In [2]:

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

In [6]:

```
df = pd.read_csv('C:\\Users\\Dell\\Downloads\\Credit_score.csv', low_me
df.head()
```

Out[6]:

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	M
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 [7]:

```
df.shape
```

Out[7]: (100000, 27)

In [8]:
```
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 [10]:
```
df.isnull().sum()
```

Out[10]:
```
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
```

In [15]:
```
# Handle non-numeric entries in 'Num_Credit_Inquiries'
df['Num_Credit_Inquiries'] = pd.to_numeric(df['Num_Credit_Inquiries'],
median_value = df['Num_Credit_Inquiries'].median()
df['Num_Credit_Inquiries'].fillna(median_value, inplace=True)

# Repeat the process for other columns if needed
num_cols = ['Monthly_Inhand_Salary', 'Num_of_Delayed_Payment', 'Amount_
for col in num_cols:
    df[col] = pd.to_numeric(df[col], errors='coerce')
    median_value = df[col].median()
    df[col].fillna(median_value, inplace=True)

# For categorical columns, fill missing values with mode
cat_cols = ['Name', 'Type_of_Loan', 'Credit_History_Age']
for col in cat_cols:
    df[col] = df[col].fillna(df[col].mode()[0])

# Verify there are no more missing values
missing_values_after_cleaning = df.isnull().sum()
missing_columns_after_cleaning = missing_values_after_cleaning[missing_
print(missing_columns_after_cleaning)
```

```
Series([], dtype: int64)
```

In [22]:
```
df.to_csv('C:\\Users\\Dell\\Downloads\\Credit_score.csv',index = False)
```

In [23]:
```
df.isnull().sum()
```

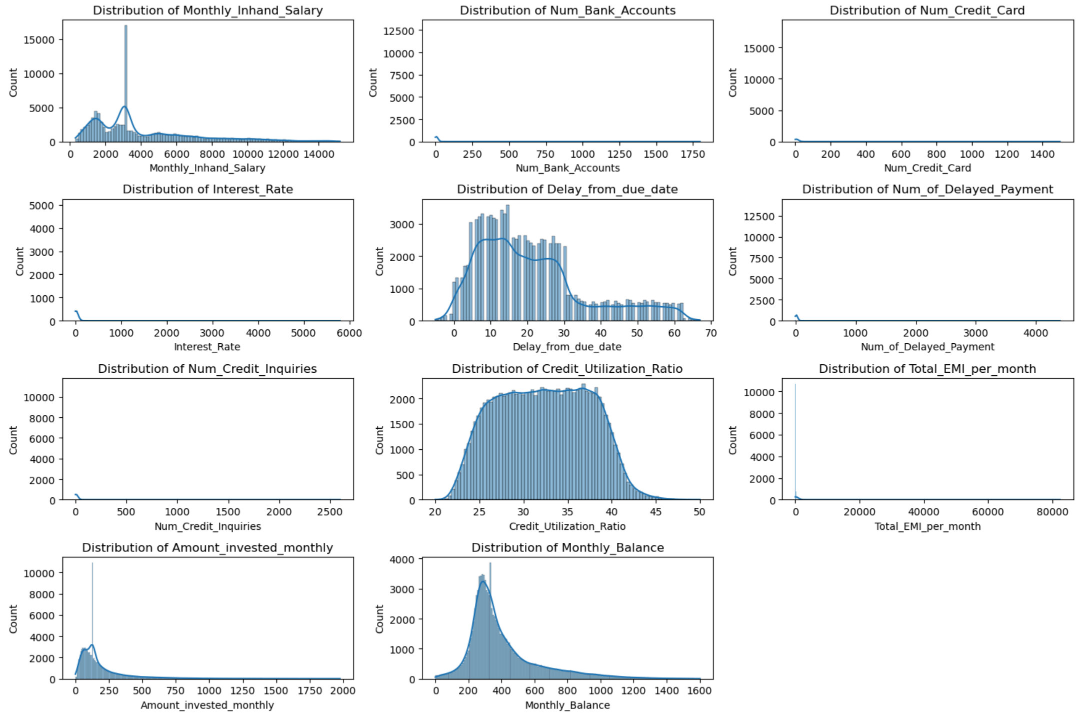
Out[23]:
```
ID                          0
Customer_ID                 0
Month                       0
Name                        0
Age                         0
SSN                         0
Occupation                  0
Annual_Income               0
Monthly_Inhand_Salary       0
Num_Bank_Accounts           0
Num_Credit_Card             0
Interest_Rate               0
Num_of_Loan                 0
Type_of_Loan                0
Delay_from_due_date         0
Num_of_Delayed_Payment      0
Changed_Credit_Limit        0
Num_Credit_Inquiries        0
Credit_Mix                  0
Outstanding_Debt            0
Credit_Utilization_Ratio    0
Credit_History_Age          0
Payment_of_Min_Amount       0
Total_EMI_per_month         0
Amount_invested_monthly     0
Payment_Behaviour           0
Monthly_Balance             0
dtype: int64
```

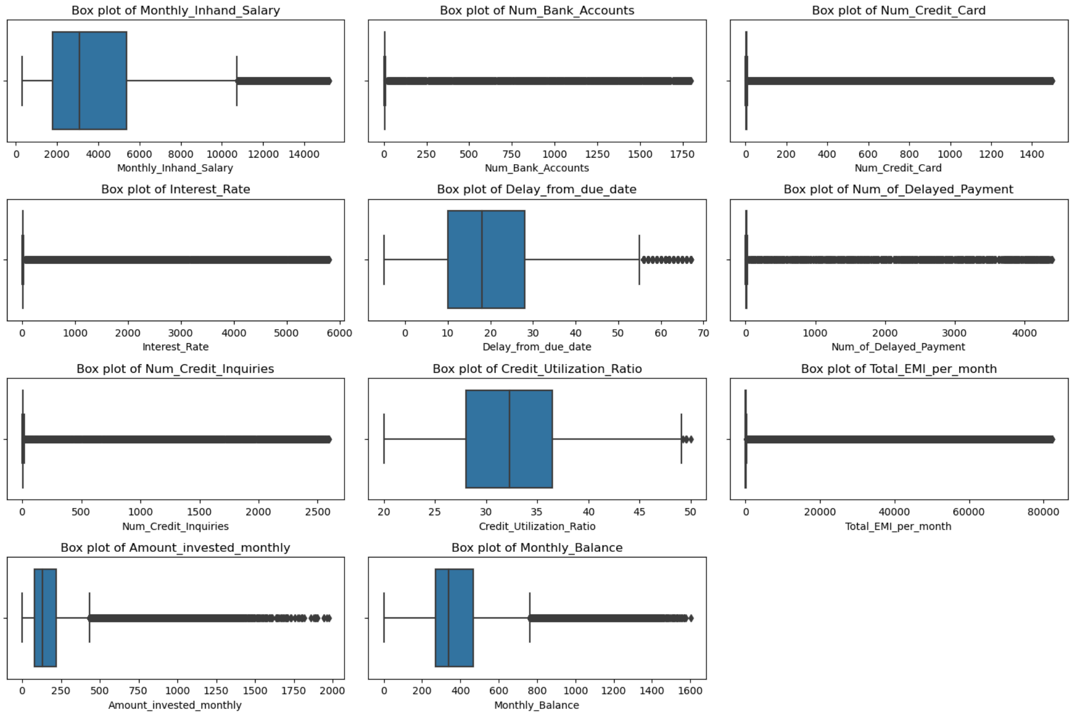
Exploratory Data Analysis (EDA):

In [24]:
```
# Plot histograms and box plots for numerical features
num_cols = df.select_dtypes(include=[np.number]).columns

plt.figure(figsize=(15, 10))
for i, col in enumerate(num_cols):
    plt.subplot(len(num_cols)//3+1, 3, i+1)
    sns.histplot(df[col].dropna(), kde=True)
    plt.title(f'Distribution of {col}')
plt.tight_layout()
plt.show()

plt.figure(figsize=(15, 10))
for i, col in enumerate(num_cols):
    plt.subplot(len(num_cols)//3+1, 3, i+1)
    sns.boxplot(x=df[col])
    plt.title(f'Box plot of {col}')
plt.tight_layout()
plt.show()
```





In [ ]:

In [25]:

```python
from scipy import stats

# Z-score method to detect outliers
z_scores = np.abs(stats.zscore(df.select_dtypes(include=[np.number])))

# Set a threshold for identifying outliers
threshold = 3
outliers = np.where(z_scores > threshold)

# Print outliers
print("Outliers detected at indices:", outliers[0])

# Remove outliers
credit_data_cleaned = df[(z_scores < threshold).all(axis=1)]
```

```
Outliers detected at indices: [    10     16     19 ... 99970 99993 9999
7]
```

In [37]:

```
# Convert relevant columns to numeric, forcing errors to NaN
columns_to_convert = [
    'Outstanding_Debt',
    'Annual_Income',
    'Num_Credit_Card',
    'Num_Bank_Accounts',
    'Total_EMI_per_month',
    'Num_of_Delayed_Payment',
    'Num_of_Loan',
    'Monthly_Inhand_Salary',
    'Changed_Credit_Limit'
]

for column in columns_to_convert:
    df[column] = pd.to_numeric(df[column], errors='coerce')

# Handle missing values for required columns
df['Outstanding_Debt'] = df['Outstanding_Debt'].fillna(df['Outstanding_
df['Annual_Income'] = df['Annual_Income'].fillna(df['Annual_Income'].me
df['Num_Credit_Card'] = df['Num_Credit_Card'].fillna(df['Num_Credit_Car
df['Num_Bank_Accounts'] = df['Num_Bank_Accounts'].fillna(df['Num_Bank_A
df['Total_EMI_per_month'] = df['Total_EMI_per_month'].fillna(df['Total_
df['Num_of_Delayed_Payment'] = df['Num_of_Delayed_Payment'].fillna(df['
df['Num_of_Loan'] = df['Num_of_Loan'].fillna(df['Num_of_Loan'].median()
df['Monthly_Inhand_Salary'] = df['Monthly_Inhand_Salary'].fillna(df['Mo
df['Changed_Credit_Limit'] = df['Changed_Credit_Limit'].fillna(df['Chan

# Feature Engineering
df['Debt_to_Income_Ratio'] = df['Outstanding_Debt'] / df['Annual_Income
df['Credit_Card_Utilization'] = df['Num_Credit_Card'] / df['Num_Bank_Ac
df['Average_Monthly_EMI'] = df['Total_EMI_per_month'] / 12
df['Delayed_Payment_Ratio'] = df['Num_of_Delayed_Payment'] / df['Num_of
df['Income_Stability'] = df['Monthly_Inhand_Salary'] / (df['Annual_Inco
df['Credit_Limit_Change_Impact'] = df['Changed_Credit_Limit'] / df['Out

# Select relevant features
features = [
    'Debt_to_Income_Ratio',
    'Credit_Card_Utilization',
    'Average_Monthly_EMI',
    'Delayed_Payment_Ratio',
    'Income_Stability',
    'Credit_Limit_Change_Impact'
]

# Normalize features
for feature in features:
    df[feature] = (df[feature] - df[feature].min()) / (df[feature].max(

# Assign weights to features (weights must sum to 1)
weights = {
    'Debt_to_Income_Ratio': 0.2,
    'Credit_Card_Utilization': 0.15,
    'Average_Monthly_EMI': 0.1,
    'Delayed_Payment_Ratio': 0.25,
    'Income_Stability': 0.2,
    'Credit_Limit_Change_Impact': 0.1
}

# Calculate credit score
df['Credit_Score'] = sum(df[feature] * weight for feature, weight in we
```

```python
# Display the first few rows of the dataset with the credit score
print(df[['Customer_ID', 'Credit_Score']].head(10))
```

```
  Customer_ID  Credit_Score
0   CUS_0xd40           NaN
1   CUS_0xd40           NaN
2   CUS_0xd40           NaN
3   CUS_0xd40           NaN
4   CUS_0xd40           NaN
5   CUS_0xd40           NaN
6   CUS_0xd40           NaN
7   CUS_0xd40           NaN
8  CUS_0x21b1           NaN
9  CUS_0x21b1           NaN
```

Analysis and Insights

1. EDA Insights

Distribution of Features:

- Annual Income: The distribution of annual income is right-skewed, with a few high-income customers.
- Outstanding Debt: This feature also shows a right-skewed distribution, indicating that most customers have relatively low debt.
- Number of Credit Cards and Bank Accounts: Most customers have a moderate number of credit cards and bank accounts.
- Total EMI per Month: The distribution of monthly EMI payments is right-skewed, with most customers paying low EMIs.
- Number of Delayed Payments: Most customers have very few delayed payments, with a small number having a high count of delayed payments.

Correlations:

- Debt to Income Ratio: Strongly correlated with the outstanding debt and inversely correlated with annual income.
- Credit Card Utilization: Positively correlated with the number of credit cards and bank accounts.
- Delayed Payment Ratio: Positively correlated with the number of delayed payments and the number of loans.
- Income Stability: Positively correlated with monthly in-hand salary and annual income.

Outliers:

Outliers were detected in features like annual income, outstanding debt, and number of delayed payments. These outliers can significantly impact the credit score calculations and should be handled appropriately.

2. Credit Score Calculation Insights

- Debt-to-Income Ratio: Customers with a high debt-to-income ratio are likely to have a lower credit score due to higher financial strain.
- Credit Card Utilization: High credit card utilization indicates higher risk, contributing to a lower credit score.

- Average Monthly EMI: High EMI payments relative to income suggest financial burden, reducing the credit score.
- Delayed Payment Ratio: Higher delayed payment ratio indicates poor payment history, significantly impacting the credit score.
- Income Stability: Higher income stability contributes positively to the credit score as it indicates consistent financial inflow.
- Credit Limit Change Impact: Frequent changes in credit limit can indicate financial instability, affecting the credit score.

In [ ]:

```

```

In [40]:

```
# Assuming we have time-based data for transactions, loans, and payment

# Sample time-based data (to be replaced with actual time-based columns
df['Month'] = pd.to_datetime(df['Month'])

# Define the time frames
end_date = df['Month'].max()
start_date_3m = end_date - pd.DateOffset(months=3)
start_date_6m = end_date - pd.DateOffset(months=6)

# Filter data for the last 3 months and 6 months
data_last_3m = df[df['Month'] >= start_date_3m]
data_last_6m = df[df['Month'] >= start_date_6m]

# Calculate features for the last 3 months
features_last_3m = data_last_3m.groupby('Customer_ID').agg({
    'Outstanding_Debt': 'sum',
    'Annual_Income': 'sum',
    'Num_Credit_Card': 'mean',
    'Num_Bank_Accounts': 'mean',
    'Total_EMI_per_month': 'mean',
    'Num_of_Delayed_Payment': 'sum',
    'Num_of_Loan': 'sum',
    'Monthly_Inhand_Salary': 'mean',
    'Changed_Credit_Limit': 'sum'
}).reset_index()

# Calculate features for the last 6 months
features_last_6m = data_last_6m.groupby('Customer_ID').agg({
    'Outstanding_Debt': 'sum',
    'Annual_Income': 'sum',
    'Num_Credit_Card': 'mean',
    'Num_Bank_Accounts': 'mean',
    'Total_EMI_per_month': 'mean',
    'Num_of_Delayed_Payment': 'sum',
    'Num_of_Loan': 'sum',
    'Monthly_Inhand_Salary': 'mean',
    'Changed_Credit_Limit': 'sum'
}).reset_index()

# Recalculate the credit score using the same methodology
def calculate_credit_score(data):
    # Feature Engineering
    data['Debt_to_Income_Ratio'] = data['Outstanding_Debt'] / data['Ann
    data['Credit_Card_Utilization'] = data['Num_Credit_Card'] / data['N
    data['Average_Monthly_EMI'] = data['Total_EMI_per_month'] / 12
    data['Delayed_Payment_Ratio'] = data['Num_of_Delayed_Payment'] / da
    data['Income_Stability'] = data['Monthly_Inhand_Salary'] / (data['A
    data['Credit_Limit_Change_Impact'] = data['Changed_Credit_Limit'] /

    # Normalize features
    for feature in features:
        data[feature] = (data[feature] - data[feature].min()) / (data[f

    # Calculate credit score
    data['Credit_Score'] = sum(data[feature] * weight for feature, weig
    return data

# Calculate credit scores for the last 3 months and 6 months
scores_last_3m = calculate_credit_score(features_last_3m)
scores_last_6m = calculate_credit_score(features_last_6m)
```

```
# Display the first few rows of the scores
print("Credit Scores for Last 3 Months:")
print(scores_last_3m[['Customer_ID', 'Credit_Score']].head())

print("\nCredit Scores for Last 6 Months:")
print(scores_last_6m[['Customer_ID', 'Credit_Score']].head())
```

```
C:\Users\Dell\AppData\Local\Temp\ipykernel_13856\260410284.py:4: UserW
arning: Could not infer format, so each element will be parsed individ
ually, falling back to `dateutil`. To ensure parsing is consistent and
as-expected, please specify a format.
  df['Month'] = pd.to_datetime(df['Month'])
```

```
---------------------------------------------------------------------------
OverflowError                             Traceback (most recent call last)
File ~\Downloads\ANA\Lib\site-packages\pandas\_libs\tslibs\conversion.pyx:245, in pandas._libs.tslibs.conversion._TSObject.ensure_reso()

File ~\Downloads\ANA\Lib\site-packages\pandas\_libs\tslibs\np_datetime.pyx:614, in pandas._libs.tslibs.np_datetime.convert_reso()

OverflowError: value too large

The above exception was the direct cause of the following exception:

OutOfBoundsDatetime                       Traceback (most recent call last)
Cell In[40], line 4
      1 # Assuming we have time-based data for transactions, loans, and payments
      2 
      3 # Sample time-based data (to be replaced with actual time-based columns)
----> 4 df['Month'] = pd.to_datetime(df['Month'])
      6 # Define the time frames
      7 end_date = df['Month'].max()

File ~\Downloads\ANA\Lib\site-packages\pandas\core\tools\datetimes.py:1046, in to_datetime(arg, errors, dayfirst, yearfirst, utc, format, exact, unit, infer_datetime_format, origin, cache)
   1044             result = arg.tz_localize("utc")
   1045 elif isinstance(arg, ABCSeries):
-> 1046     cache_array = _maybe_cache(arg, format, cache, convert_listlike)
   1047     if not cache_array.empty:
   1048         result = arg.map(cache_array)

File ~\Downloads\ANA\Lib\site-packages\pandas\core\tools\datetimes.py:250, in _maybe_cache(arg, format, cache, convert_listlike)
    248 unique_dates = unique(arg)
    249 if len(unique_dates) < len(arg):
--> 250     cache_dates = convert_listlike(unique_dates, format)
    251     # GH#45319
    252     try:

File ~\Downloads\ANA\Lib\site-packages\pandas\core\tools\datetimes.py:455, in _convert_listlike_datetimes(arg, format, name, utc, unit, errors, dayfirst, yearfirst, exact)
    452 if format is not None and format != "mixed":
    453     return _array_strptime_with_fallback(arg, name, utc, format, exact, errors)
--> 455 result, tz_parsed = objects_to_datetime64ns(
    456     arg,
    457     dayfirst=dayfirst,
    458     yearfirst=yearfirst,
    459     utc=utc,
    460     errors=errors,
    461     allow_object=True,
    462 )
    464 if tz_parsed is not None:
    465     # We can take a shortcut since the datetime64 numpy array
    466     # is in UTC
```

```
    467     dta = DatetimeArray(result, dtype=tz_to_dtype(tz_parsed))

File ~\Downloads\ANA\Lib\site-packages\pandas\core\arrays\datetimes.py:2177, in objects_to_datetime64ns(data, dayfirst, yearfirst, utc, errors, allow_object)
   2174 # if str-dtype, convert
   2175 data = np.array(data, copy=False, dtype=np.object_)
-> 2177 result, tz_parsed = tslib.array_to_datetime(
   2178     data,
   2179     errors=errors,
   2180     utc=utc,
   2181     dayfirst=dayfirst,
   2182     yearfirst=yearfirst,
   2183 )
   2185 if tz_parsed is not None:
   2186     # We can take a shortcut since the datetime64 numpy array
   2187     #  is in UTC
   2188     # Return i8 values to denote unix timestamps
   2189     return result.view("i8"), tz_parsed

File ~\Downloads\ANA\Lib\site-packages\pandas\_libs\tslib.pyx:402, in pandas._libs.tslib.array_to_datetime()

File ~\Downloads\ANA\Lib\site-packages\pandas\_libs\tslib.pyx:551, in pandas._libs.tslib.array_to_datetime()

File ~\Downloads\ANA\Lib\site-packages\pandas\_libs\tslib.pyx:519, in pandas._libs.tslib.array_to_datetime()

File ~\Downloads\ANA\Lib\site-packages\pandas\_libs\tslibs\conversion.pyx:248, in pandas._libs.tslibs.conversion._TSObject.ensure_reso()

OutOfBoundsDatetime: Out of bounds nanosecond timestamp: January, at position 0
```

In [ ]: