+09
Name: Monthly_Balance, dtype: float64

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

Observation

- Age and Credit Mix:

Individuals with a "Good" credit mix have a median age of 36 years, while those with a "Bad" credit mix have a median age of 29 years. Standard credit mix users have a median age of 32 years.

- Monthly Inhand Salary:

Good credit mix individuals have a significantly higher median salary (4,509 USD) compared to those with a bad credit mix (1,879 USD).

- Outstanding Debt:

Those with a "Bad" credit mix have higher outstanding debt (2,849 USD) compared to those with a "Good" credit mix (732 USD). Monthly Balance:

- The monthly balance is highest for "Good" credit mix individuals (3.69 billion) compared to those with "Bad" credit mix (2.56 billion).

In [305…
```python
# Median values for Payment_of_Min_Amount
print("Median values for Payment_of_Min_Amount:")
print("-" * 45)
for elem in (['Age', 'Monthly_Inhand_Salary', 'Outstanding_Debt', 'Monthly_Balance']):
  print(f"Column Name: {elem}")
  print(df_aggregated.groupby('Payment_of_Min_Amount')[elem].median())
  print()
  print("-" * 50)
```

```
Median values for Payment_of_Min_Amount:
---------------------------------------------
Column Name: Age
Payment_of_Min_Amount
No     35.0
Yes    30.0
Name: Age, dtype: float64

--------------------------------------------------
Column Name: Monthly_Inhand_Salary
Payment_of_Min_Amount
No     3621.152084
Yes    2682.483750
Name: Monthly_Inhand_Salary, dtype: float64

--------------------------------------------------
Column Name: Outstanding_Debt
Payment_of_Min_Amount
No      807.0
Yes    1639.9
Name: Outstanding_Debt, dtype: float64

--------------------------------------------------
Column Name: Monthly_Balance
Payment_of_Min_Amount
No     3.490774e+09
Yes    2.825928e+09
Name: Monthly_Balance, dtype: float64

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

Observation

- **Age:** Those who pay the minimum amount have a median age of 30, while those who don't pay have a median age of 35.
- **Monthly Inhand Salary**: Median salary is higher for non-minimum payers (₹3621.15) compared to those paying the minimum amount (₹2682.48).
- **Outstanding Debt**: Median outstanding debt is higher for minimum payers (₹1639.9) compared to non-payers (₹807.0).
- **Monthly Balance:** Median monthly balance is higher for non-payers (₹3.49B) compared to those paying the minimum (₹2.83B).

Hypothetical Credit Score Calculation ⏳

In [306…
```python
# Deep copy
df_cleaned_final = df_cleaned.copy()
df_aggregated_final = df_aggregated.copy()
```

Objective:

To develop a hypothetical credit score calculation methodology inspired by FICO scores using a relevant set of features. The methodology will include calculating scores based on selected features, applying a weighting scheme, and scaling the final scores.

Credit Score Calculation 🧮

Feature Selection

The selected features for calculating the hypothetical credit score include:

- **Monthly_Inhand_Salary:** Positively correlates with Monthly Balance, indicating financial health.
- **Amount_invested_monthly:** Strong correlation with Monthly Balance, affecting savings.
- **Credit_Utilization_Ratio:** Influences creditworthiness.
- **Outstanding_Debt:** Negatively correlates with Monthly Balance, indicating higher risk.
- **Num_Credit_Inquiries:** More inquiries may indicate higher credit risk.
- **Interest_Rate:** Affects borrowing costs.
- **Num_of_Loan:** Reflects debt obligations.
- **Delay_from_due_date:** Highlights payment behavior.
- **Monthly_Balance:** Key measure of financial health.

In [307…
```python
features = {
    'Monthly_Inhand_Salary': 0.15,
    'Amount_invested_monthly': 0.15,
    'Credit_Utilization_Ratio': 0.10,
    'Outstanding_Debt': 0.10,
    'Num_Credit_Inquiries': 0.10,
    'Interest_Rate': 0.10,
    'Num_of_Loan': 0.10,
    'Delay_from_due_date': 0.10,
    'Monthly_Balance': 0.10
}
```

In [308…
```python
from sklearn.preprocessing import MinMaxScaler
```

```
# Normalize the selected features
scaler = MinMaxScaler()
df_aggregated_final[list(features.keys())] = scaler.fit_transform(df_aggregated_final[list(features.keys())])

# Calculate credit score
df_aggregated_final['Credit_Score'] = sum(df_aggregated_final[feature] * weight for feature, weight in features.items())

# Scale to 300-850
df_aggregated_final['Credit_Score'] = df_aggregated_final['Credit_Score'] * (850 - 300) + 300
```

Bin scores 💢

In [309…
```
bins = [300, 499, 649, 749, 850]
labels = ['Poor Credit', 'Fair Credit', 'Good Credit', 'Excellent Credit']
df_aggregated_final['Credit_Score_Binned'] = pd.cut(df_aggregated_final['Credit_Score'], bins=bins, labels=labels)
```

Distribution of Credit Scores

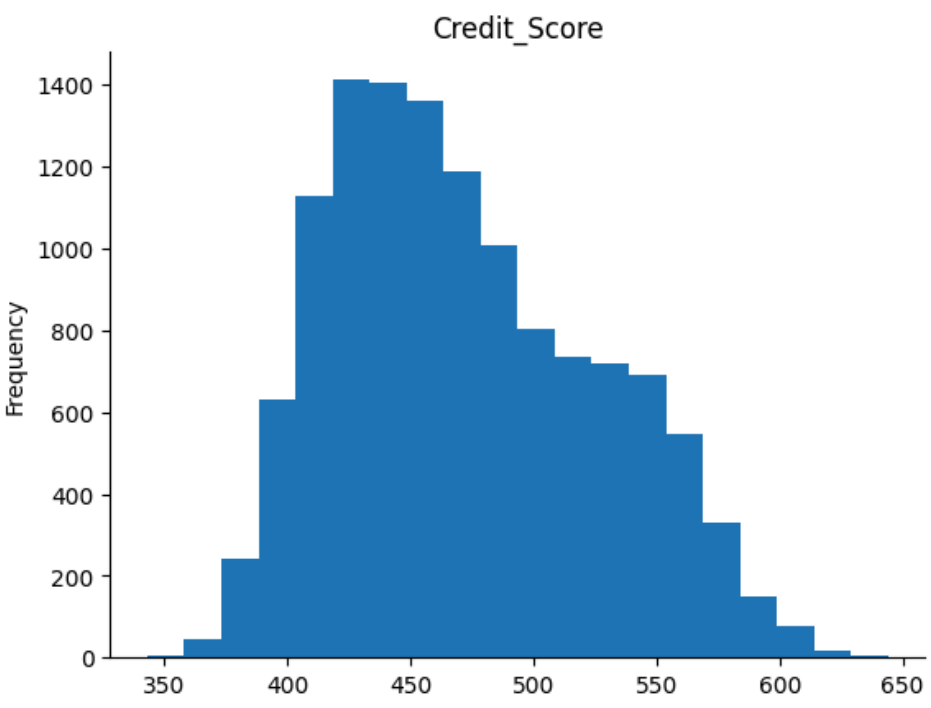
In [310…
```
df_aggregated_final[['Customer_ID','Credit_Score']]
```

Out[310…

	Customer_ID	Credit_Score
0	CUS_0x1000	533.272064
1	CUS_0x1009	430.711104
2	CUS_0x100b	446.498808
3	CUS_0x1011	474.017582
4	CUS_0x1013	452.441537
...	...	...
12495	CUS_0xff3	428.353262
12496	CUS_0xff4	475.296677
12497	CUS_0xff6	436.181428
12498	CUS_0xffc	560.671254
12499	CUS_0xffd	481.747919

12500 rows × 2 columns

In [311…
```
from matplotlib import pyplot as plt
_df_0['Credit_Score'].plot(kind='hist', bins=20, title='Credit_Score')
plt.gca().spines[['top', 'right',]].set_visible(False)
```



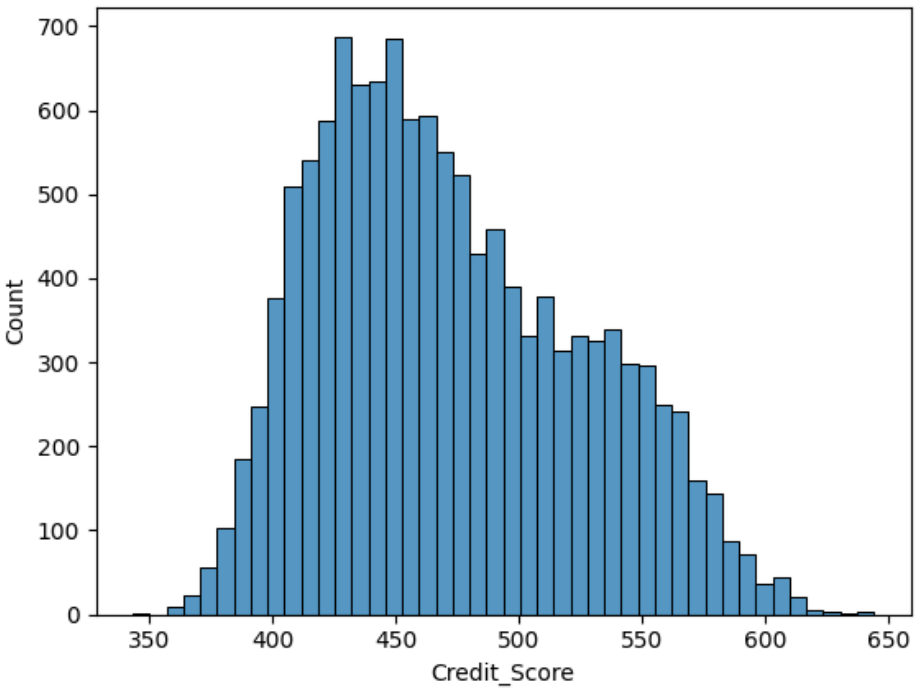
In [312…
```
df_aggregated_final['Credit_Score_Binned'].value_counts()
```

Out[312…

Credit_Score_Binned	count
Poor Credit	8738
Fair Credit	3762
Good Credit	0
Excellent Credit	0

dtype: int64

In [313…
```
sns.histplot(df_aggregated_final['Credit_Score'])
plt.show()
```



Observation

- **Increase in Poor Credit Customers:** The number of "Poor Credit" customers has risen to 10,712, reflecting potential financial challenges over the last 3 months.
- **Drop in Fair Credit Customers:** The "Fair Credit" category has reduced to 1,788, possibly due to recent changes in customer financial behavior.
- **No Higher Credit Scores:** No customers are classified as "Good" or "Excellent Credit," suggesting limitations in the scoring model.
- **Impact of Recency, Frequency, Monetary Metrics:** These factors seem to push scores into lower categories, highlighting recent customer activity.

Need for Further Investigation: The changes in credit score distribution suggest re-evaluating the scoring method and feature weights for better accuracy.

Insights And Recommendations ✍️

- **Credit Mix Impact:** Individuals with "Bad" credit have higher debt and lower income than those with "Good" or "Standard" credit, emphasizing the importance of debt reduction for better credit scores.
- **RFM Analysis:** Recent customer activity and higher spending are linked to better credit behavior, highlighting the significance of recent transactions in credit scoring.
- **Time Frame Analysis:** Recent behavior strongly predicts creditworthiness, suggesting the value of recency in credit scoring models.
- **Model Evaluation:** The current model mostly categorizes customers as "Poor Credit," suggesting recalibration and more refined feature selection to improve accuracy.
- **Debt Management Programs:** Individuals with "Bad" credit often have high outstanding debt. Introducing personalized debt reduction strategies can improve their financial stability and credit scores.
- **Recency-Driven Credit Scoring:** Place greater emphasis on recent payment behaviors and financial activities in credit scoring, as recent interactions correlate with better credit behavior.
- **Tailored Financial Products:** Offer targeted financial products for customers in lower credit categories to help them rebuild their credit, such as low-interest loans or educational resources.

These strategies can lead to more effective credit risk management and help customers improve their credit health.

__By__

Malarvizhi K

In [313…