Outlier Detection & Log Transformation

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In [16]:
```
import numpy as np
import pandas as pd
import os
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.graph_objects as go
from scipy.stats import gaussian_kde
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier,
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
import plotly.express as px
```

```
import plotly.figure_factory as ff
from sklearn.metrics import confusion_matrix, classification_report
import warnings
warnings.filterwarnings('ignore')


RUN_CNT = 0
MAIN_FOLDER = "/kaggle/input/playground-series-s4e10"
TEST = os.path.join(MAIN_FOLDER, 'test.csv')
TRAIN = os.path.join(MAIN_FOLDER, 'train.csv')
```

In [17]:
```
def IQR(train_df, column, range1, range2) -> pd.DataFrame:
    Q1 = train_df[column].quantile(range1)
    Q3 = train_df[column].quantile(range2)
    IQR = Q3 - Q1

    print("Q1 = {}, Q3 = {}, IQR = {}".format(Q1, Q3, IQR))

    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    print("lower_bound = {}, upper_bound = {}".format(lower_bound, upper_bound))
    train_df_filtered = train_df[(train_df[column] >= lower_bound) & (train_df[c
    return train_df_filtered

def bar_plotter(df, column_name):

    plt.figure(figsize=(8, 6))
    sns.histplot(df[column_name], bins=30, kde=True, color='blue')
    plt.title(f'Distribution of {column_name}')
    plt.xlabel(column_name)
    plt.ylabel('Frequency')
    plt.show()


def scatter(df, column):
    col = df[column]
    plt.scatter(x=list(range(len(col))), y=list(col), marker='.', color='red', a
    plt.xlabel("Datapoint")
    plt.ylabel("frequemcy of person age")
    plt.show()

def outlier_remover(df, column, range1=0.22, range2=0.99) -> pd.DataFrame:
    scatter(df, column)
    final_df = IQR(df, column, range1=range1, range2=range2)
    print("Scatter after outlier removal")
    scatter(final_df, column)
    return final_df

def compare_series_barchart_compact(series1, series2, column_name):
    if series1.shape != series2.shape:
        raise ValueError("Series must have the same length")

    # Combine the series into a DataFrame for plotting
    df = pd.DataFrame({'DF1': series1, 'DF2': series2})

    # Melt the DataFrame to long format for plotting
    melted_df = df.reset_index().melt(id_vars='index', var_name='DataFrame', val

    # Plotting
    plt.figure(figsize=(10, 6))
```

```
    sns.barplot(x='index', y='Values', hue='DataFrame', data=melted_df, palette=

    # Adjust bar width and layout
    plt.title(f"train vs test dataset comparison with {column_name}")
    plt.xticks(rotation=45)
    plt.xlabel('Index')
    plt.tight_layout()
    plt.show()
```

In [25]:
```
import seaborn as sns
import matplotlib.pyplot as plt
import pandas as pd

# Apply a dark background globally
plt.style.use('dark_background')

def IQR(train_df, column, range1, range2) -> pd.DataFrame:
    Q1 = train_df[column].quantile(range1)
    Q3 = train_df[column].quantile(range2)
    IQR = Q3 - Q1

    print("Q1 = {}, Q3 = {}, IQR = {}".format(Q1, Q3, IQR))

    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    print("lower_bound = {}, upper_bound = {}".format(lower_bound, upper_bound))
    train_df_filtered = train_df[(train_df[column] >= lower_bound) & (train_df[c
    return train_df_filtered

def bar_plotter(df, column_name):
    plt.figure(figsize=(8, 6))
    sns.set_style("dark")
    sns.histplot(df[column_name], bins=30, kde=True, color='gray')  # Gray color
    plt.title(f'Distribution of {column_name}', color='gray')  # Gray title
    plt.xlabel(column_name, color='gray')  # Gray label
    plt.ylabel('Frequency', color='gray')  # Gray label
    plt.xticks(color='gray')  # Gray ticks
    plt.yticks(color='gray')  # Gray ticks
    plt.show()

def scatter(df, column):
    col = df[column]
    plt.scatter(x=list(range(len(col))), y=list(col), marker='.', color='gray',
    plt.xlabel("Datapoint", color='gray')  # Gray label
    plt.ylabel("Frequency of person age", color='gray')  # Gray label
    plt.xticks(color='gray')  # Gray ticks
    plt.yticks(color='gray')  # Gray ticks
    plt.show()

def outlier_remover(df, column, range1=0.22, range2=0.99) -> pd.DataFrame:
    scatter(df, column)
    final_df = IQR(df, column, range1=range1, range2=range2)
    print("Scatter after outlier removal")
    scatter(final_df, column)
    return final_df

def compare_series_barchart_compact(series1, series2, column_name):
    if series1.shape != series2.shape:
        raise ValueError("Series must have the same length")
```

```python
    # Combine the series into a DataFrame for plotting
    df = pd.DataFrame({'DF1': series1, 'DF2': series2})

    # Melt the DataFrame to long format for plotting
    melted_df = df.reset_index().melt(id_vars='index', var_name='DataFrame', val

    # Plotting
    plt.figure(figsize=(10, 6))
    sns.set_style("dark")
    sns.barplot(x='index', y='Values', hue='DataFrame', data=melted_df, palette=

    # Adjust bar width and layout
    plt.title(f"Train vs Test Dataset Comparison with {column_name}", color='gra
    plt.xlabel('Index', color='gray')
    plt.xticks(rotation=45, color='gray')  # Gray ticks
    plt.yticks(color='gray')  # Gray ticks
    plt.tight_layout()
    plt.show()
```

In [26]:

```python
original_df_train = pd.read_csv(TRAIN)
train_df = original_df_train.applymap(lambda x: x + 0.00001 if x == 0 else x)
original_df_test = pd.read_csv(TEST)
test_df = original_df_test.applymap(lambda x: x + 0.00001 if x == 0 else x)
train_df_copy = train_df.copy()
test_df_copy = test_df.copy()

train_df.head()
```

Out[26]:

	id	person_age	person_income	person_home_ownership	person_emp_length	l
0	0.00001	37	35000	RENT	0.00001	E
1	1.00000	22	56000	OWN	6.00000	
2	2.00000	29	28800	OWN	8.00000	
3	3.00000	30	70000	RENT	14.00000	
4	4.00000	22	60000	RENT	2.00000	

----> 📊 *Preprocessing* 📊

In [27]:

```python
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 58645 entries, 0 to 58644
Data columns (total 13 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   id                          58645 non-null  float64
 1   person_age                  58645 non-null  int64
 2   person_income               58645 non-null  int64
 3   person_home_ownership       58645 non-null  object
 4   person_emp_length           58645 non-null  float64
 5   loan_intent                 58645 non-null  object
 6   loan_grade                  58645 non-null  object
 7   loan_amnt                   58645 non-null  int64
 8   loan_int_rate               58645 non-null  float64
 9   loan_percent_income         58645 non-null  float64
 10  cb_person_default_on_file   58645 non-null  object
 11  cb_person_cred_hist_length  58645 non-null  int64
 12  loan_status                 58645 non-null  float64
dtypes: float64(5), int64(4), object(4)
memory usage: 5.8+ MB
```

In [28]:
```
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39098 entries, 0 to 39097
Data columns (total 12 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   id                          39098 non-null  int64
 1   person_age                  39098 non-null  int64
 2   person_income               39098 non-null  int64
 3   person_home_ownership       39098 non-null  object
 4   person_emp_length           39098 non-null  float64
 5   loan_intent                 39098 non-null  object
 6   loan_grade                  39098 non-null  object
 7   loan_amnt                   39098 non-null  int64
 8   loan_int_rate               39098 non-null  float64
 9   loan_percent_income         39098 non-null  float64
 10  cb_person_default_on_file   39098 non-null  object
 11  cb_person_cred_hist_length  39098 non-null  int64
dtypes: float64(3), int64(5), object(4)
memory usage: 3.6+ MB
```

In [29]:
```
train_df.describe()
```

Out[29]:

	id	person_age	person_income	person_emp_length	loan_amnt	l
count	58645.000000	58645.000000	5.864500e+04	58645.000000	58645.000000	5
mean	29322.000000	27.550857	6.404617e+04	4.701016	9217.556518	
std	16929.497605	6.033216	3.793111e+04	3.959783	5563.807384	
min	0.000010	20.000000	4.200000e+03	0.000010	500.000000	
25%	14661.000000	23.000000	4.200000e+04	2.000000	5000.000000	
50%	29322.000000	26.000000	5.800000e+04	4.000000	8000.000000	
75%	43983.000000	30.000000	7.560000e+04	7.000000	12000.000000	
max	58644.000000	123.000000	1.900000e+06	123.000000	35000.000000	

In [30]:
```
test_df.describe()
```

Out[30]:

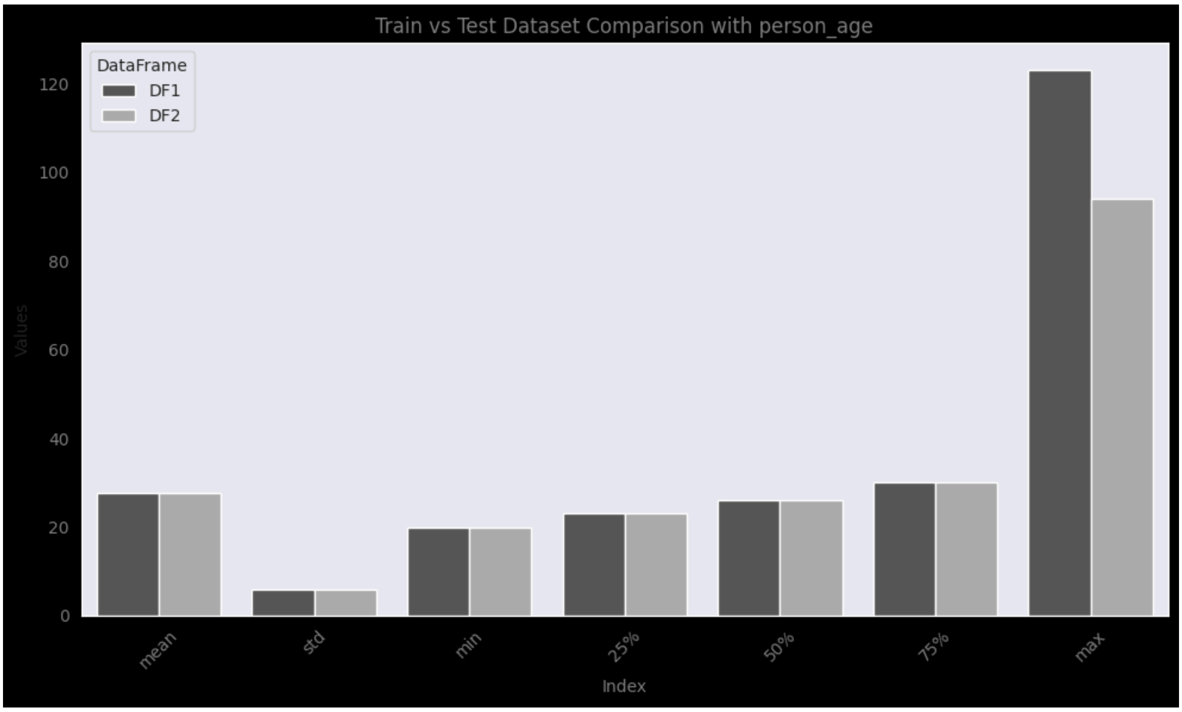
	id	person_age	person_income	person_emp_length	loan_amnt	l
count	39098.000000	39098.000000	3.909800e+04	39098.000000	39098.000000	3
mean	78193.500000	27.566781	6.406046e+04	4.687070	9251.466188	
std	11286.764749	6.032761	3.795583e+04	3.868393	5576.254680	
min	58645.000000	20.000000	4.000000e+03	0.000010	700.000000	
25%	68419.250000	23.000000	4.200000e+04	2.000000	5000.000000	
50%	78193.500000	26.000000	5.800000e+04	4.000000	8000.000000	
75%	87967.750000	30.000000	7.588500e+04	7.000000	12000.000000	
max	97742.000000	94.000000	1.900000e+06	42.000000	35000.000000	

In [31]:
```
train_report = train_df.describe().drop(['id', 'loan_status'], axis='columns')
test_report = test_df.describe().drop(['id'], axis='columns')
test_report.index
```

Out[31]:
```
Index(['count', 'mean', 'std', 'min', '25%', '50%', '75%', 'max'], dtype='objec
t')
```

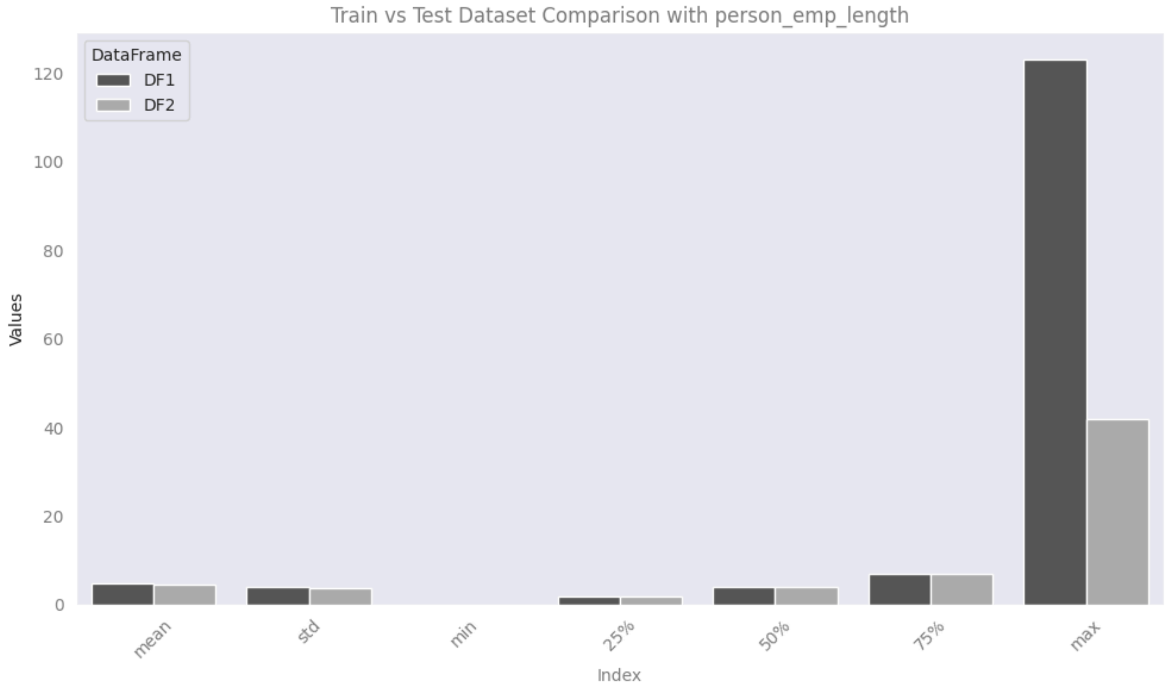
----> 📊 *Train Data vs Test Data* 📊

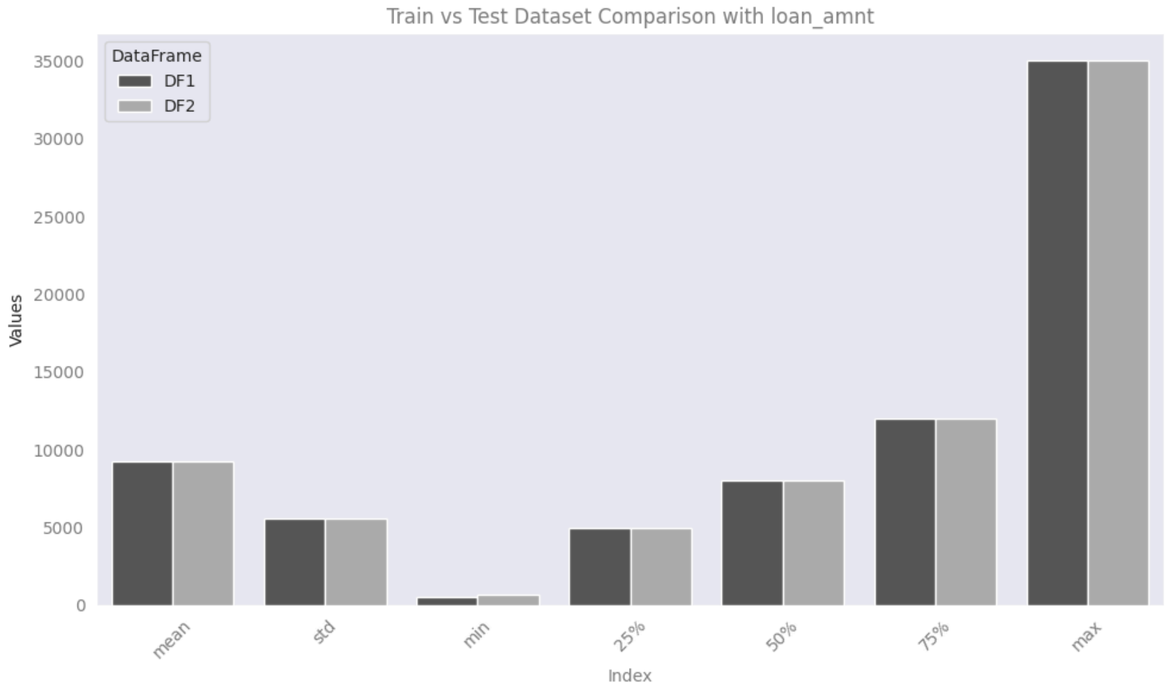
In [32]:
```
for row in train_report.columns:
    compare_series_barchart_compact(train_report[row][1:], test_report[row][1:],
```

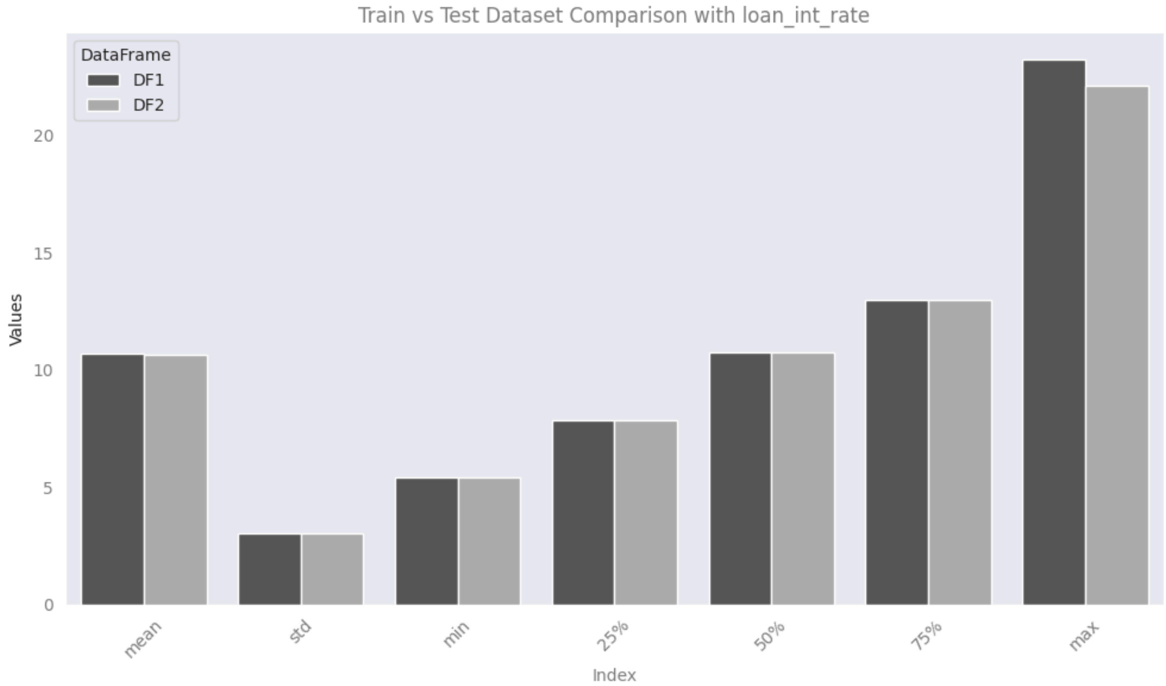


Train vs Test Dataset Comparison with person_age
DataFrame
DF1
DF2
Values
0
20
40
60
80
100
120
mean
std
min
25%
50%
75%
max
Index

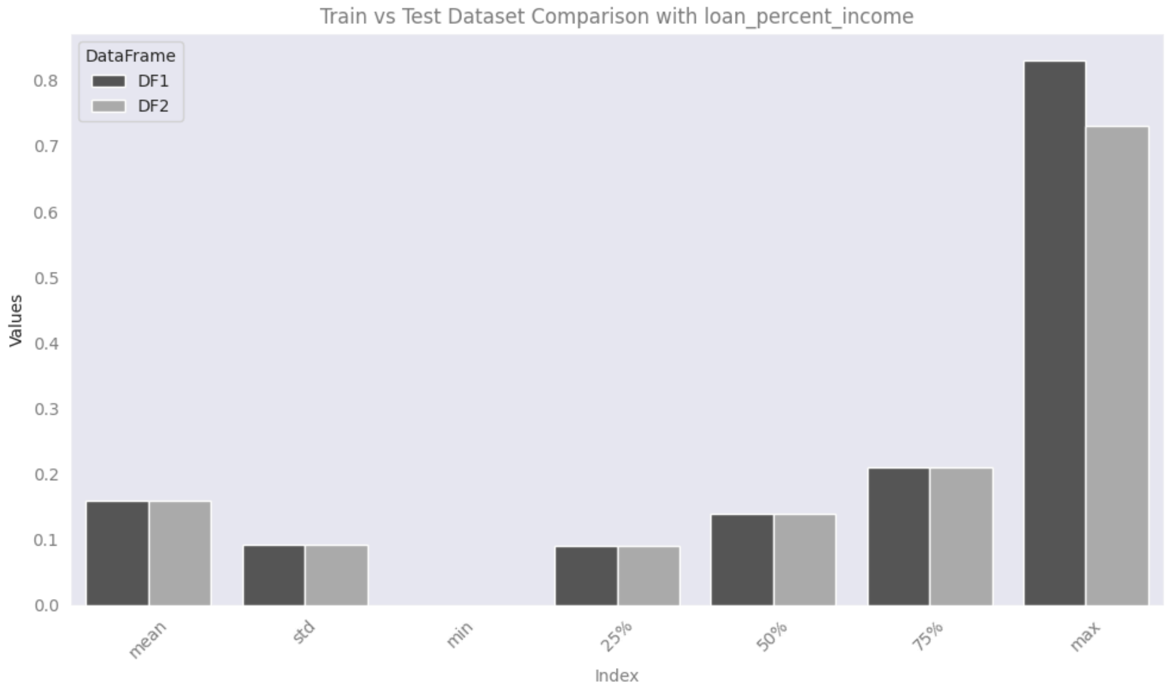
Train vs Test Dataset Comparison with person_income
1e6
DataFrame
DF1
DF2
Values
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
mean
std
min
25%
50%
75%
max
Index


Train vs Test Dataset Comparison with person_emp_length
DataFrame
DF1
DF2
Values
Index
0
20
40
60
80
100
120
mean
std
min
25%
50%
75%
max

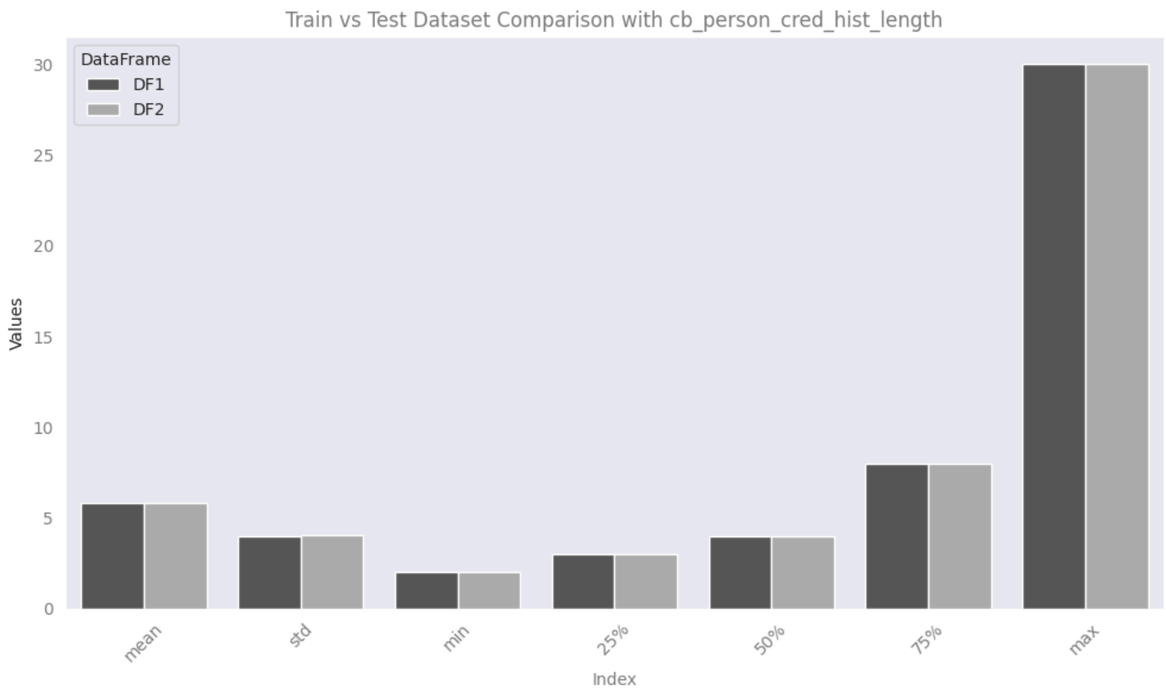

Train vs Test Dataset Comparison with loan_amnt
DataFrame
DF1
DF2
Values
Index
0
5000
10000
15000
20000
25000
30000
35000
mean
std
min
25%
50%
75%
max



Train vs Test Dataset Comparison with loan_int_rate
DataFrame
DF1
DF2
Values
Index
mean
std
min
25%
50%
75%
max
0
5
10
15
20



Train vs Test Dataset Comparison with loan_percent_income
DataFrame
DF1
DF2
Values
Index
mean
std
min
25%
50%
75%
max
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8

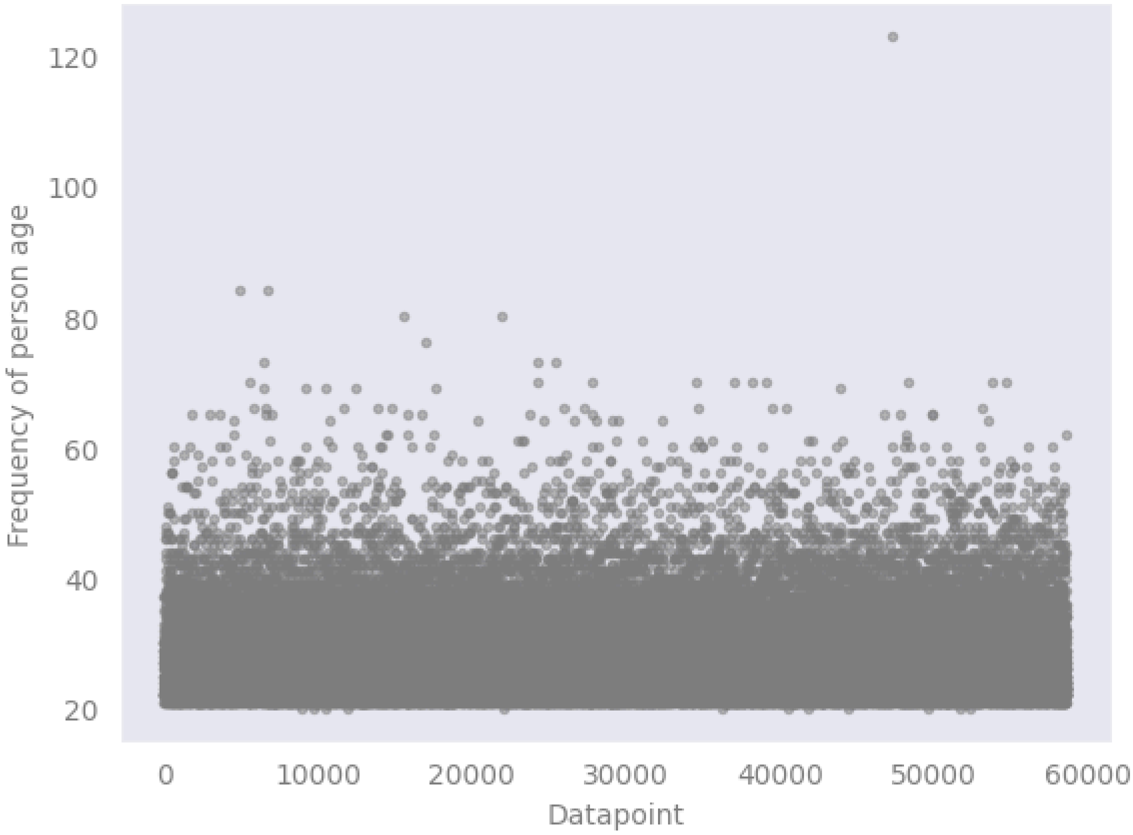


📋 Univariate Analysis

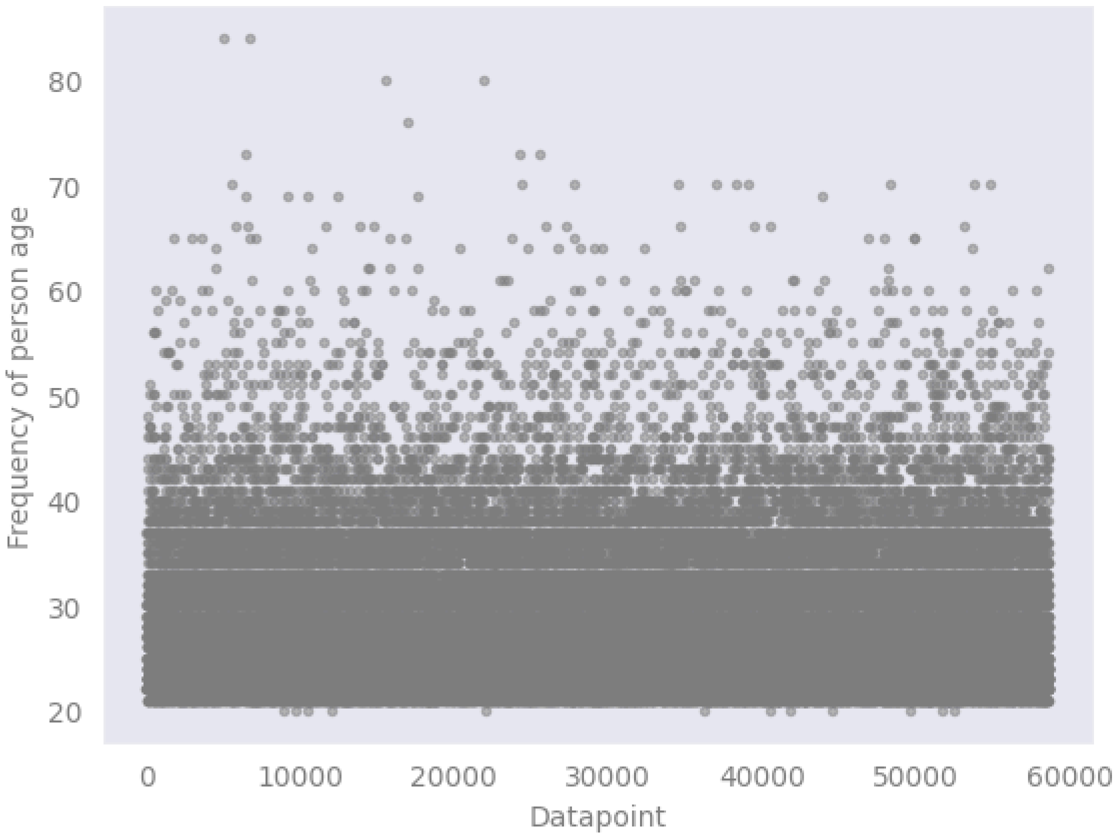
- **Outlier Detection:** Identifying extreme values in the dataset that may skew model performance.
- **Log Transformation:** Applying a logarithmic function to reduce skewness in data distribution.

----> 👥 Person Age Column 📊

In [33]:
```
df1 = outlier_remover(train_df, 'person_age', 0.22, 0.99)
```




```
Q1 = 23.0, Q3 = 49.0, IQR = 26.0
lower_bound = -16.0, upper_bound = 88.0
Scatter after outlier removal
```



Outlier Detection

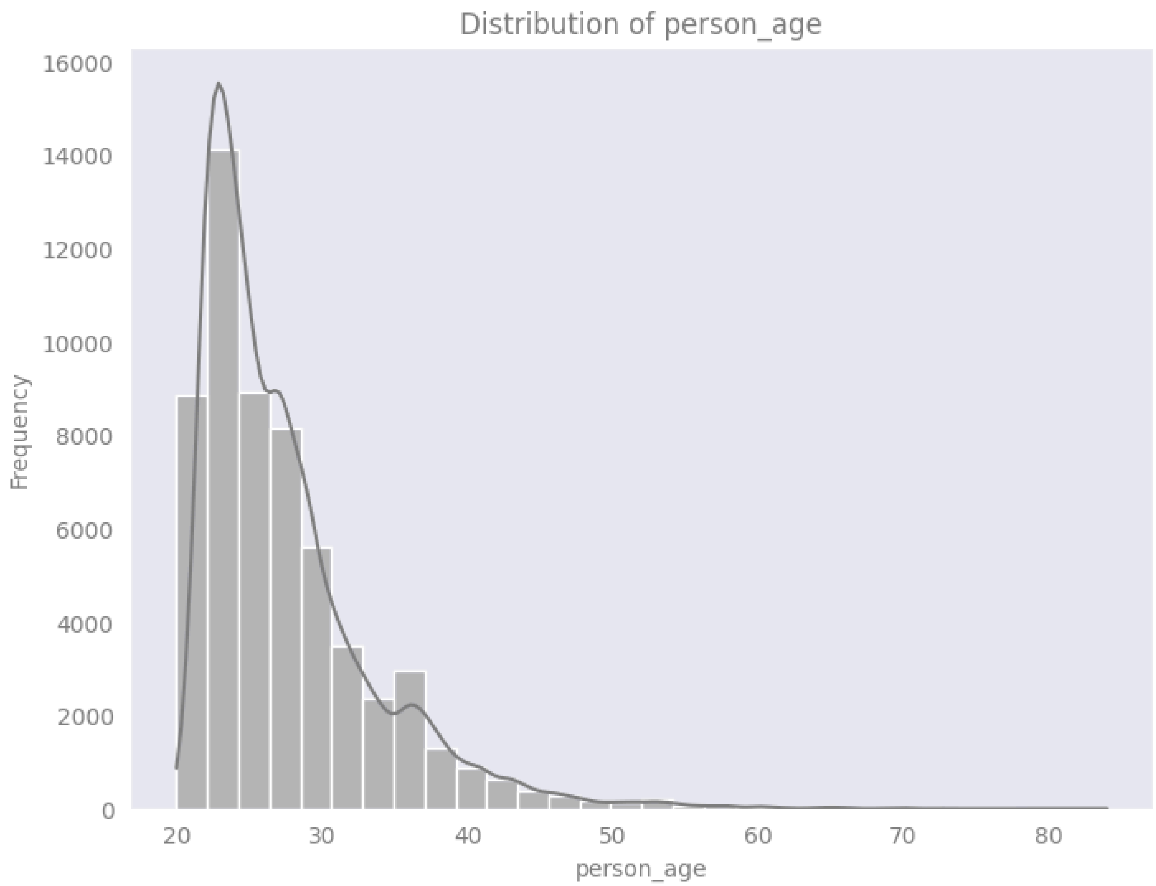
The Interquartile Range (IQR) is a measure of statistical dispersion that describes the spread of the middle 50% of a dataset. It is calculated as the difference between the third quartile (Q3) and the first quartile (Q1):

1. **First Quartile (Q1)**: The 25th percentile, meaning 25% of the data points fall below this value.
2. **Third Quartile (Q3)**: The 75th percentile, meaning 75% of the data points fall below this value.
3. **IQR Formula**:
   [\text{IQR} = Q3 - Q1]

Purpose:

- IQR is used to identify outliers, with values falling below (Q1 - 1.5 \times \text{IQR}) or above (Q3 + 1.5 \times \text{IQR}) considered as outliers.

In [34]:
```
bar_plotter(df1, 'person_age')
```



Right skewed data handling

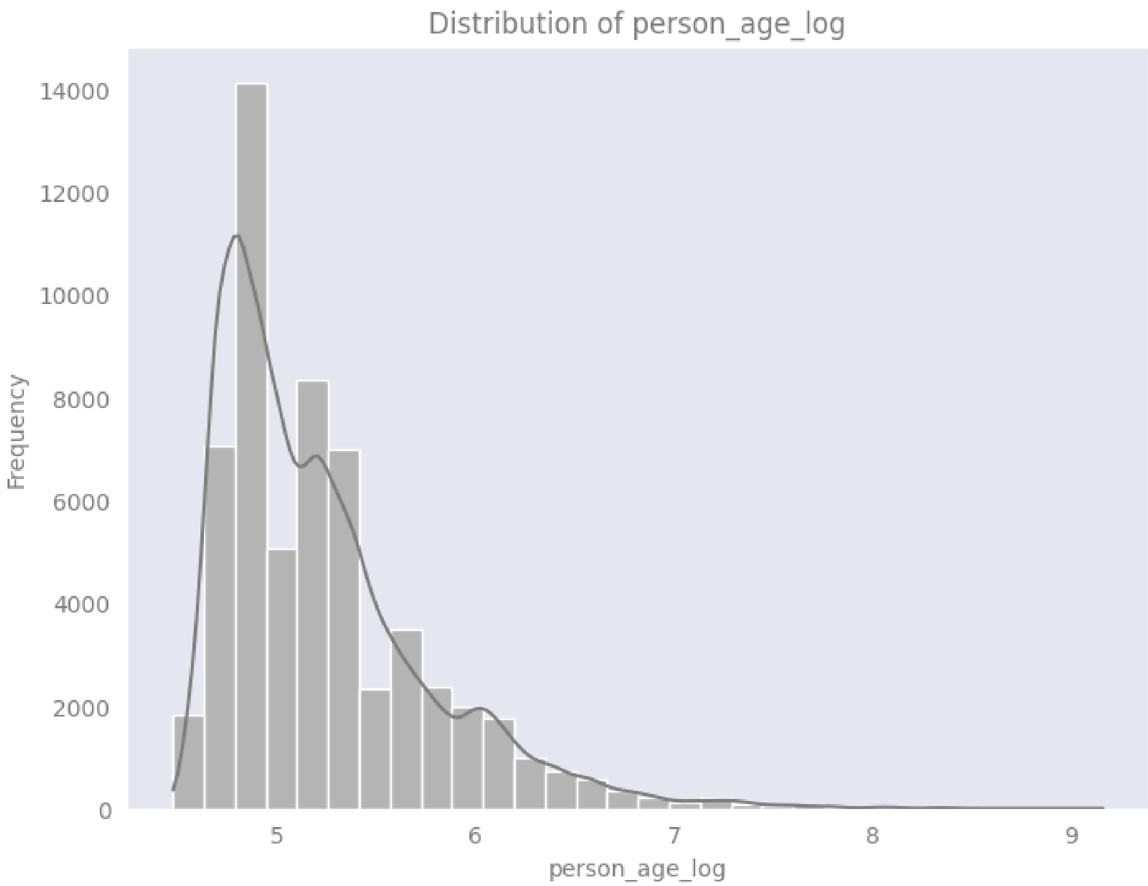
To handle a right-skewed histogram, you can apply the following techniques:

1. **Log Transformation**: Apply `log(x)` to compress larger values and stretch smaller ones.
2. **Square Root Transformation**: Use `sqrt(x)` to reduce skewness.
3. **Reciprocal Transformation**: Apply `1/x` to handle extreme skewness.
4. **Power Transformation (Box-Cox)**: Use `scipy.stats.boxcox` to normalize the data.

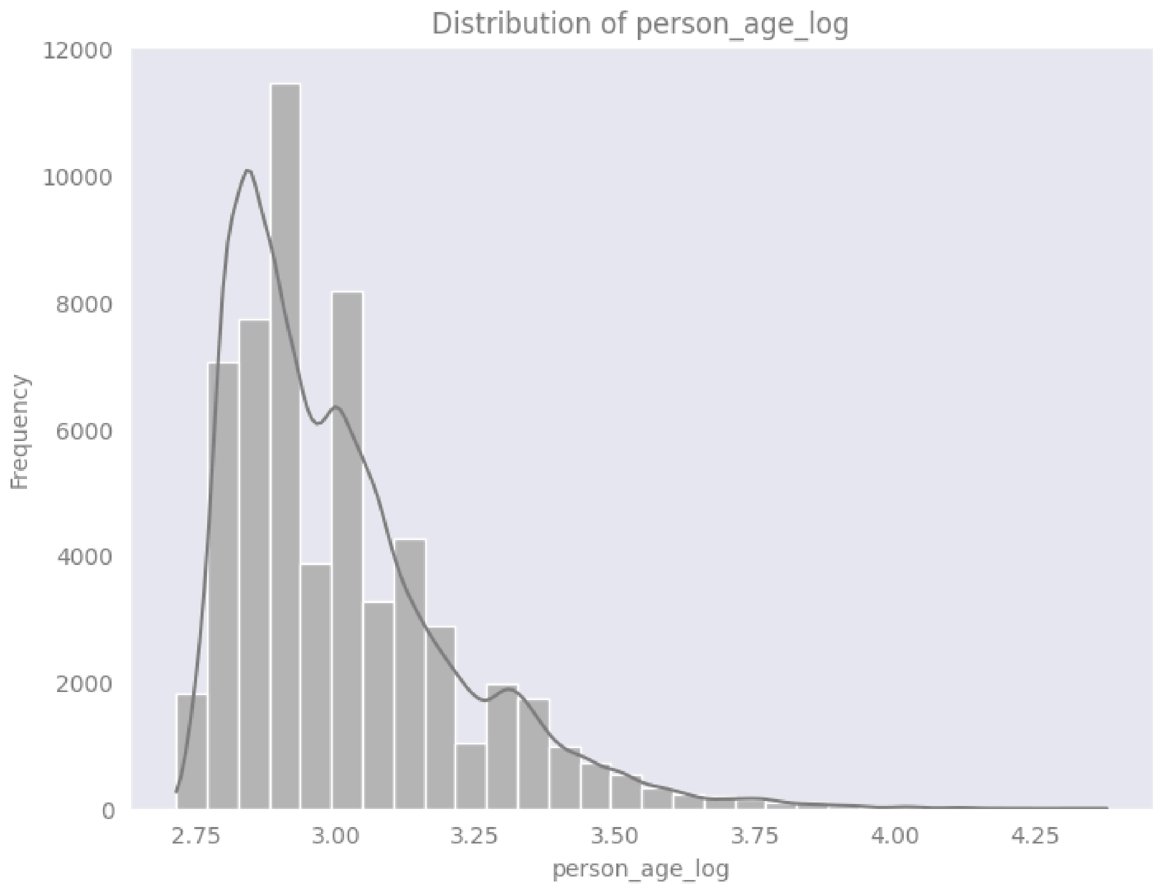
5. **Binning**: Group data into intervals to reduce skewness.

These techniques help in making the distribution more symmetric for statistical analysis.

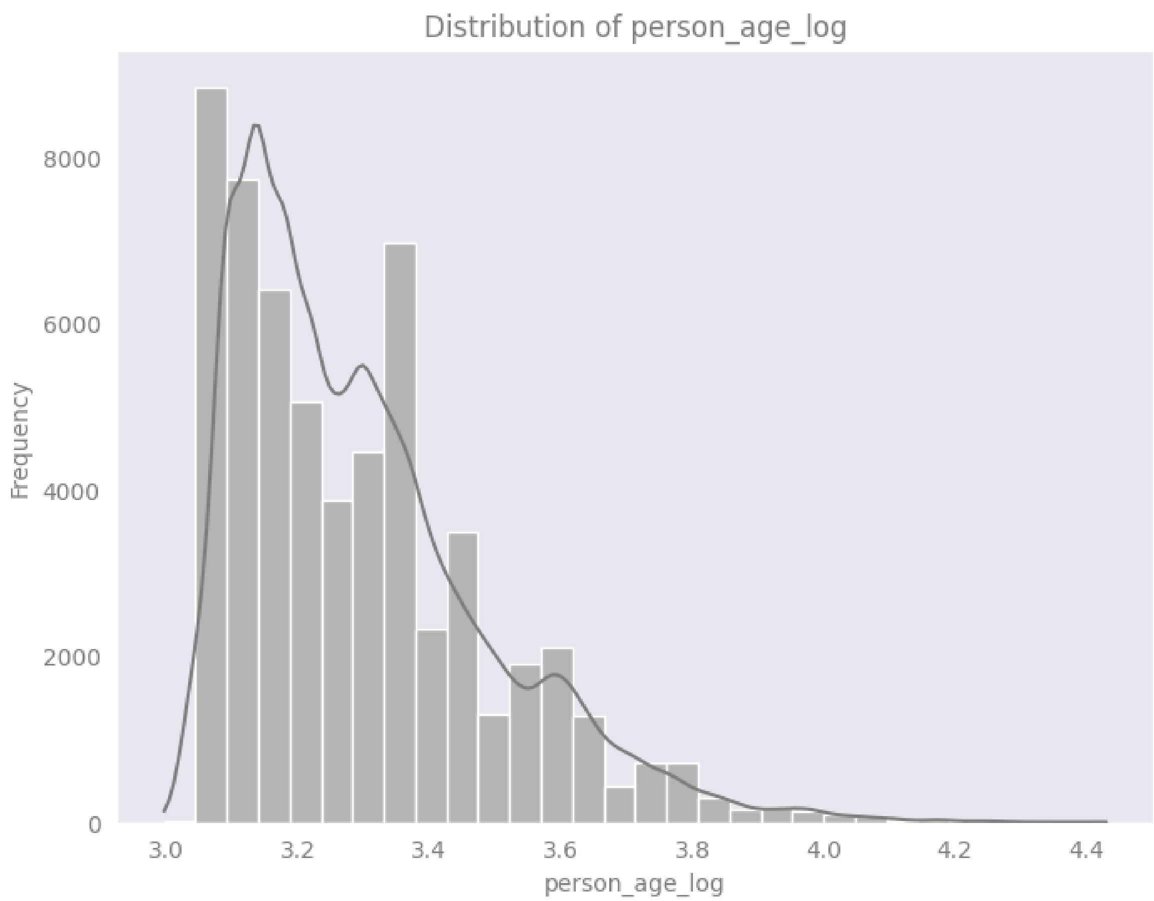
In [35]:
```
# square root
df1.loc[:,'person_age_log'] = df1['person_age'].apply(lambda x: np.sqrt(x))
bar_plotter(df=df1, column_name='person_age_log')
```



In [36]:
```
# cube root
df1.loc[:,'person_age_log'] = df1['person_age'].apply(lambda x: x**(1/3))
bar_plotter(df=df1, column_name='person_age_log')
```

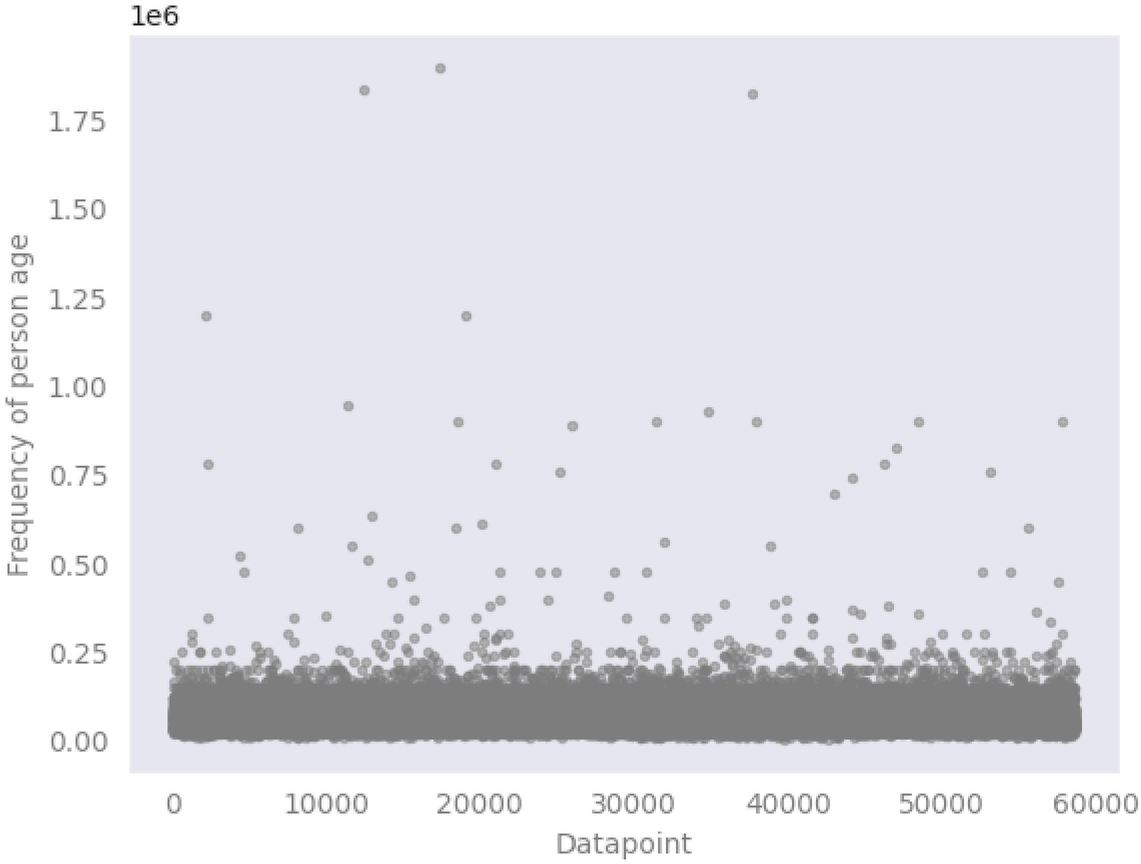


In [37]:
```
# log transformation"
df1.loc[:,'person_age_log'] = df1['person_age'].apply(lambda x: np.log(x))
bar_plotter(df=df1, column_name='person_age_log')
```

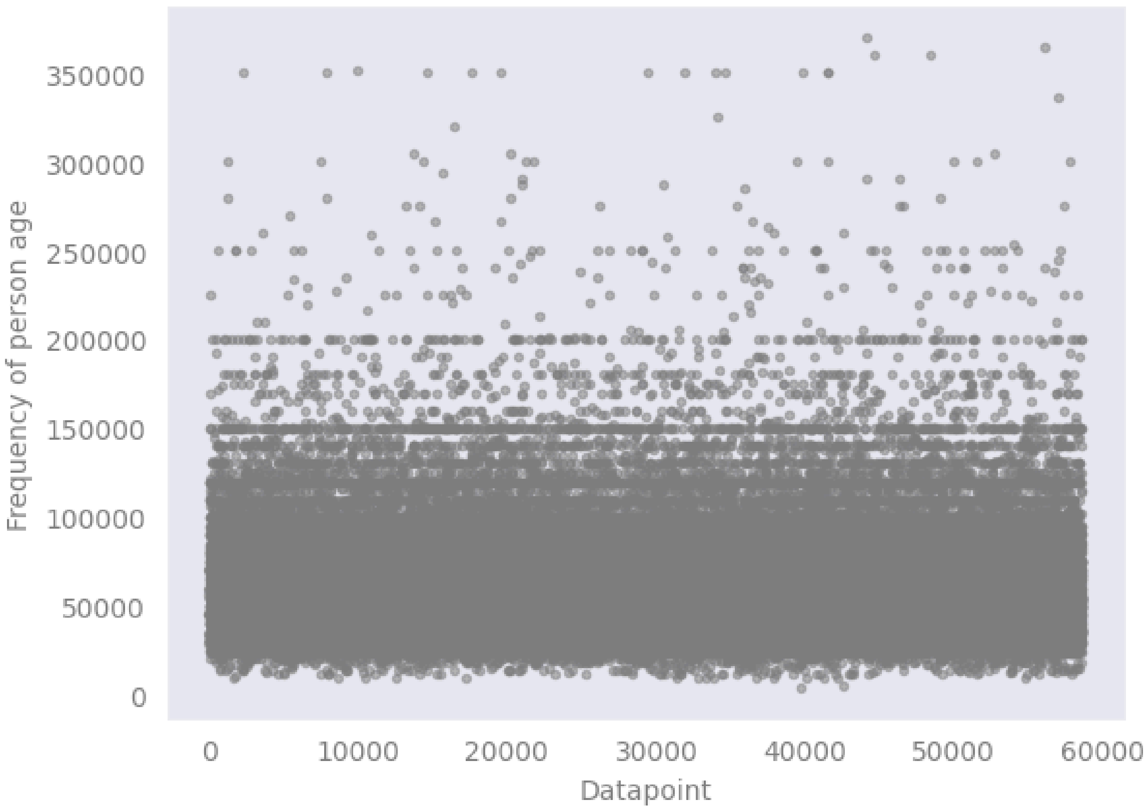


----> 👥 *Person Income Column* 📊

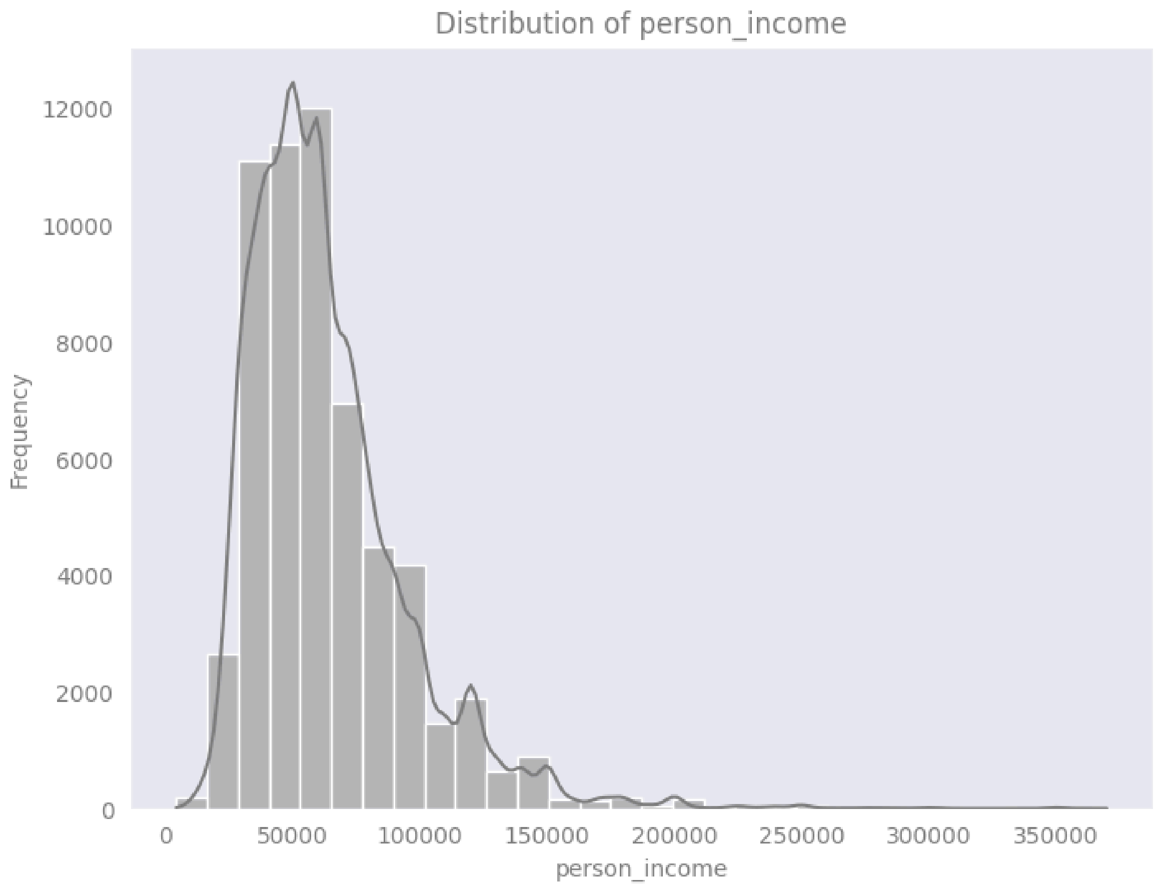
In [38]:
```
df2 = outlier_remover(df1, 'person_income')
```



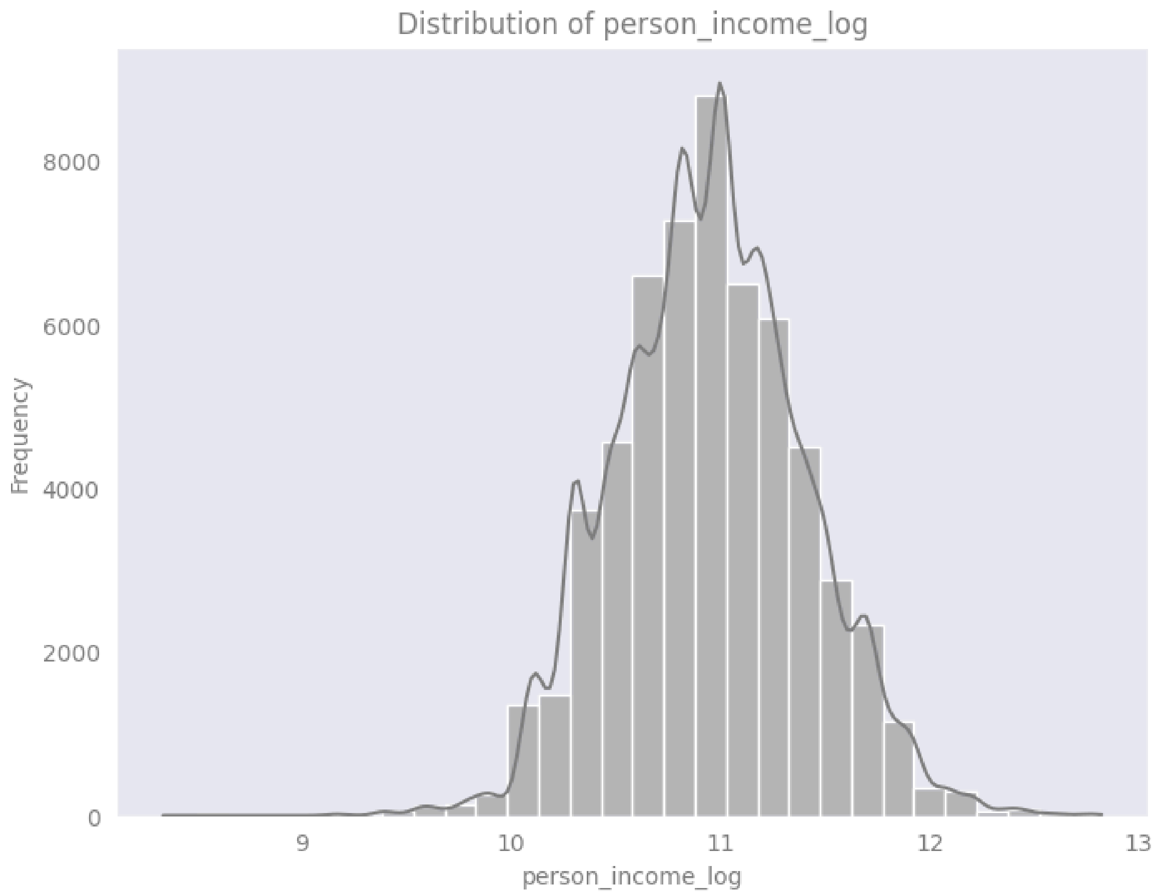

```
Q1 = 40000.0, Q3 = 175000.0, IQR = 135000.0
lower_bound = -162500.0, upper_bound = 377500.0
Scatter after outlier removal
```



In [39]:
```
bar_plotter(df2, 'person_income')
```



In [40]:
```
# log transformation
df2['person_income_log'] = df2['person_income'].apply(lambda x: np.log(x))
bar_plotter(df2, 'person_income_log')
```

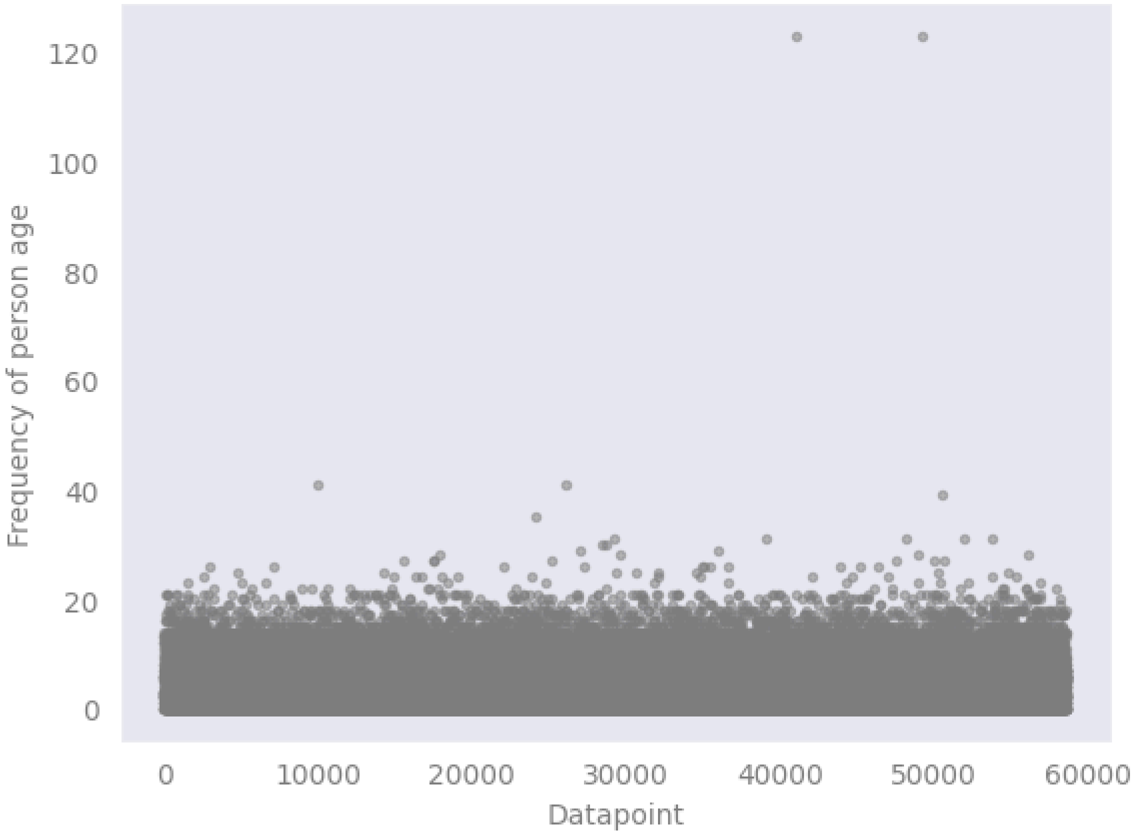


----> person_emp_length column

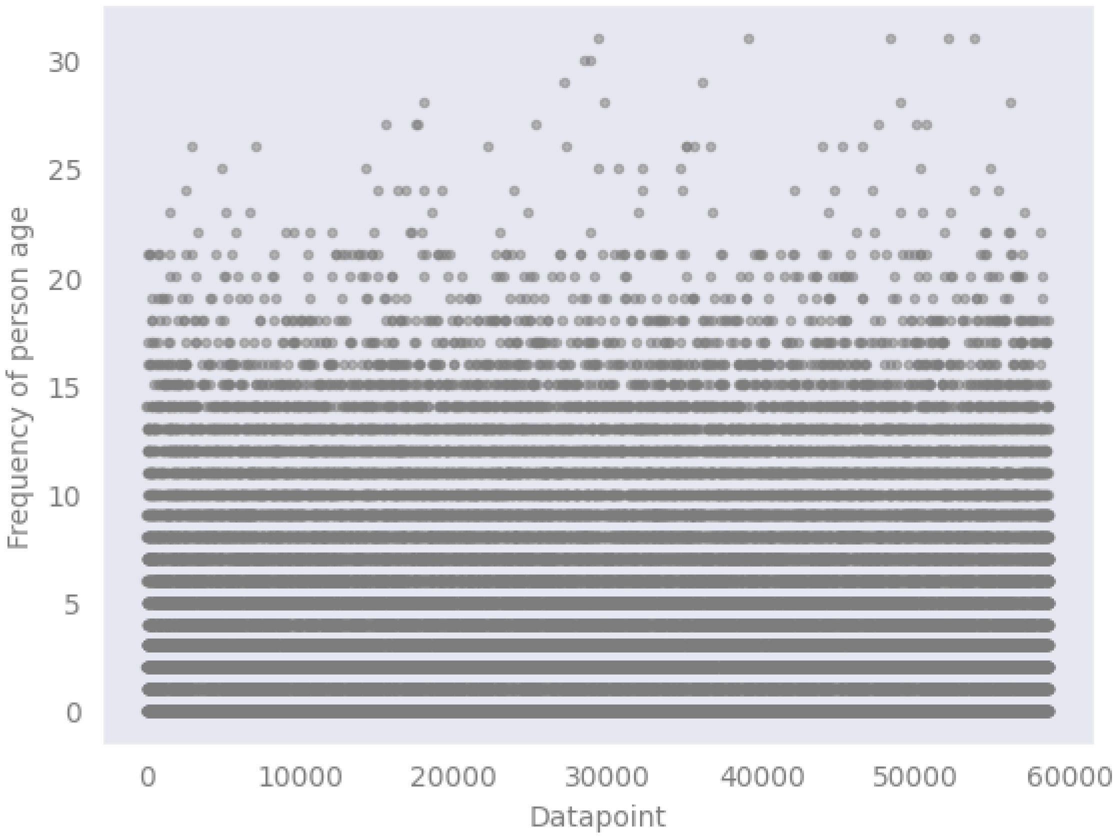
Data Transformation Techniques

- **Outlier Detection:** Identifying extreme values in the dataset that may skew model performance.
- **Log Transformation:** Applying a logarithmic function to reduce skewness in data distribution.

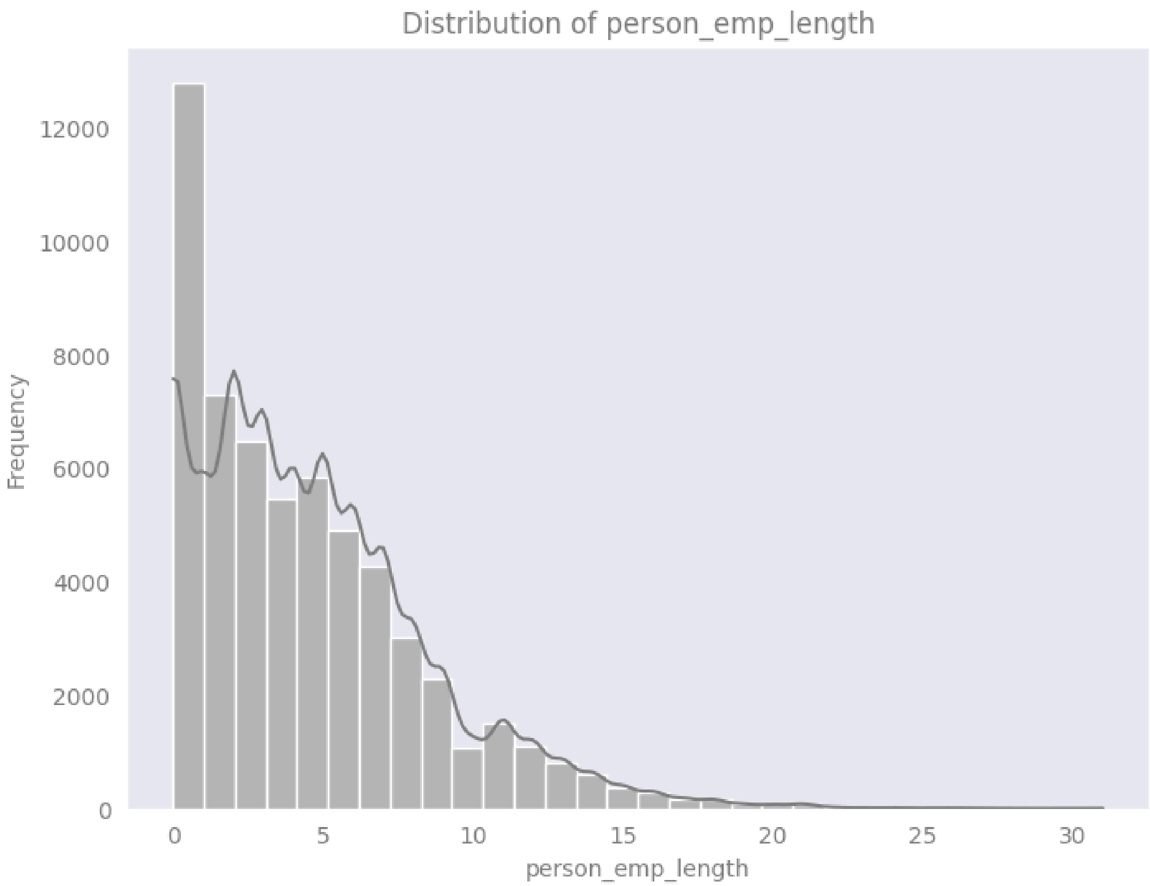
In [41]:
```
df3 = outlier_remover(df1, 'person_emp_length', 0.25, 0.98)
```



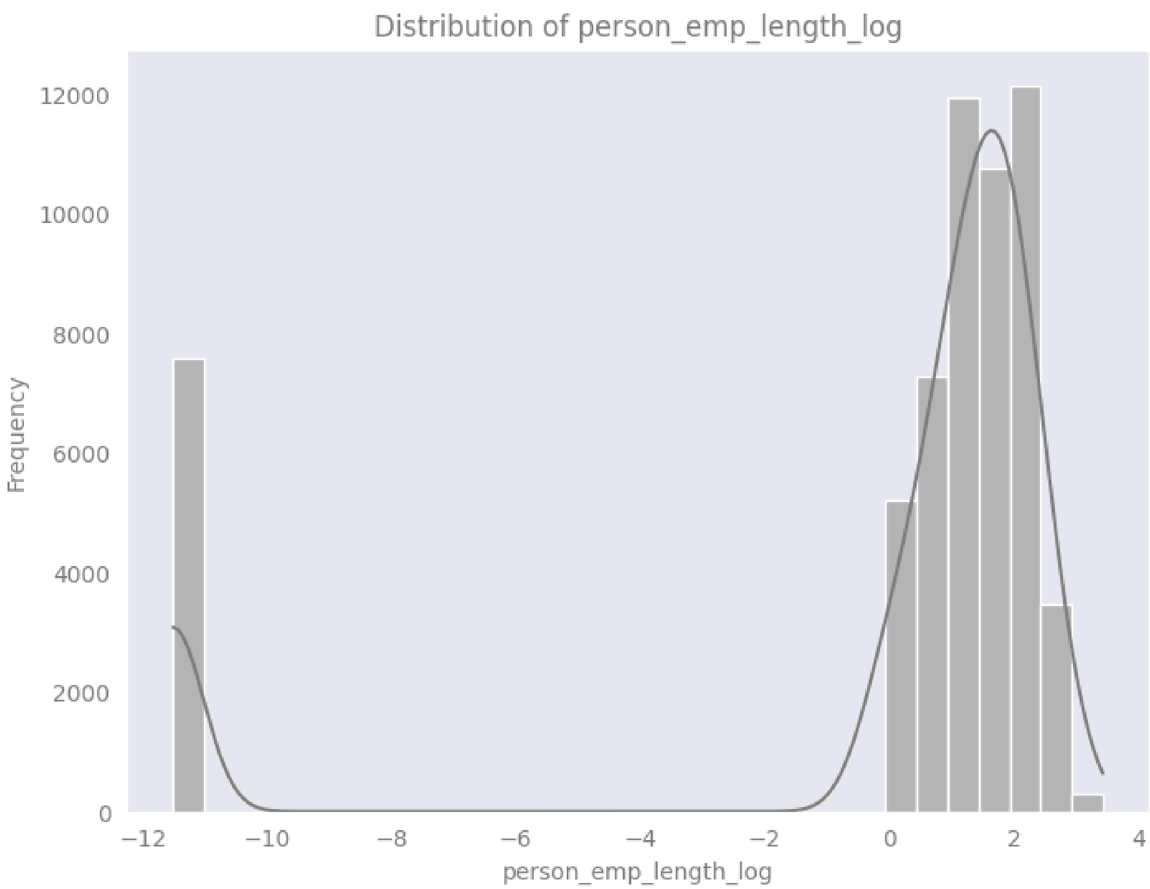

```
Q1 = 2.0, Q3 = 15.0, IQR = 13.0
lower_bound = -17.5, upper_bound = 34.5
Scatter after outlier removal
```



In [42]:
```
bar_plotter(df3, 'person_emp_length')
```

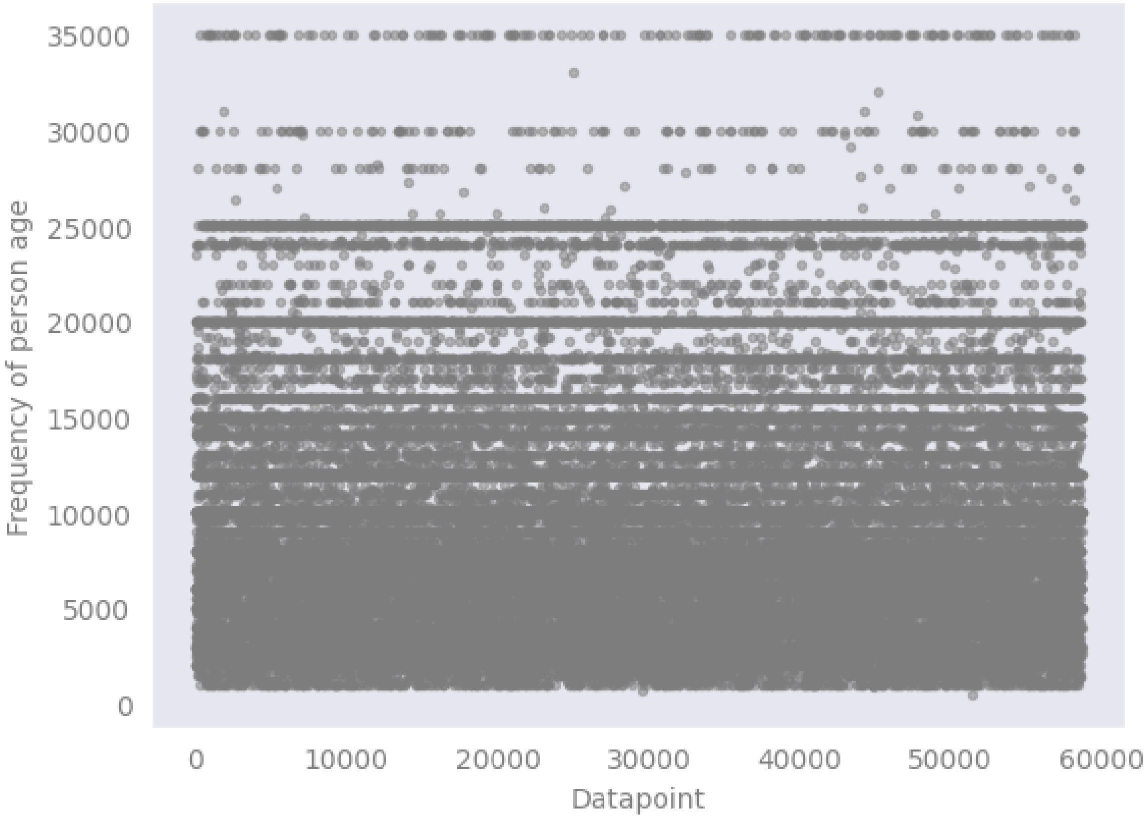


In [43]:
```
# log transformation
df3['person_emp_length_log'] = df3['person_emp_length'].apply(lambda x: np.log(x
bar_plotter(df3, 'person_emp_length_log')
```

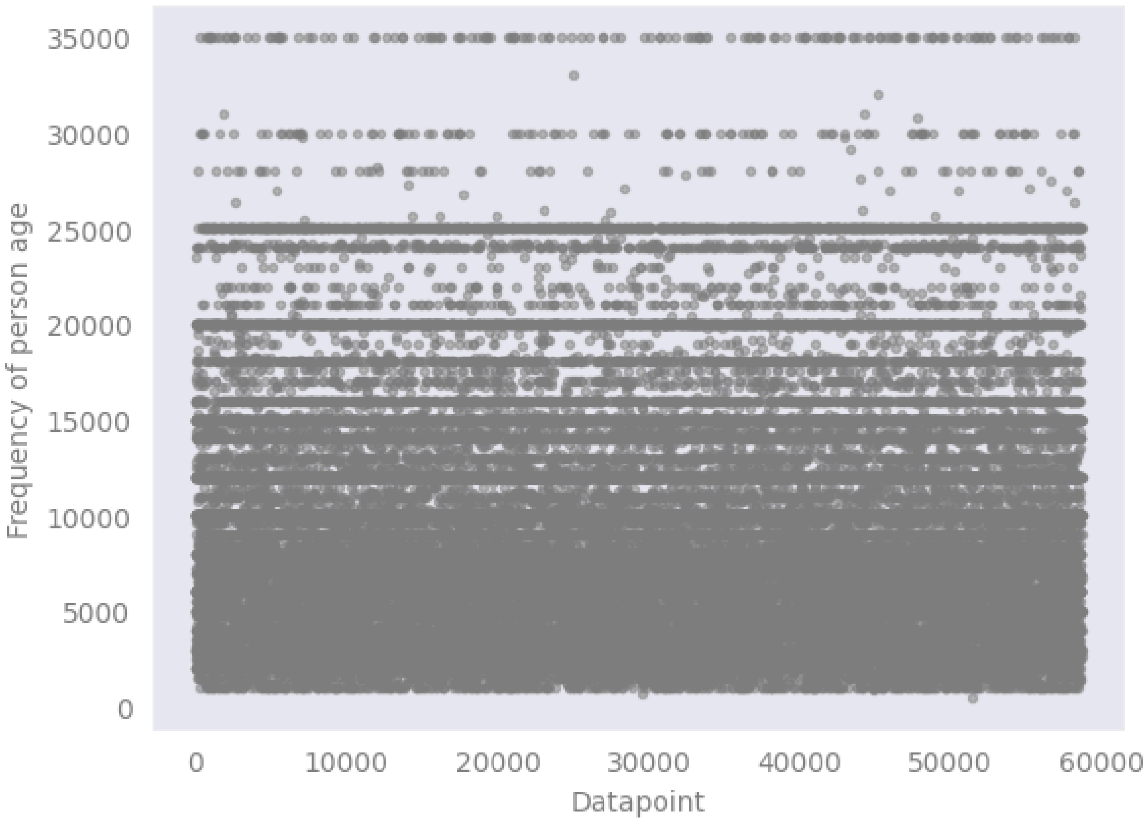


----> loan amount column

In [44]:
```
outlier_remover(df3, 'loan_amnt', 0.25, 0.99)
```




```
Q1 = 5000.0, Q3 = 25000.0, IQR = 20000.0
lower_bound = -25000.0, upper_bound = 55000.0
Scatter after outlier removal
```

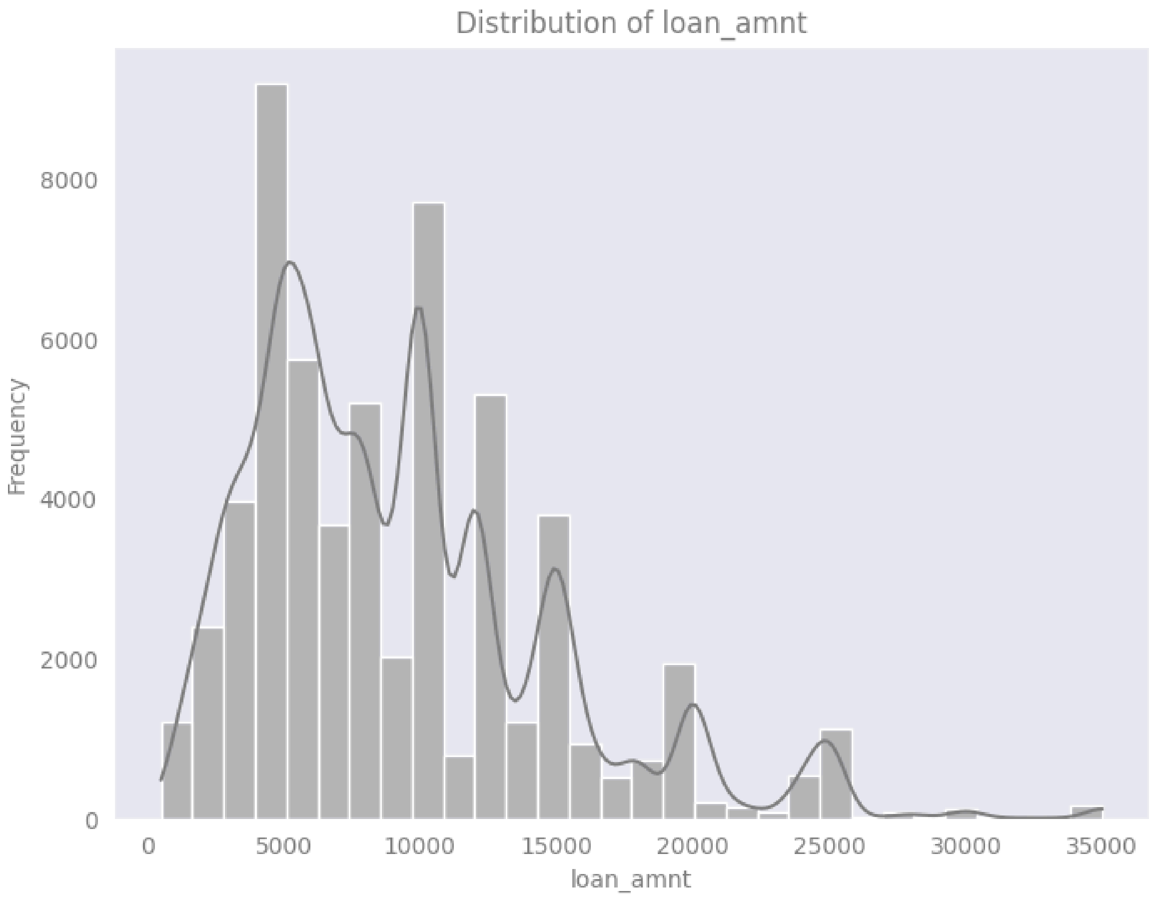


Out[44]:

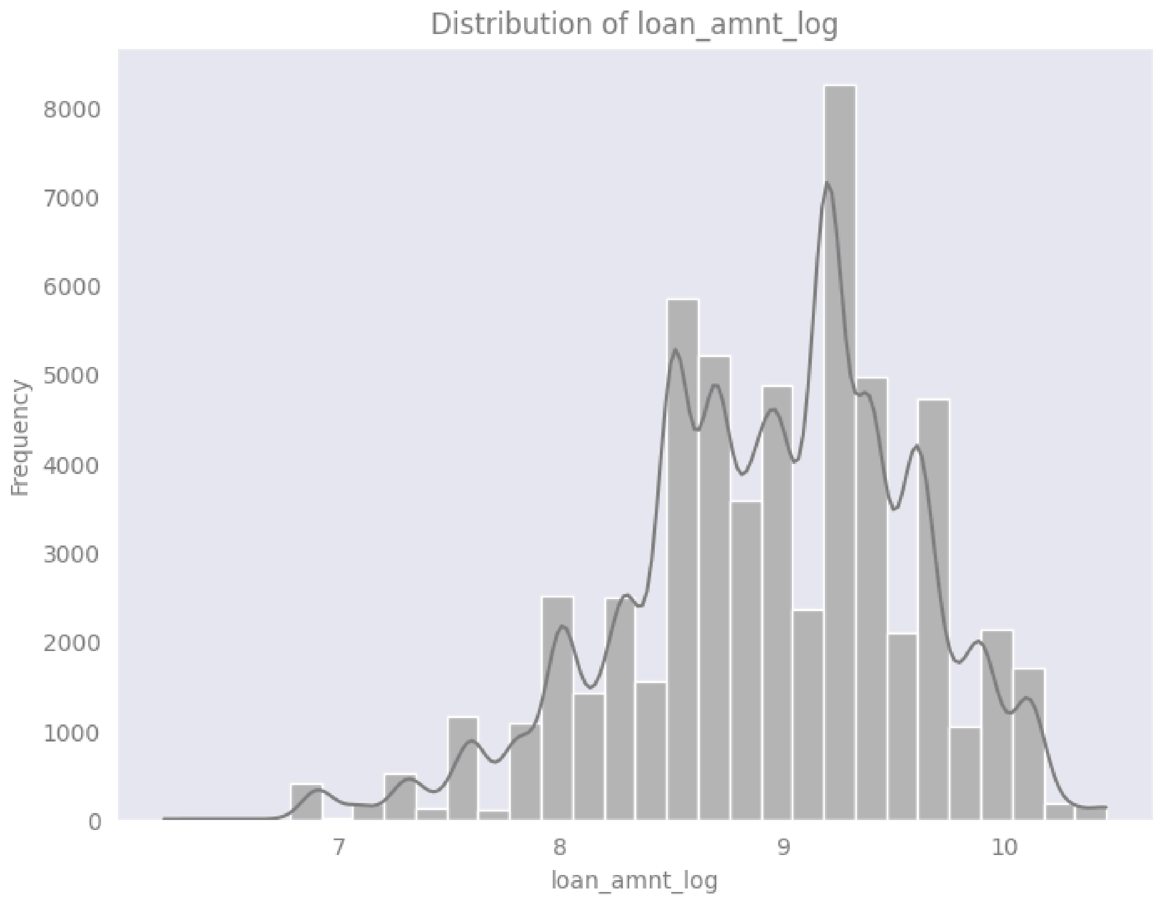
	id	person_age	person_income	person_home_ownership	person_emp_l
0	0.00001	37	35000	RENT	0
1	1.00000	22	56000	OWN	6
2	2.00000	29	28800	OWN	8
3	3.00000	30	70000	RENT	14
4	4.00000	22	60000	RENT	2
...	...	...	...	...	
58640	58640.00000	34	120000	MORTGAGE	5
58641	58641.00000	28	28800	RENT	0
58642	58642.00000	23	44000	RENT	7
58643	58643.00000	22	30000	RENT	2
58644	58644.00000	31	75000	MORTGAGE	2

58638 rows × 15 columns

In [45]:
```
bar_plotter(df3, 'loan_amnt')
```

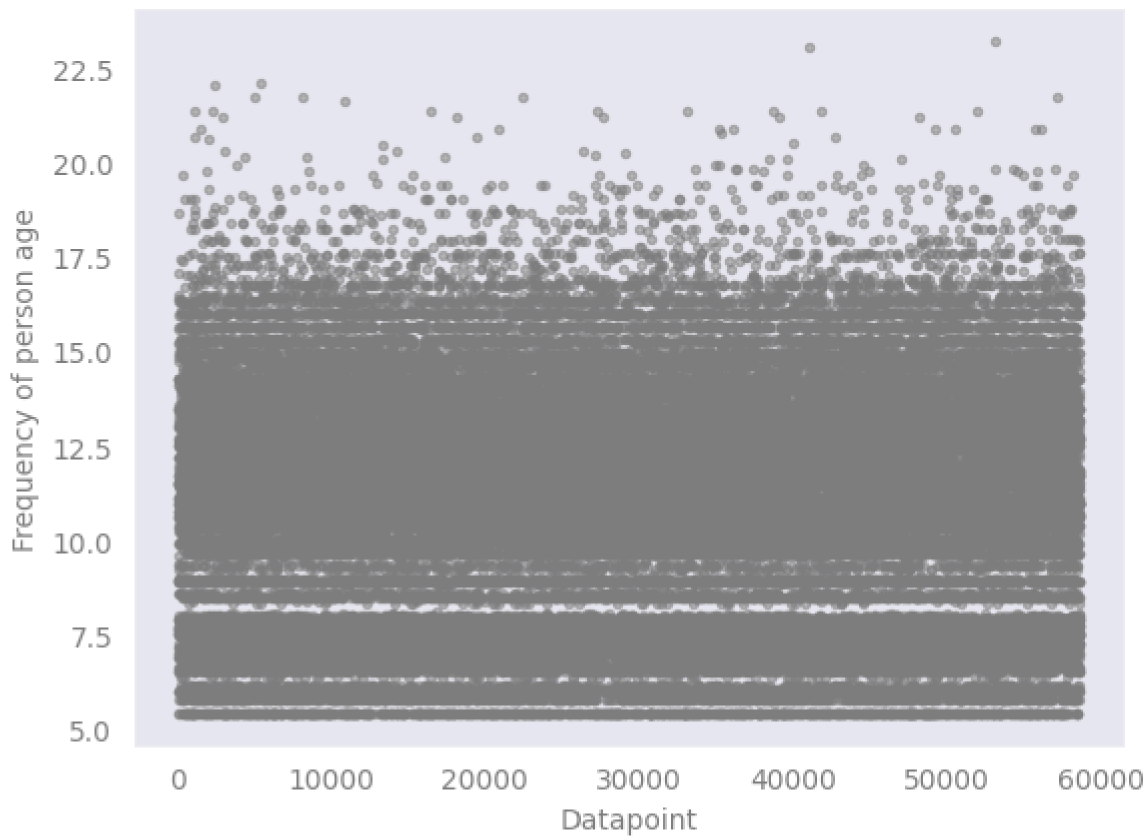


In [46]:
```
# log transformation
df3['loan_amnt_log'] = df3['loan_amnt'].apply(lambda x: np.log(x))
bar_plotter(df3, 'loan_amnt_log')
```

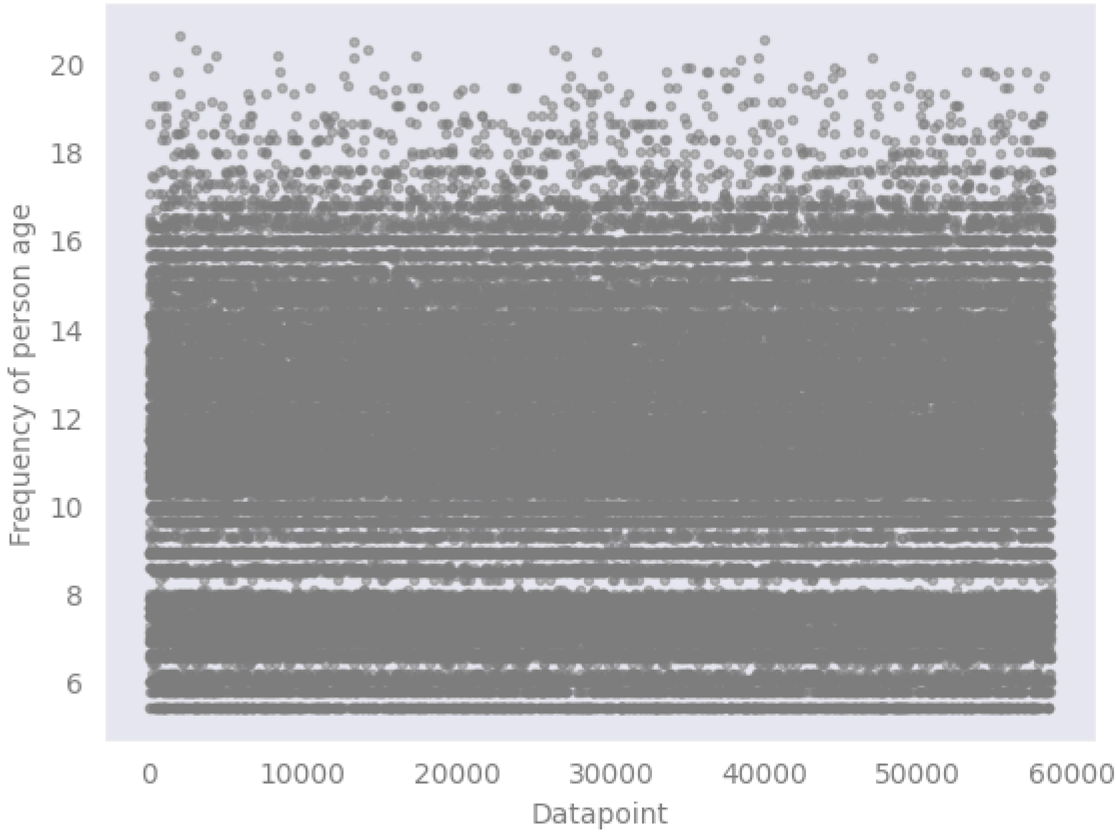


----> *loan_int_rate column*

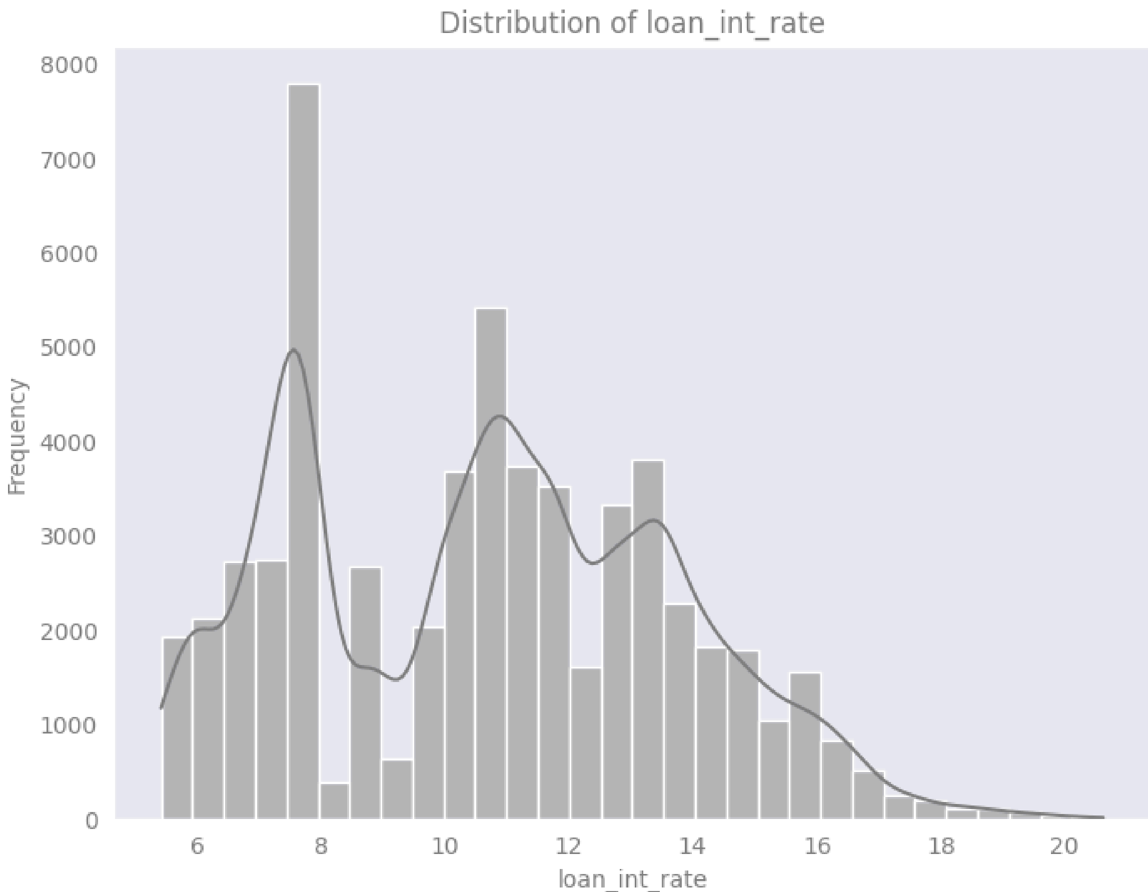
In [47]:
```
df4 = outlier_remover(df3, 'loan_int_rate', 0.25, 0.75)
```



```
Q1 = 7.88, Q3 = 12.99, IQR = 5.11
lower_bound = 0.21499999999999897, upper_bound = 20.655
Scatter after outlier removal
```

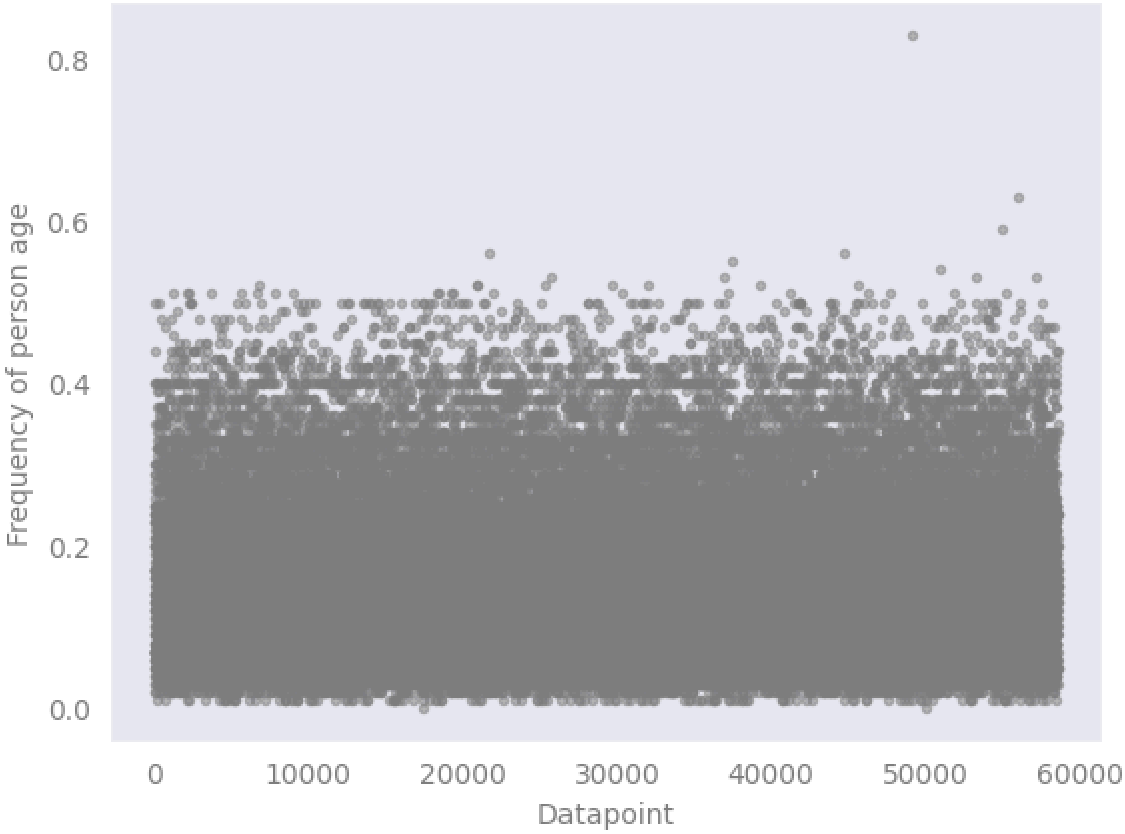


In [48]:
```
bar_plotter(df4, 'loan_int_rate')
```

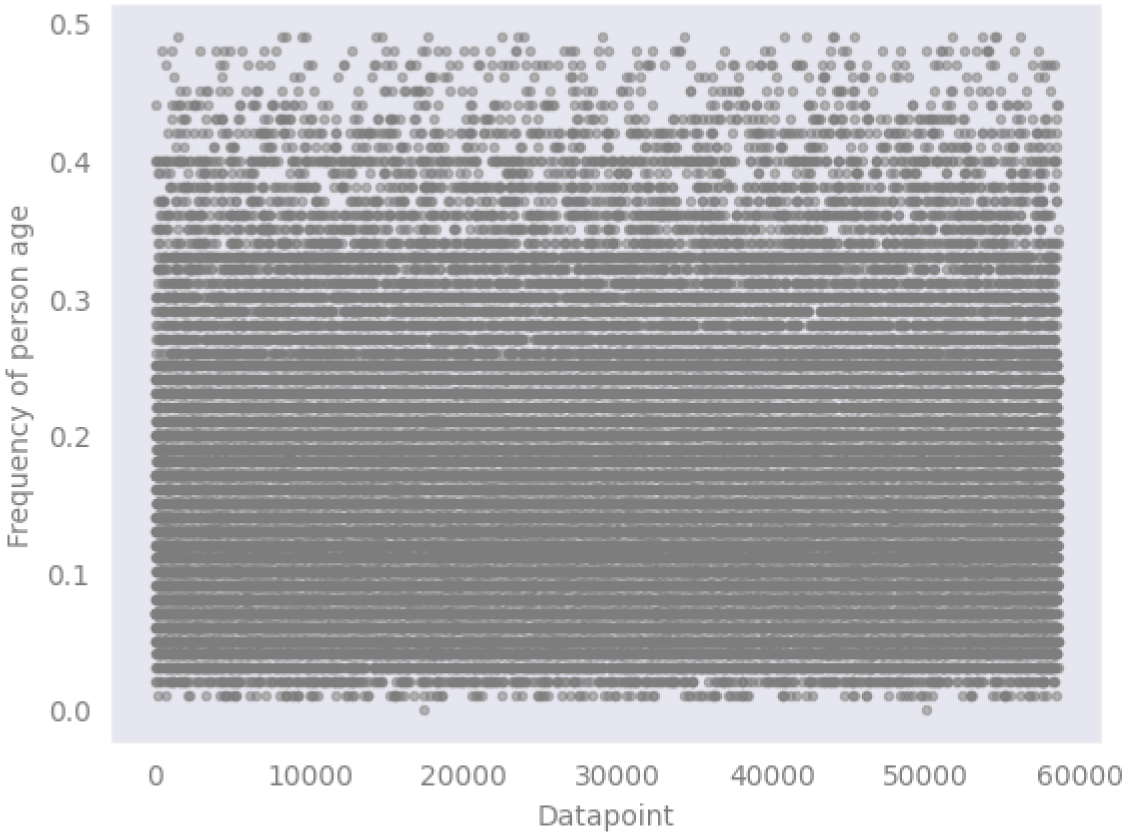


----> loan_percent_income column

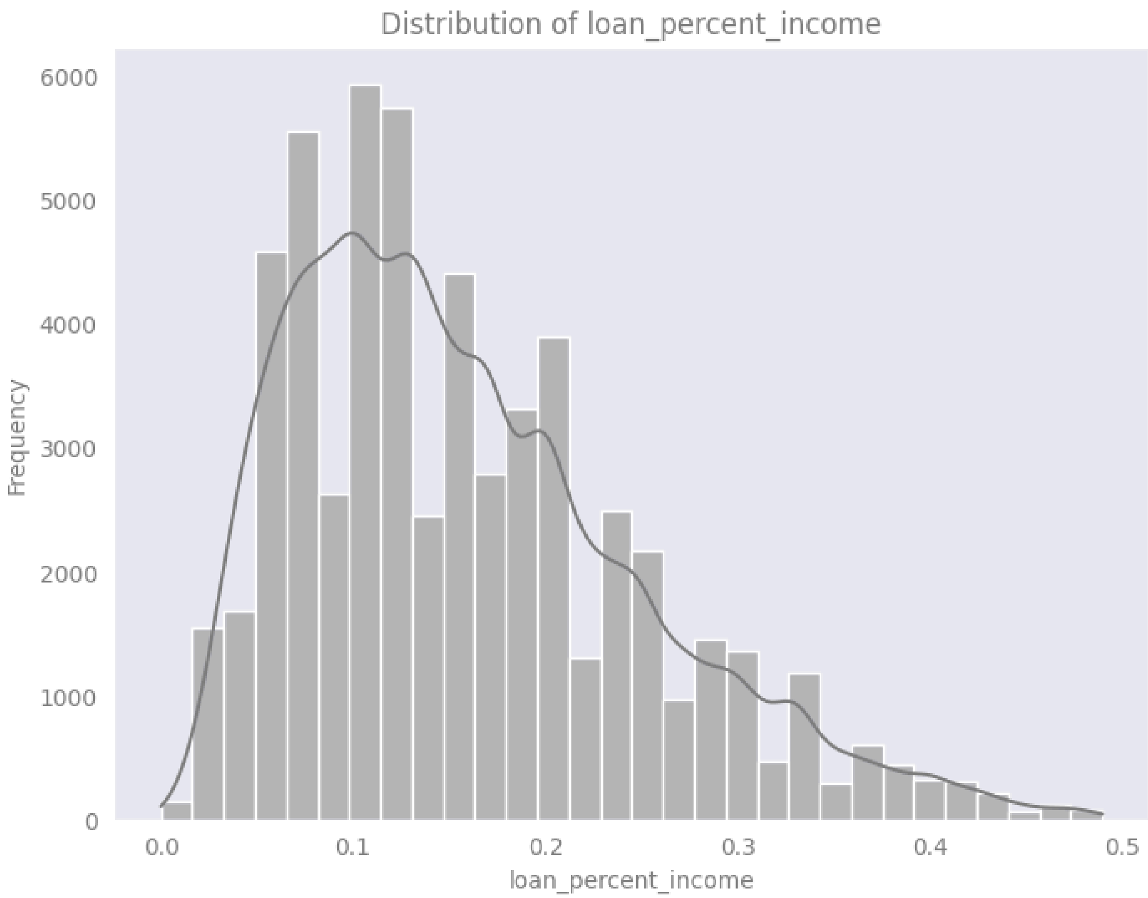
In [49]:
```
df5 = outlier_remover(df4, 'loan_percent_income', 0.25, 0.85)
```




```
Q1 = 0.09, Q3 = 0.25, IQR = 0.16
lower_bound = -0.15, upper_bound = 0.49
Scatter after outlier removal
```



In [50]:
```python
bar_plotter(df5, 'loan_percent_income')
```

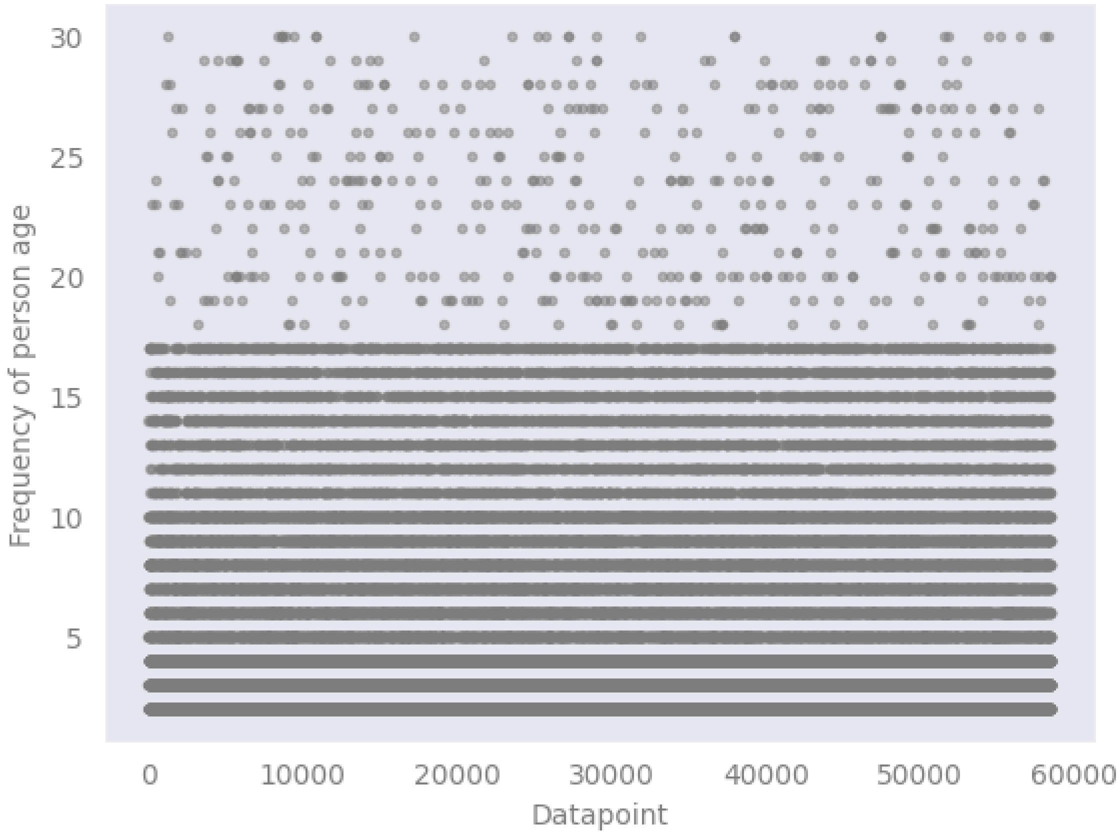


----> cb_person_cred_hist_length column

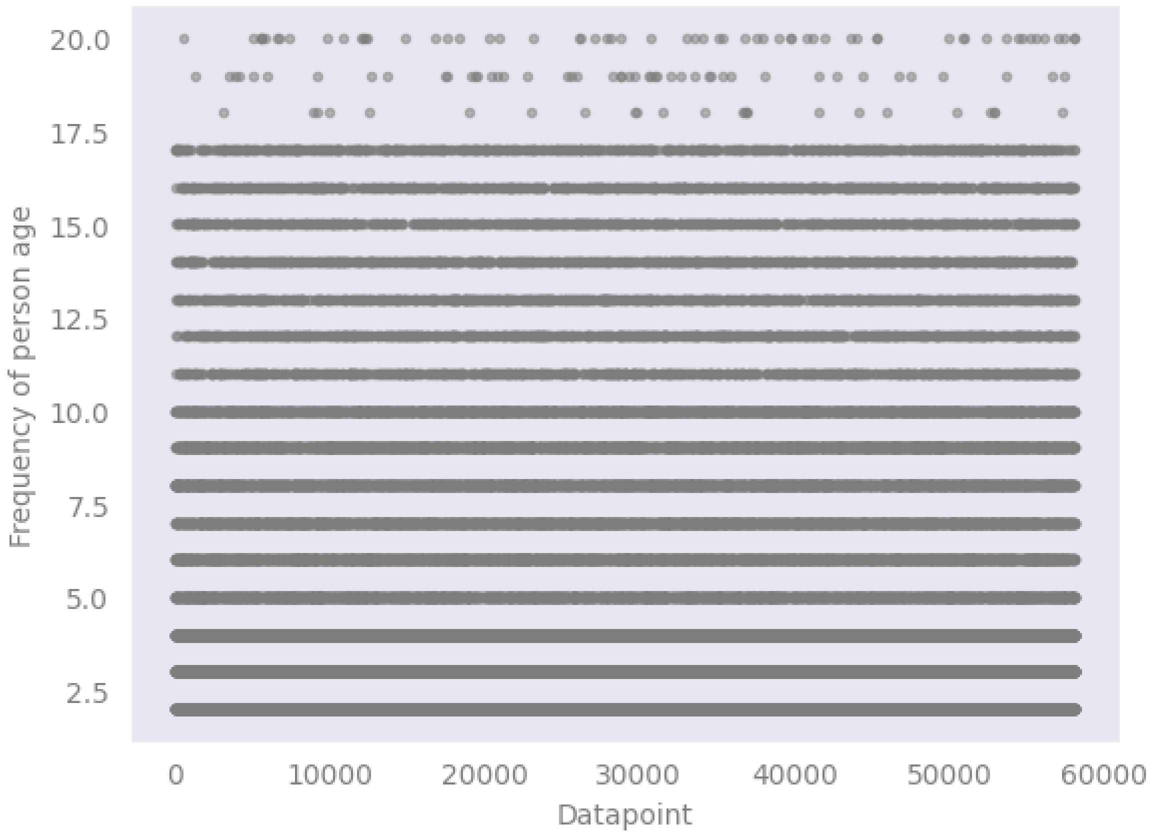
Data Transformation Techniques

- **Outlier Detection:** Identifying extreme values in the dataset that may skew model performance.

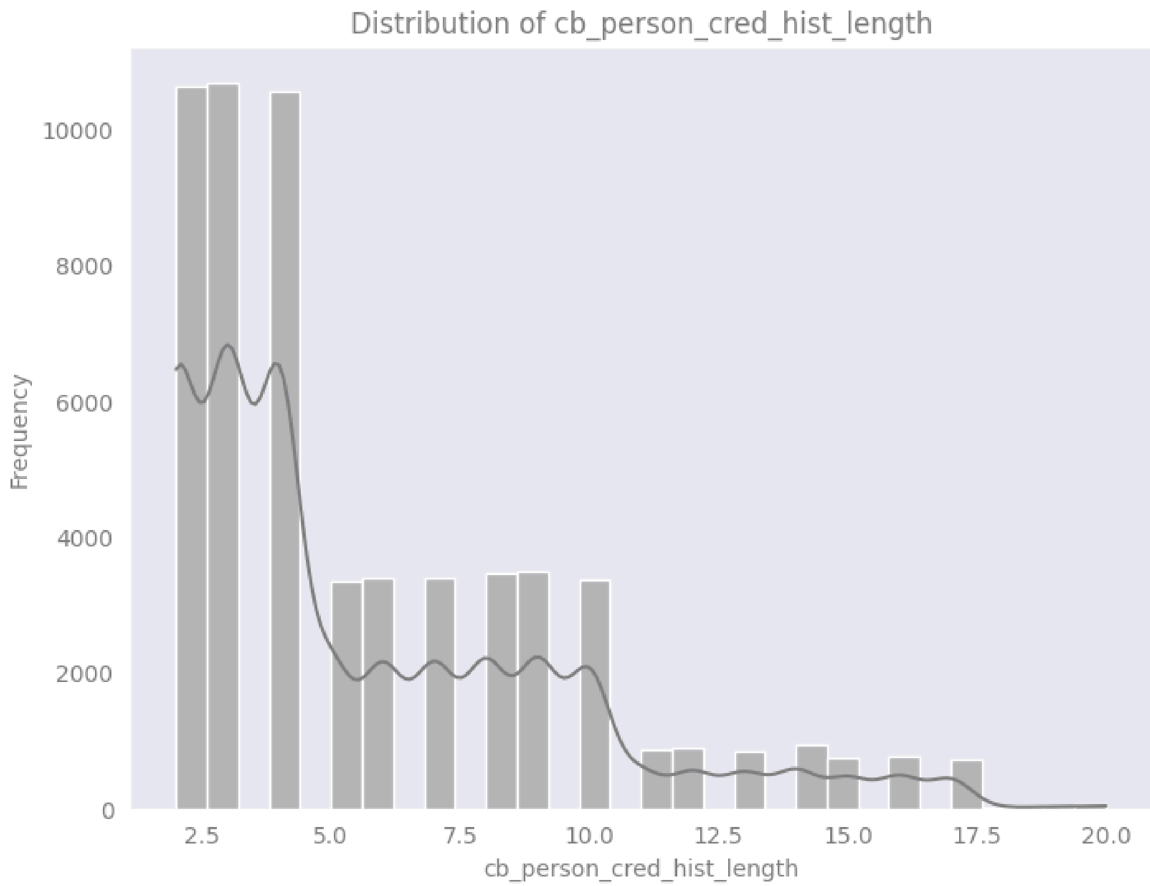
In [51]:
```python
df6 = outlier_remover(df5, 'cb_person_cred_hist_length', 0.25, 0.85)
```




```
Q1 = 3.0, Q3 = 10.0, IQR = 7.0
lower_bound = -7.5, upper_bound = 20.5
Scatter after outlier removal
```



In [52]:
```
bar_plotter(df6, 'cb_person_cred_hist_length')
```



In [53]:
```
original_df_train.shape[0] - df6.shape[0]
```

Out[53]:
```
513
```

📋 Categorical Column [Label Encoding]

- 1. Label Encoding

In [54]:
```
cat_columns = ['loan_intent','loan_grade','cb_person_default_on_file','person_hc

for col in cat_columns:
    print(f"{col} Unique values = ", df6[col].unique())
```

```
loan_intent Unique values =  ['EDUCATION' 'MEDICAL' 'PERSONAL' 'VENTURE' 'DEBTCON
SOLIDATION'
 'HOMEIMPROVEMENT']
loan_grade Unique values =  ['B' 'C' 'A' 'D' 'E' 'F' 'G']
cb_person_default_on_file Unique values =  ['N' 'Y']
person_home_ownership Unique values =  ['RENT' 'OWN' 'MORTGAGE' 'OTHER']
```

In [55]:
```
from sklearn.preprocessing import LabelEncoder

encoder = LabelEncoder()

for col in cat_columns:
```

```
    df6.loc[:,col+"_en"] = encoder.fit_transform(df6[col])
df6.head()
```

Out[55]:

	id	person_age	person_income	person_home_ownership	person_emp_length	l
0	0.00001	37	35000	RENT	0.00001	E
1	1.00000	22	56000	OWN	6.00000	
2	2.00000	29	28800	OWN	8.00000	
3	3.00000	30	70000	RENT	14.00000	
4	4.00000	22	60000	RENT	2.00000	

In [56]:

```
updated_columns = ['person_age_log','person_emp_length_log','loan_amnt_log','loa
original_columns = ['_'.join(val.split('_')[:-1]) for val in updated_columns]

# removing source columns
df7 = df6.drop(original_columns, axis='columns')
df7.head()
```

Out[56]:

	id	person_income	loan_int_rate	loan_percent_income	cb_person_cred_hist_leng
0	0.00001	35000	11.49	0.17	
1	1.00000	56000	13.35	0.07	
2	2.00000	28800	8.90	0.21	
3	3.00000	70000	11.11	0.17	
4	4.00000	60000	6.92	0.10	

In [57]:

```
df7['loan_status_up'] = df7['loan_status'].apply(lambda x: int(x))
df8 = df7.copy()

df8['loan_status'] = df8['loan_status_up']

if 'loan_status_up' in df8.columns:
    df8.drop('loan_status_up', axis = 'columns', inplace=True)

df8.head()
```

Out[57]:

	id	person_income	loan_int_rate	loan_percent_income	cb_person_cred_hist_leng
0	0.00001	35000	11.49	0.17	
1	1.00000	56000	13.35	0.07	
2	2.00000	28800	8.90	0.21	
3	3.00000	70000	11.11	0.17	
4	4.00000	60000	6.92	0.10	

In [58]:
```
df8.shape, original_df_train.shape
```

Out[58]: ((58132, 13), (58645, 13))

In [59]:
```
def post_remover(val):
    if '_log' in val:
        val = val.replace('_log','')
    elif "_en" in val:
        val = val.replace('_en','')
    return val

input_columns = [post_remover(val) for val in df8.columns]
input_columns
```

Out[59]:
```
['id',
 'person_income',
 'loan_int_rate',
 'loan_percent_income',
 'cb_person_cred_hist_length',
 'loan_status',
 'person_age',
 'person_emp_length',
 'loan_amnt',
 'loan_intent',
 'loan_grade',
 'cb_person_default_on_file',
 'person_home_ownership']
```

In [60]:
```
for c1,c2 in zip(input_columns, df8.columns):
    if c1 not in c2:
        print(c1, c2)
        print("Not matched")
```

In [61]:
```
df8.columns = input_columns
df8.head()
```

Out[61]:

	id	person_income	loan_int_rate	loan_percent_income	cb_person_cred_hist_leng
0	0.00001	35000	11.49	0.17	
1	1.00000	56000	13.35	0.07	
2	2.00000	28800	8.90	0.21	
3	3.00000	70000	11.11	0.17	
4	4.00000	60000	6.92	0.10	

In [97]:

📋 Data Processing [Test Data]

- 1. Label Encoding

- 2. Log Transformation

In [98]:
```
num_cols, cat_cols = original_columns[:3], original_columns[3:]
num_cols, cat_cols
```

Out[98]:
```
(['person_age', 'person_emp_length', 'loan_amnt'],
 ['loan_intent',
  'loan_grade',
  'cb_person_default_on_file',
  'person_home_ownership'])
```

In [99]:
```
test_df.head()
```

Out[99]:

	person_age	person_income	person_home_ownership	person_emp_length	l
0	23	69000	RENT	3.0	HOMEIMPF
1	26	96000	MORTGAGE	6.0	
2	26	30000	RENT	5.0	
3	33	50000	RENT	4.0	DEBTCONS(
4	26	102000	MORTGAGE	8.0	HOMEIMPF

In [100…
```
if 'id' in test_df.columns:
    test_df = test_df.drop('id', axis='columns')
```

In [101…
```
test_df.shape, df8.shape
```

Out[101…
```
((39098, 11), (58132, 13))
```

In [102…
```
test_df_log = test_df[num_cols]
test_df_en = test_df[cat_cols]
test_remain = test_df.drop(num_cols+cat_cols, axis='columns')
```

In [103…
```
test_df_log_up = test_df_log.applymap(lambda x: np.log(x))
test_df_log_up.head()
```

Out[103…

	person_age	person_emp_length	loan_amnt
0	3.135494	1.098612	10.126631
1	3.258097	1.791759	9.210340
2	3.258097	1.609438	8.294050
3	3.496508	1.386294	8.853665
4	3.258097	2.079442	9.615805

In [104…
```
for col in cat_cols:
    test_df_en.loc[:,col] = encoder.fit_transform(test_df_en[col])
test_df_en.head()
```

Out[104…

	loan_intent	loan_grade	cb_person_default_on_file	person_home_ownership
0	2	5	0	3
1	4	2	1	0
2	5	4	1	3
3	0	0	0	3
4	2	3	1	0

In [105…

```
final_test_df = pd.concat([test_df_log_up, test_df_en, test_remain], axis='colum
final_test_df.head()
```

Out[105…

	person_age	person_emp_length	loan_amnt	loan_intent	loan_grade	cb_person_defau
0	3.135494	1.098612	10.126631	2	5	
1	3.258097	1.791759	9.210340	4	2	
2	3.258097	1.609438	8.294050	5	4	
3	3.496508	1.386294	8.853665	0	0	
4	3.258097	2.079442	9.615805	2	3	

In [106…

```
final_test_df.shape
```

Out[106…

```
(39098, 11)
```

In [107…

```
final_test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39098 entries, 0 to 39097
Data columns (total 11 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   person_age                  39098 non-null  float64
 1   person_emp_length           39098 non-null  float64
 2   loan_amnt                   39098 non-null  float64
 3   loan_intent                 39098 non-null  object 
 4   loan_grade                  39098 non-null  object 
 5   cb_person_default_on_file   39098 non-null  object 
 6   person_home_ownership       39098 non-null  object 
 7   person_income               39098 non-null  int64  
 8   loan_int_rate               39098 non-null  float64
 9   loan_percent_income         39098 non-null  float64
 10  cb_person_cred_hist_length  39098 non-null  int64  
dtypes: float64(5), int64(2), object(4)
memory usage: 3.3+ MB
```

In [110…

```
X = df8.drop(['id','loan_status'], axis='columns').columns
y = ['loan_status']
```

In [111…

```
last_one = final_test_df[X]

last_one.head()
```

Out[111...

	person_income	loan_int_rate	loan_percent_income	cb_person_cred_hist_length	perso
0	69000	15.76	0.36	2	3.1
1	96000	12.68	0.10	4	3.2
2	30000	17.19	0.13	2	3.2
3	50000	8.90	0.14	7	3.4
4	102000	16.32	0.15	4	3.2

In [112...

```
df8.head()
```

Out[112...

	id	person_income	loan_int_rate	loan_percent_income	cb_person_cred_hist_leng
0	0.00001	35000	11.49	0.17	
1	1.00000	56000	13.35	0.07	
2	2.00000	28800	8.90	0.21	
3	3.00000	70000	11.11	0.17	
4	4.00000	60000	6.92	0.10	

📋 Model Training

- 1. Hyperparameter Tuning [Grid Search CV]
- 2. Model Training

In [114...

```
X_train, X_test, y_train, y_test = train_test_split(df8.drop(['loan_status', 'id

model = RandomForestClassifier()
model.fit(X_train, y_train)
"Train score", model.score(X_train, y_train), "Test score", model.score(X_test,
```

Out[114...

```
('Train score', 0.9999770636941214, 'Test score', 0.9504575793022776)
```

In [115...

```
from sklearn.metrics import accuracy_score, classification_report

def train_and_predict(classifier, X_train, X_test, y_train, y_test):
    classifier.fit(X_train, y_train)

    predictions = classifier.predict(X_test)

    train_score = classifier.score(X_train, y_train)
    test_score = accuracy_score(y_test, predictions)

    print(f"Model: {classifier.__class__.__name__}")
```

```
    print(f"Training Score: {train_score:.4f}")
    print(f"Testing Score: {test_score:.4f}")
    print("\nClassification Report:")
    print(classification_report(y_test, predictions))

    return classifier, predictions


classifiers = [
    LogisticRegression(),
    SVC(),
    DecisionTreeClassifier(),
    RandomForestClassifier(),
    GradientBoostingClassifier(),
    AdaBoostClassifier(),
    KNeighborsClassifier(),
    GaussianNB()
]

for classifier in classifiers:
    print(f'Using classifier: {classifier.__class__.__name__}')
    trained_model, predictions = train_and_predict(classifier, X_train, X_test,
    print("\n" + "-" * 50 + "\n")
```

```
Using classifier: LogisticRegression
Model: LogisticRegression
Training Score: 0.8593
Testing Score: 0.8594

Classification Report:
              precision    recall  f1-score   support

           0       0.86      1.00      0.92     12489
           1       0.00      0.00      0.00      2044

    accuracy                           0.86     14533
   macro avg       0.43      0.50      0.46     14533
weighted avg       0.74      0.86      0.79     14533


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

Using classifier: SVC
Model: SVC
Training Score: 0.8593
Testing Score: 0.8594

Classification Report:
              precision    recall  f1-score   support

           0       0.86      1.00      0.92     12489
           1       0.00      0.00      0.00      2044

    accuracy                           0.86     14533
   macro avg       0.43      0.50      0.46     14533
weighted avg       0.74      0.86      0.79     14533


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

Using classifier: DecisionTreeClassifier
Model: DecisionTreeClassifier
Training Score: 1.0000
Testing Score: 0.9131

Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.94      0.95     12489
           1       0.68      0.73      0.70      2044

    accuracy                           0.91     14533
   macro avg       0.82      0.84      0.83     14533
weighted avg       0.92      0.91      0.91     14533


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

Using classifier: RandomForestClassifier
Model: RandomForestClassifier
Training Score: 1.0000
Testing Score: 0.9508

Classification Report:
```

```
              precision    recall  f1-score   support

           0       0.95      0.99      0.97     12489
           1       0.92      0.71      0.80      2044

    accuracy                           0.95     14533
   macro avg       0.94      0.85      0.89     14533
weighted avg       0.95      0.95      0.95     14533


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

Using classifier: GradientBoostingClassifier
Model: GradientBoostingClassifier
Training Score: 0.9466
Testing Score: 0.9468

Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.99      0.97     12489
           1       0.90      0.70      0.79      2044

    accuracy                           0.95     14533
   macro avg       0.93      0.84      0.88     14533
weighted avg       0.95      0.95      0.94     14533


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

Using classifier: AdaBoostClassifier
Model: AdaBoostClassifier
Training Score: 0.9278
Testing Score: 0.9269

Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.97      0.96     12489
           1       0.80      0.65      0.71      2044

    accuracy                           0.93     14533
   macro avg       0.87      0.81      0.84     14533
weighted avg       0.92      0.93      0.92     14533


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

Using classifier: KNeighborsClassifier
Model: KNeighborsClassifier
Training Score: 0.9140
Testing Score: 0.8858

Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.96      0.94     12489
           1       0.64      0.42      0.51      2044

    accuracy                           0.89     14533
```

```
   macro avg       0.78      0.69      0.72     14533
weighted avg       0.87      0.89      0.88     14533


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

Using classifier: GaussianNB
Model: GaussianNB
Training Score: 0.8717
Testing Score: 0.8686

Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.94      0.93     12489
           1       0.54      0.41      0.47      2044

    accuracy                           0.87     14533
   macro avg       0.73      0.68      0.70     14533
weighted avg       0.86      0.87      0.86     14533


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

----> Grid Search CV

In [116…

```python
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.model_selection import GridSearchCV

rf_param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [None, 120, 30],
    'min_samples_split': [5, 10],
    'min_samples_leaf': [2, 4]
}

gb_param_grid = {
    'n_estimators': [50, 100, 200],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 5, 7],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

rf_grid_search = GridSearchCV(estimator=RandomForestClassifier(), param_grid=rf_
                              scoring='accuracy', cv=5, n_jobs=-1, verbose=1)
rf_grid_search.fit(X_train, y_train)

print("Best parameters for RandomForestClassifier:")
print(rf_grid_search.best_params_)
print("Best training score:", rf_grid_search.best_score_)
```

```
Fitting 5 folds for each of 24 candidates, totalling 120 fits
Best parameters for RandomForestClassifier:
{'max_depth': 30, 'min_samples_leaf': 2, 'min_samples_split': 10, 'n_estimators':
200}
Best training score: 0.9488750182823338
```

----> *Model Training*

In [117…

```
best_params = {
    'max_depth': 30,
    'min_samples_leaf': 2,
    'min_samples_split': 5,
    'n_estimators': 200
}
final_model = RandomForestClassifier(**best_params)
final_model.fit(X_train, y_train)
y_pred = final_model.predict(X_test)
test_accuracy = accuracy_score(y_test, y_pred)
print(f'Test Accuracy: {test_accuracy:.4f}')
```

```
Test Accuracy: 0.9511
```

In [125…

```
sub_model = RandomForestClassifier(**best_params)
sub_model.fit(df8.drop(['loan_status', 'id'], axis='columns'), df8['loan_status'
result = sub_model.predict(last_one)
print(len(result), test_df.shape)
```

```
39098 (39098, 11)
```

----> *Model Evaluation*

📋 Model Evaluation

- 1. Confusion Matrix
- 2. Classification Report

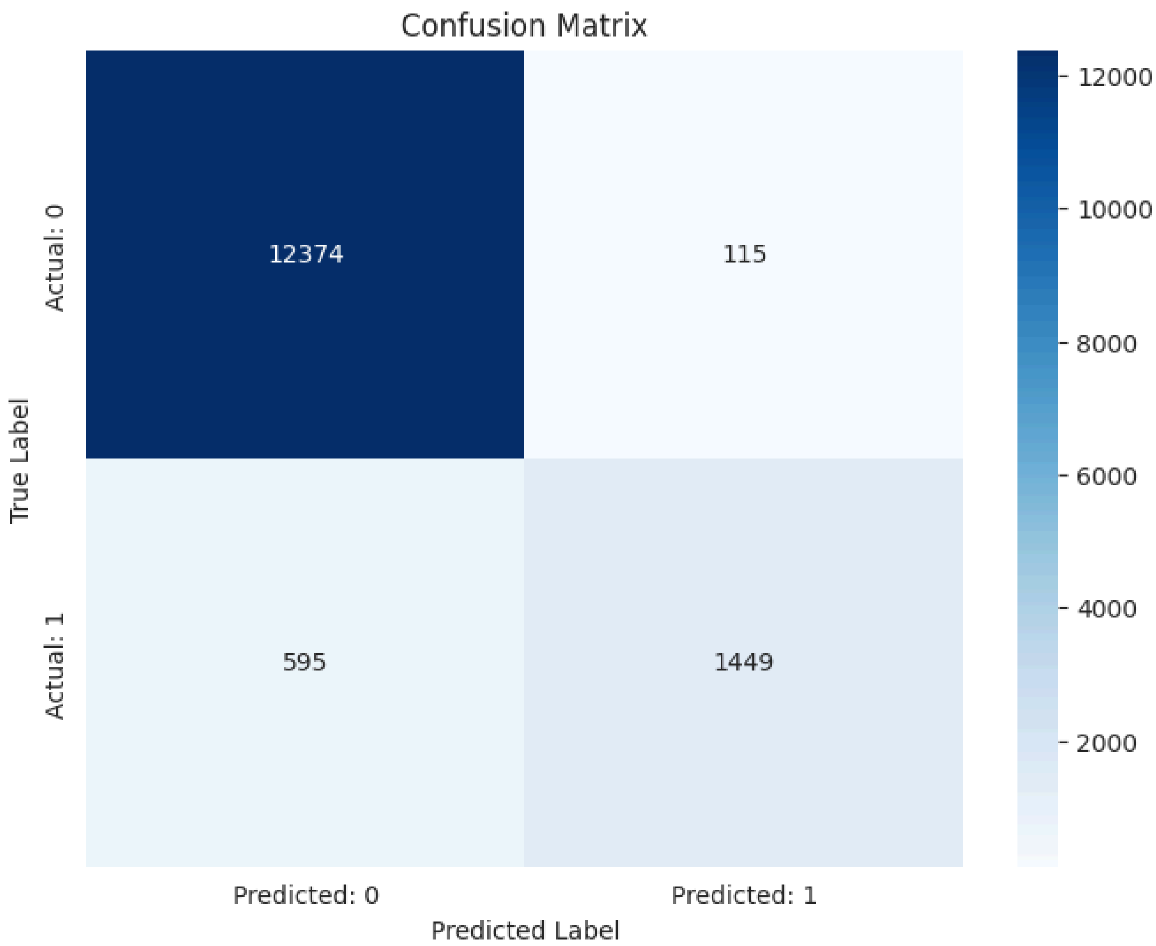
In [126…

```
cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Predicted: 0', 'Predicted: 1'],
            yticklabels=['Actual: 0', 'Actual: 1'])

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

plt.show()
```



In [127…
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.95      0.99      0.97     12489
           1       0.93      0.71      0.80      2044

    accuracy                           0.95     14533
   macro avg       0.94      0.85      0.89     14533
weighted avg       0.95      0.95      0.95     14533
```

In [128…
```
import joblib
joblib.dump(final_model, "loan_status.pkl")
```

Out[128…
```
['loan_status.pkl']
```

📋 Submission

- 1. Confusion Matrix
- 2. Classification Report

In [129…

```
final = pd.concat([original_df_test['id'] , pd.DataFrame(result)], axis='columns
final.columns = ['id', 'loan_status']
final.head()
```

Out[129…

	id	loan_status
0	58645	1
1	58646	0
2	58647	1
3	58648	0
4	58649	0

In [131…

```
final.to_csv("loan_status_submission_2.csv", index=False)
print("Collected submissions")
```

```
Collected submissions
```

In [ ]: