Sustain_Farmers_Assignment

November 26, 2024

[7]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

[2]:
```
dataset = pd.read_csv(r"E:\Users\TANISHQ\Desktop\Sustain Farmers Project\family_financial_and_transactions_data.csv")
```

[3]:
```
dataset
```

[3]:

	Family ID	Member ID	Transaction Date	Category	Amount	\
0	FAM001	FAM001_Member1	07-10-2024	Travel	409.12	
1	FAM001	FAM001_Member1	16-10-2024	Travel	270.91	
2	FAM001	FAM001_Member1	17-10-2024	Groceries	91.10	
3	FAM001	FAM001_Member1	25-10-2024	Healthcare	198.23	
4	FAM001	FAM001_Member1	25-10-2024	Education	206.42	
…	…	…	…	…	…	
16301	FAM200	FAM200_Member6	10-10-2024	Groceries	79.99	
16302	FAM200	FAM200_Member6	22-10-2024	Education	228.39	
16303	FAM200	FAM200_Member6	29-10-2024	Travel	258.63	
16304	FAM200	FAM200_Member6	26-10-2024	Travel	467.46	
16305	FAM200	FAM200_Member6	27-10-2024	Entertainment	475.34	

	Income	Savings	Monthly Expenses	Loan Payments	Credit Card Spending	\
0	113810	20234	5781	2422	2959	
1	113810	20234	5781	2422	2959	
2	113810	20234	5781	2422	2959	
3	113810	20234	5781	2422	2959	
4	113810	20234	5781	2422	2959	
…	…	…	…	…	…	
16301	44621	44081	4296	2470	2831	
16302	44621	44081	4296	2470	2831	
16303	44621	44081	4296	2470	2831	
16304	44621	44081	4296	2470	2831	
16305	44621	44081	4296	2470	2831	

	Dependents	Financial Goals Met (%)
0	2	68
1	2	68

```
2                2                        68
3                2                        68
4                2                        68
…              …                        …
16301            4                        92
16302            4                        92
16303            4                        92
16304            4                        92
16305            4                        92

[16306 rows x 12 columns]
```

[5]:
```
dataset.isna().any()
```

[5]:
```
Family ID                 False
Member ID                 False
Transaction Date          False
Category                  False
Amount                    False
Income                    False
Savings                   False
Monthly Expenses          False
Loan Payments             False
Credit Card Spending      False
Dependents                False
Financial Goals Met (%)   False
dtype: bool
```

[9]:
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16306 entries, 0 to 16305
Data columns (total 12 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Family ID                16306 non-null  object
 1   Member ID                16306 non-null  object
 2   Transaction Date         16306 non-null  object
 3   Category                 16306 non-null  object
 4   Amount                   16306 non-null  float64
 5   Income                   16306 non-null  int64
 6   Savings                  16306 non-null  int64
 7   Monthly Expenses         16306 non-null  int64
 8   Loan Payments            16306 non-null  int64
 9   Credit Card Spending     16306 non-null  int64
 10  Dependents               16306 non-null  int64
 11  Financial Goals Met (%)  16306 non-null  int64
dtypes: float64(1), int64(7), object(4)
```

```
memory usage: 1.5+ MB
```

[10]:
```
dataset.describe()
```

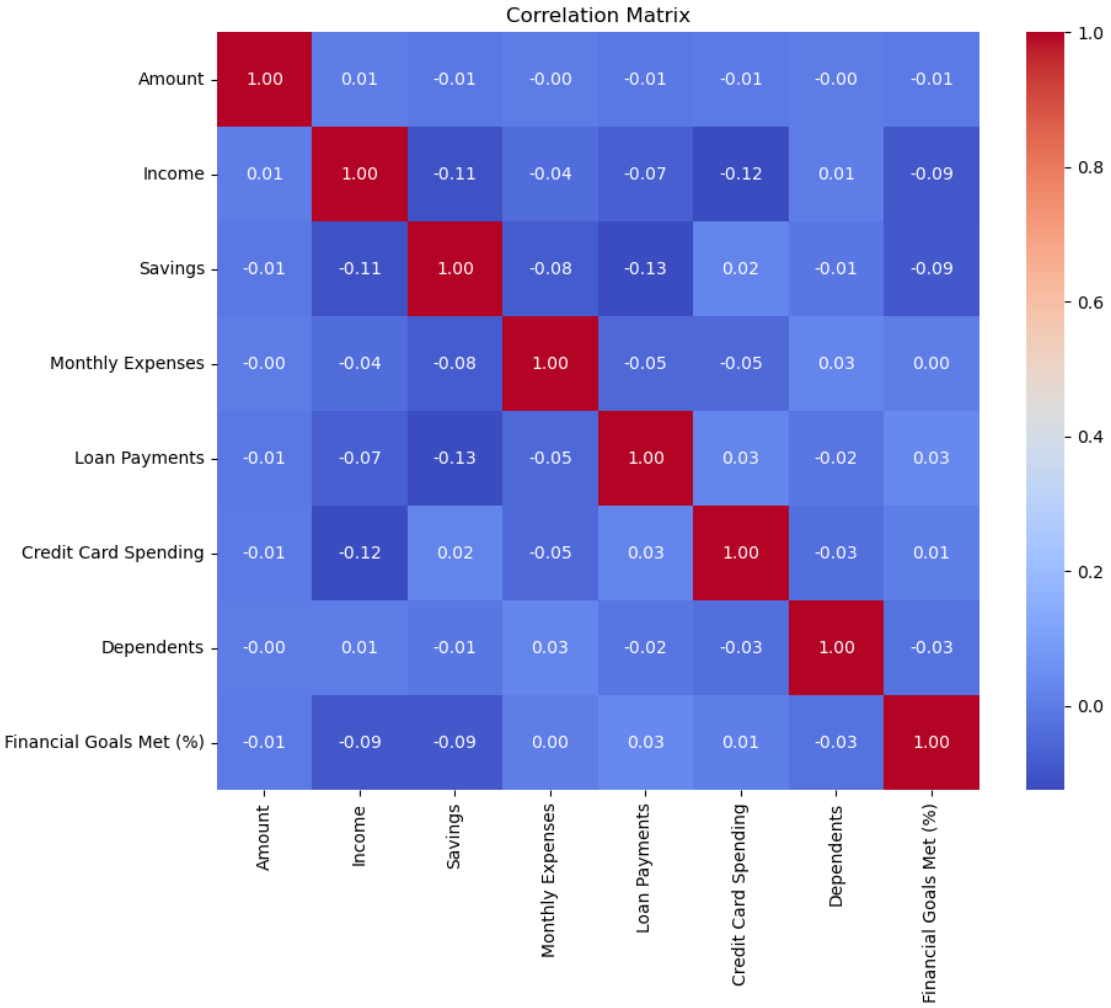
[10]:
```
              Amount         Income       Savings  Monthly Expenses  \
count  16306.000000   16306.000000  16306.000000      16306.000000
mean     256.368534   90340.503925  24473.998038       3948.522384
std      141.153813   34740.834136  14828.955695       1689.987801
min       10.030000   30851.000000   1037.000000       1013.000000
25%      134.820000   59871.000000  11016.000000       2582.000000
50%      256.055000   90142.000000  25504.000000       3721.000000
75%      379.240000  119733.000000  37422.000000       5450.000000
max      499.910000  149871.000000  49217.000000       6968.000000

       Loan Payments  Credit Card Spending    Dependents  \
count   16306.000000          16306.000000  16306.000000
mean     2529.978965           1782.880535      3.201521
std      1384.105561            716.595101      1.468880
min         3.000000            510.000000      0.000000
25%      1390.000000           1221.000000      2.000000
50%      2548.000000           1705.000000      3.000000
75%      3724.000000           2422.000000      4.000000
max      4974.000000           2999.000000      5.000000

       Financial Goals Met (%)
count             16306.000000
mean                 59.418006
std                  23.444304
min                  21.000000
25%                  37.000000
50%                  58.000000
75%                  79.000000
max                 100.000000
```

-
-
-

[84]:
```
# Member Category wise expense
member_data = dataset.groupby(['Family ID', 'Member ID']).agg({
    'Monthly Expenses': 'sum',
    'Category': lambda x: x.value_counts().idxmax()
}).reset_index()
print(member_data.head(10))
```

	Family ID	Member ID	Monthly Expenses	Category
0	FAM001	FAM001_Member1	156087	Healthcare
1	FAM001	FAM001_Member2	167649	Travel
2	FAM001	FAM001_Member3	63591	Education
3	FAM001	FAM001_Member4	150306	Entertainment
4	FAM002	FAM002_Member1	67560	Healthcare
5	FAM002	FAM002_Member2	78820	Utilities
6	FAM002	FAM002_Member3	152010	Entertainment
7	FAM002	FAM002_Member4	67560	Groceries
8	FAM002	FAM002_Member5	129490	Utilities
9	FAM003	FAM003_Member1	100358	Education

[24]:
```
# Extract relevant numerical data from dataset
df = dataset.iloc[:,4:]

# Computer correlation matrix
correlation_matrix = df.corr()

# Visualise correlation matrix using heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Matrix")
plt.show()
```



[65]:
```
# Compute correlation between Savings and Monthly Expenses
savings_monthlyexpenses_correlation = df['Savings'].corr(df['Monthly Expenses'])
print(f"Correlation between Savings and Monthly Expenses:␣
  ↪{savings_monthlyexpenses_correlation}")
```

```
Correlation between Savings and Monthly Expenses: -0.08209422498296176
```

[178]:
```
custom_aggregation = dataset.groupby('Family ID').agg(
    total_expenses=('Monthly Expenses', 'sum'),
    average_income=('Income', 'mean'),
    max_savings=('Savings', 'max')
).reset_index()
print(custom_aggregation)
```

```
    Family ID  total_expenses  average_income  max_savings
0      FAM001          537633        113810.0        20234
1      FAM002          495440         44592.0        29492
2      FAM003          248254         33278.0        11365
3      FAM004          341145        127196.0        30735
4      FAM005          517440         66048.0         1212
..        …               …               …           …
195    FAM196          438092         64973.0         3604
196    FAM197          122797        130741.0        41591
197    FAM198          330220        114012.0         6372
198    FAM199          429624         74587.0        28474
199    FAM200          446784         44621.0        44081

[200 rows x 4 columns]
```

[192]:
```
dataset['Category'].unique()
```

[192]:
```
array(['Travel', 'Groceries', 'Healthcare', 'Education', 'Utilities',
       'Food', 'Entertainment'], dtype=object)
```

[198]:
```
#Compute Savings-to-Income Ratio
dataset['Savings_to_Income_Ratio'] = dataset['Savings'] / dataset['Income']

#Compute Monthly Expenses as a Percentage of Income
dataset['Monthly_Expenses_Ratio'] = dataset['Monthly Expenses'] /␣
 ↪dataset['Income']

#Compute Loan Payments as a Percentage of Income
dataset['Loan_Payments_Ratio'] = dataset['Loan Payments'] / dataset['Income']

#Compute Credit Card Spending Ratio
dataset['Credit_Card_Spending_Ratio'] = dataset['Credit Card Spending'] /␣
 ↪dataset['Income']
```

[200]:
```
dataset.head()
```

[200]:
```
  Family ID       Member ID Transaction Date    Category  Amount  Income  \
0    FAM001  FAM001_Member1       07-10-2024      Travel  409.12  113810
1    FAM001  FAM001_Member1       16-10-2024      Travel  270.91  113810
2    FAM001  FAM001_Member1       17-10-2024   Groceries   91.10  113810
3    FAM001  FAM001_Member1       25-10-2024  Healthcare  198.23  113810
4    FAM001  FAM001_Member1       25-10-2024   Education  206.42  113810

   Savings  Monthly Expenses  Loan Payments  Credit Card Spending  Dependents  \
0    20234              5781           2422                  2959           2
1    20234              5781           2422                  2959           2
2    20234              5781           2422                  2959           2
3    20234              5781           2422                  2959           2
```

```
4    20234              5781           2422                   2959           2

   Financial Goals Met (%)  Savings_to_Income_Ratio  Monthly_Expenses_Ratio  \
0                       68                 0.177788                0.050795
1                       68                 0.177788                0.050795
2                       68                 0.177788                0.050795
3                       68                 0.177788                0.050795
4                       68                 0.177788                0.050795

   Loan_Payments_Ratio  Credit_Card_Spending_Ratio
0             0.021281                    0.025999
1             0.021281                    0.025999
2             0.021281                    0.025999
3             0.021281                    0.025999
4             0.021281                    0.025999
```

[201]:
```
#Normalize Savings (Higher is better)
dataset['Normalized_Savings'] = dataset['Savings_to_Income_Ratio'].clip(0, 1)

#Normalize Monthly Expenses (Lower is better, so use 1 - ratio)
dataset['Normalized_Expenses'] = (1 - dataset['Monthly_Expenses_Ratio']).
 ↪clip(0, 1)

#Normalize Loan Payments (Lower is better, so use 1 - ratio)
dataset['Normalized_Loans'] = (1 - dataset['Loan_Payments_Ratio']).clip(0, 1)

#Normalize Credit Card Spending (Lower is better, so use 1 - ratio)
dataset['Normalized_Credit'] = (1 - dataset['Credit_Card_Spending_Ratio']).
 ↪clip(0, 1)

#Normalize Financial Goals Met (Already a percentage, divide by 100)
dataset['Normalized_Goals'] = dataset['Financial Goals Met (%)'] / 100
```

[202]:
```
dataset.head()
```

[202]:
```
  Family ID       Member ID Transaction Date    Category  Amount  Income  \
0    FAM001  FAM001_Member1       07-10-2024      Travel  409.12  113810
1    FAM001  FAM001_Member1       16-10-2024      Travel  270.91  113810
2    FAM001  FAM001_Member1       17-10-2024   Groceries   91.10  113810
3    FAM001  FAM001_Member1       25-10-2024  Healthcare  198.23  113810
4    FAM001  FAM001_Member1       25-10-2024   Education  206.42  113810

   Savings  Monthly Expenses  Loan Payments  Credit Card Spending  …  \
0    20234              5781           2422                  2959  …
1    20234              5781           2422                  2959  …
2    20234              5781           2422                  2959  …
3    20234              5781           2422                  2959  …
```

```
4    20234              5781           2422                   2959  …

   Financial Goals Met (%)  Savings_to_Income_Ratio  Monthly_Expenses_Ratio  \
0                       68                 0.177788                0.050795
1                       68                 0.177788                0.050795
2                       68                 0.177788                0.050795
3                       68                 0.177788                0.050795
4                       68                 0.177788                0.050795

   Loan_Payments_Ratio  Credit_Card_Spending_Ratio  Normalized_Savings  \
0             0.021281                    0.025999            0.177788
1             0.021281                    0.025999            0.177788
2             0.021281                    0.025999            0.177788
3             0.021281                    0.025999            0.177788
4             0.021281                    0.025999            0.177788

   Normalized_Expenses  Normalized_Loans  Normalized_Credit  Normalized_Goals
0             0.949205          0.978719           0.974001              0.68
1             0.949205          0.978719           0.974001              0.68
2             0.949205          0.978719           0.974001              0.68
3             0.949205          0.978719           0.974001              0.68
4             0.949205          0.978719           0.974001              0.68

[5 rows x 21 columns]
```

[217]:
```
#Identify discretionary categories
discretionary_categories = ['Travel', 'Entertainment']

#Calculate discretionary spending proportion for each family
discretionary_spending = dataset[dataset['Category'].
 ↪isin(discretionary_categories)].groupby('Family ID')['Amount'].sum() #sum of␣
 ↪Amount of travel & entertainment for each family
total_spending = dataset.groupby('Family ID')['Amount'].sum()  #Sum of amount␣
 ↪of families

spending_distribution = (discretionary_spending / total_spending).fillna(0).
 ↪reset_index(name='Discretionary_Spending_Ratio')

#Merge the discretionary spending ratio back into the dataset
family_data = dataset[['Family ID']].drop_duplicates().
 ↪merge(spending_distribution, on='Family ID', how='left')

family_data['Discretionary_Spending_Ratio'] =␣
 ↪family_data['Discretionary_Spending_Ratio'].fillna(0)

#Normalize Discretionary Spending (Lower is better, so use 1 - ratio)
```

```
family_data['Normalized_Discretionary_Spending'] = (1 -␣
↪family_data['Discretionary_Spending_Ratio']).clip(0, 1)
```

[218]:
```
dataset.head(1)
```

[218]:
```
  Family ID       Member ID Transaction Date Category  Amount  Income  \
0    FAM001  FAM001_Member1       07-10-2024   Travel  409.12  113810

   Savings  Monthly Expenses  Loan Payments  Credit Card Spending  …  \
0    20234              5781           2422                  2959  …

   Financial Goals Met (%)  Savings_to_Income_Ratio  Monthly_Expenses_Ratio  \
0                       68                 0.177788                0.050795

   Loan_Payments_Ratio  Credit_Card_Spending_Ratio  Normalized_Savings  \
0             0.021281                    0.025999            0.177788

   Normalized_Expenses  Normalized_Loans  Normalized_Credit  Normalized_Goals
0             0.949205          0.978719           0.974001              0.68

[1 rows x 21 columns]
```

[219]:
```
family_data.head()
```

[219]:
```
  Family ID  Discretionary_Spending_Ratio  Normalized_Discretionary_Spending
0    FAM001                      0.377149                           0.622851
1    FAM002                      0.256324                           0.743676
2    FAM003                      0.350888                           0.649112
3    FAM004                      0.265068                           0.734932
4    FAM005                      0.283776                           0.716224
```

[222]:
```
weights = {
    'Savings_to_Income_Ratio': 0.25,  # Savings are highly important
    'Monthly_Expenses_Ratio': 0.25,  # Expenses directly affect financial health
    'Loan_Payments_Ratio': 0.20,      # Loan payments are moderately important
    'Credit_Card_Spending_Ratio': 0.15,  # Credit card spending has moderate␣
↪impact
    'Financial_Goals_Met': 0.10,      # Goals met have a smaller impact
    'Discretionary_Spending_Ratio': 0.05  # Discretionary spending has the␣
↪least weight
}
```

[223]:
```
#Compute the Financial Score
family_data['Financial_Score'] = (
    weights['Savings_to_Income_Ratio'] * dataset['Normalized_Savings'] +
    weights['Monthly_Expenses_Ratio'] * dataset['Normalized_Expenses'] +
    weights['Loan_Payments_Ratio'] * dataset['Normalized_Loans'] +
```

```
    weights['Credit_Card_Spending_Ratio'] * dataset['Normalized_Credit'] +
    weights['Financial_Goals_Met'] * dataset['Normalized_Goals'] +
    weights['Discretionary_Spending_Ratio'] *␣
  ↪family_data['Normalized_Discretionary_Spending']
) * 100
```

[224]:
```
#Display the updated scores
print(family_data[['Family ID', 'Financial_Score']])
```

```
    Family ID  Financial_Score
0      FAM001        72.273450
1      FAM002        72.877576
2      FAM003        72.404756
3      FAM004        72.833855
4      FAM005        72.740316
..        …              …
195    FAM196        76.652715
196    FAM197        76.763913
197    FAM198        75.869903
198    FAM199        76.364716
199    FAM200        75.883848

[200 rows x 2 columns]
```

0.0.1 Financial Score Computation

We computed financial scores based on the following metrics:

1. **Savings-to-Income Ratio**: Higher savings relative to income increase the score.
2. **Monthly Expenses Ratio**: Lower monthly expenses relative to income increase the score.
3. **Loan Payments Ratio**: Lower loan repayments relative to income increase the score.
4. **Credit Card Spending Ratio**: Lower credit card spending relative to income increases the score.
5. **Financial Goals Met (%)**: Higher percentages positively influence the score.

Formula The score is calculated as a weighted sum of normalized metrics: - **Savings-to-Income Ratio**: 30% weight - **Monthly Expenses Ratio**: 25% weight - **Loan Payments Ratio**: 20% weight - **Credit Card Spending Ratio**: 15% weight - **Financial Goals Met (%)**: 10% weight

Result The final scores are displayed for each family, representing their overall financial health on a scale of 0–100.

[247]:
```
#Family with Maximum Financial Score
family_data[['Family ID', 'Financial_Score']].sort_values(by='Financial_Score').
↪head(1)
```

[247]:
```
   Family ID  Financial_Score
90    FAM091        71.927146
```

[248]:
```
#Family with Maximum Financial Score
family_data[['Family ID', 'Financial_Score']].sort_values(by='Financial_Score',␣
↪ascending=False).head(1)
```

[248]:
```
    Family ID  Financial_Score
177    FAM178        81.547053
```

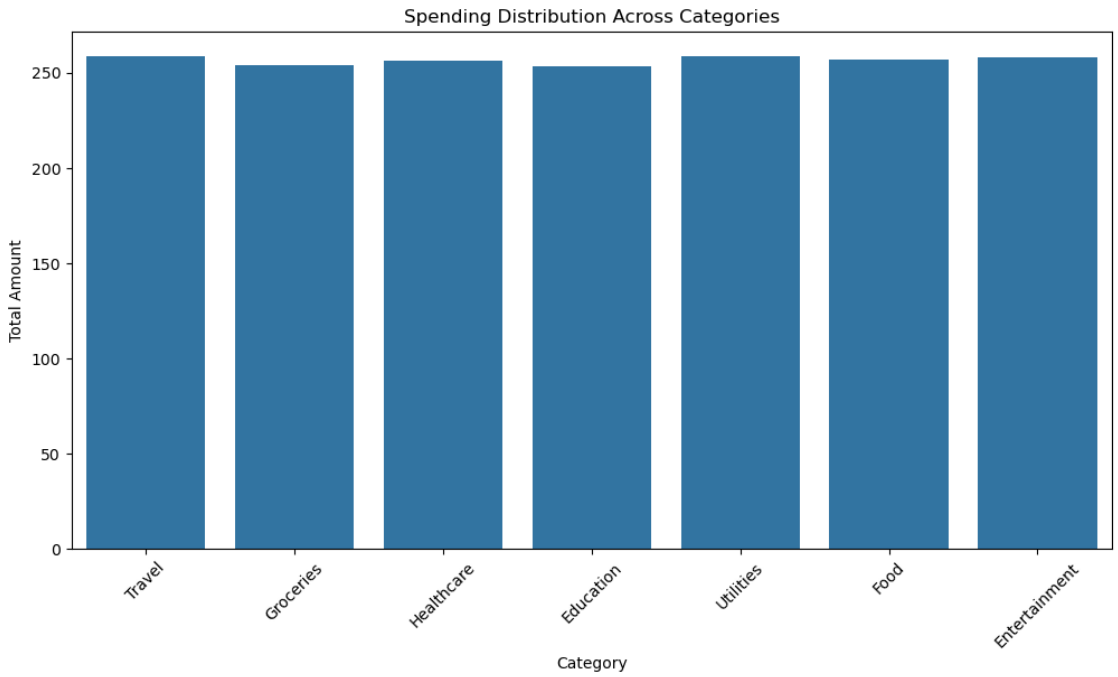
[249]:
```
family_data
```

[249]:
```
    Family ID  Discretionary_Spending_Ratio  \
0      FAM001                      0.377149
1      FAM002                      0.256324
2      FAM003                      0.350888
3      FAM004                      0.265068
4      FAM005                      0.283776
..        …                           …
195    FAM196                      0.204135
196    FAM197                      0.181895
197    FAM198                      0.360697
198    FAM199                      0.261734
199    FAM200                      0.357908

     Normalized_Discretionary_Spending  Financial_Score
0                             0.622851        72.273450
1                             0.743676        72.877576
2                             0.649112        72.404756
3                             0.734932        72.833855
4                             0.716224        72.740316
..                                 …              …
195                           0.795865        76.652715
196                           0.818105        76.763913
197                           0.639303        75.869903
198                           0.738266        76.364716
199                           0.642092        75.883848

[200 rows x 4 columns]
```

Spending Distribution Across Categories

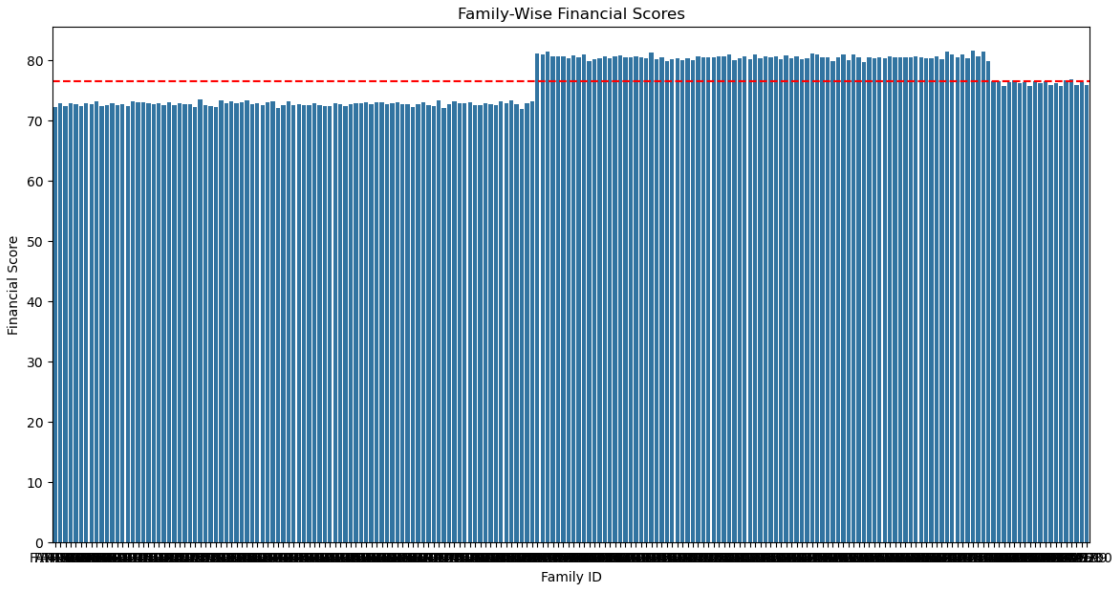
[256]:
```
plt.figure(figsize=(12, 6))
sns.barplot(data=dataset, x='Category', y='Amount', errorbar=None)
```

```
plt.xticks(rotation=45)
plt.title('Spending Distribution Across Categories')
plt.xlabel('Category')
plt.ylabel('Total Amount')
plt.show()
```

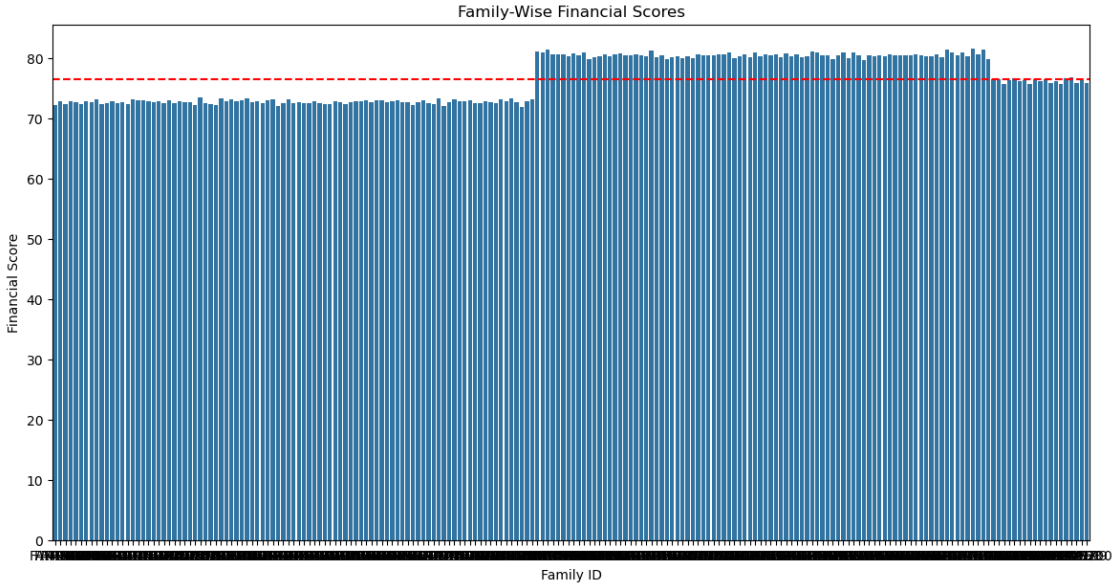


Family-wise Financial Scores.

[275]:
```
plt.figure(figsize=(14, 7))
#Compute the average financial score
average_financial_score = family_data['Financial_Score'].mean()
sns.barplot(data=family_data, x='Family ID', y='Financial_Score', errorbar=None)
plt.axhline(average_financial_score, color='red', linestyle='--',␣
 ↪label=f'Average Financial Score: {average_financial_score:.2f}')
plt.title('Family-Wise Financial Scores')
plt.xlabel('Family ID')
plt.ylabel('Financial Score')
plt.show()
```



[273]:
```
plt.figure(figsize=(14, 7))

#Compute the average financial score
average_financial_score = family_data['Financial_Score'].mean()

sns.barplot(data=family_data, x='Family ID', y='Financial_Score', errorbar=None)
plt.axhline(average_financial_score, color='red', linestyle='--',␣
 ↪label=f'Average Financial Score: {average_financial_score:.2f}')
plt.title('Family-Wise Financial Scores')
plt.xlabel('Family ID')
plt.ylabel('Financial Score')
plt.show()
```



Member-wise Spending Trends.

[272]:
```
member_spending = dataset.groupby(['Member ID']).agg(total_spent=('Amount',␣
↪'sum')).reset_index()

#Compute the average total spending
average_spending = member_spending['total_spent'].mean()

plt.figure(figsize=(20, 6))
sns.barplot(data=member_spending, x='Member ID', y='total_spent', errorbar=None)
plt.axhline(average_spending, color='red', linestyle='--', label=f'Average␣
↪Spending: {average_spending:.2f}')
plt.title('Member-Wise Spending Trends')
plt.xlabel('Member ID')
plt.ylabel('Total Spending')
plt.show()
```