**Title:** Personal Finance Advisor

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**Objective**

The aim of this project is to empower individuals with a better understanding of their financial situation by analyzing key income, expense, and savings patterns. Through data exploration and visual insights, this project identifies potential savings opportunities, evaluates financial performance, and suggests areas for improvement.

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**Tools & Technologies Used**

- Python
- Pandas
- NumPy
- Matplotlib & Seaborn
- Jupiter Notebook

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**Dataset Overview**

The dataset contains detailed financial records of individuals, covering:

- **Income** — Monthly income (INR)
- **Expense Categories** — Rent, Loan Repayment, Insurance, Groceries, Transport, Eating Out, Entertainment, Utilities, Healthcare, Education, Miscellaneous
- **Desired Savings** — Target savings amount set by individuals
- **Potential Savings Opportunities** — Estimated areas where expenses can be reduced
- **Demographic Attributes** — Age, Occupation, City Tier

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**Data Exploration & Visual Analysis**

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt
```

```
import seaborn as sns
sns.set_style('whitegrid')
plt.rcParams['figure.figsize'] = (10,6)
# Load Data
df = pd.read_csv(r"E:/Personal_Finance_Advisor/data/indian_personal_finance.csv")
print(df.head())
print(df.info())
```

```
         Income  Age  Dependents     Occupation City_Tier         Rent  \
0  44637.249636   49           0  Self_Employed    Tier_1  13391.174891
1  26858.596592   34           2        Retired    Tier_2   5371.719318
2  50367.605084   35           1        Student    Tier_3   7555.140763
3 101455.600247   21           0  Self_Employed    Tier_3  15218.340037
4  24875.283548   52           4   Professional    Tier_2   4975.056710

   Loan_Repayment    Insurance     Groceries    Transport  ...  \
0        0.000000  2206.490129   6658.768341  2636.970696  ...
1        0.000000   869.522617   2818.444460  1543.018778  ...
2     4612.103386  2201.800050   6313.222081  3221.396403  ...
3     6809.441427  4889.418087  14690.149363  7106.130005  ...
4     3112.609398   635.907170   3034.329665  1276.155163  ...

   Desired_Savings  Disposable_Income  Potential_Savings_Groceries  \
0      6200.537192       11265.627707                  1685.696222
1      1923.176434        9676.818733                   540.306561
2      7050.360422       13891.450624                  1466.073984
3     16694.965136       31617.953615                  1875.932770
4      1874.099434        6265.700532                   788.953124

   Potential_Savings_Transport  Potential_Savings_Eating_Out  \
0                   328.895281                    465.760172
1                   119.347139                    141.866089
2                   473.549752                    410.857129
3                   762.020789                   1241.017448
4                    68.160766                     61.712505

   Potential_Savings_Entertainment  Potential_Savings_Utilities  \
0                       195.151320                   678.292859
1                       234.131168                   286.668408
2                       459.965256                   488.383423
3                       320.190594                  1389.815033
4                       187.173750                   194.117130

   Potential_Savings_Healthcare  Potential_Savings_Education  \
0                     67.682471                     0.000000
1                      6.603212                    56.306874
2                      7.290892                   106.653597
3                    193.502754                     0.000000
4                     47.294591                    67.388120

   Potential_Savings_Miscellaneous
0                        85.735517
1                        97.388606
2                       138.542422
3                       296.041183
4                        96.557076

[5 rows x 27 columns]
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000 entries, 0 to 19999
Data columns (total 27 columns):
 #   Column                           Non-Null Count  Dtype
---  ------                           --------------  -----
 0   Income                           20000 non-null  float64
 1   Age                              20000 non-null  int64
 2   Dependents                       20000 non-null  int64
 3   Occupation                       20000 non-null  object
 4   City_Tier                        20000 non-null  object
 5   Rent                             20000 non-null  float64
 6   Loan_Repayment                   20000 non-null  float64
 7   Insurance                        20000 non-null  float64
 8   Groceries                        20000 non-null  float64
 9   Transport                        20000 non-null  float64
 10  Eating_Out                       20000 non-null  float64
 11  Entertainment                    20000 non-null  float64
 12  Utilities                        20000 non-null  float64
 13  Healthcare                       20000 non-null  float64
 14  Education                        20000 non-null  float64
 15  Miscellaneous                    20000 non-null  float64
 16  Desired_Savings_Percentage       20000 non-null  float64
 17  Desired_Savings                  20000 non-null  float64
 18  Disposable_Income                20000 non-null  float64
 19  Potential_Savings_Groceries      20000 non-null  float64
 20  Potential_Savings_Transport      20000 non-null  float64
 21  Potential_Savings_Eating_Out     20000 non-null  float64
 22  Potential_Savings_Entertainment  20000 non-null  float64
 23  Potential_Savings_Utilities      20000 non-null  float64
 24  Potential_Savings_Healthcare     20000 non-null  float64
 25  Potential_Savings_Education      20000 non-null  float64
 26  Potential_Savings_Miscellaneous  20000 non-null  float64
dtypes: float64(23), int64(2), object(2)
memory usage: 4.1+ MB
None
```

```
# Calculate Key Metrics
expense_cols = ['Rent','Loan_Repayment','Insurance','Groceries','Transport','Eating_Out',
                'Entertainment','Utilities','Healthcare','Education','Miscellaneous']

df['Total_Expense'] = df[expense_cols].sum(axis=1)
df['Actual_Savings'] = df['Income'] - df['Total_Expense']
df['Savings_Achievement_%'] = ((df['Actual_Savings'] / df['Desired_Savings']) * 100).round(2)
df['Recommendation'] = np.where(df['Savings_Achievement_%'] >= 100, 'On Track', 'Need Improvement')
```

print("\n--- Updated Dataset with Calculated Columns ---\n")

print(df[['Income', 'Total_Expense', 'Actual_Savings', 'Desired_Savings', 'Savings_Achievement_%', 'Recommendation']].head())

```
--- Updated Dataset with Calculated Columns ---

          Income  Total_Expense  Actual_Savings  Desired_Savings  \
0   44637.249636   33371.621929    11265.627707      6200.537192
1   26858.596592   17181.777859     9676.818733      1923.176434
2   50367.605084   36476.154459    13891.450624      7050.360422
3  101455.600247   69837.646632    31617.953615     16694.965136
4   24875.283548   18609.583016     6265.700532      1874.099434

   Savings_Achievement_% Recommendation
0                 181.69       On Track
1                 503.17       On Track
2                 197.03       On Track
3                 189.39       On Track
4                 334.33       On Track
```

# Visualizations

# Income vs Total Expense

sns.kdeplot(df['Income'], label='Income', fill=True, color='green')

sns.kdeplot(df['Total_Expense'], label='Total Expense', fill=True, color='red')

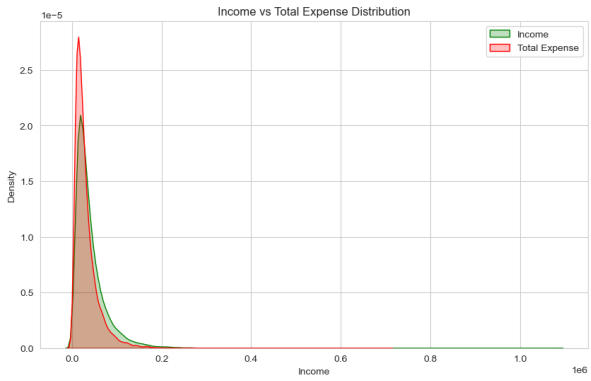
plt.title("Income vs Total Expense Distribution")

plt.legend()

plt.savefig(r"E:/Personal_Finance_Advisor/output/graphs/Income_vs_Expense.png", bbox_inches='tight')

plt.show()

plt.clf()




# Savings Achievement by Occupation

sns.barplot(x='Occupation', y='Savings_Achievement_%', data=df, estimator=np.mean, palette='viridis')

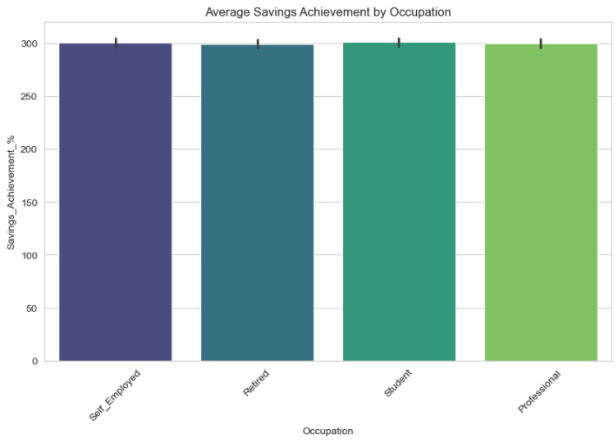
plt.title("Average Savings Achievement by Occupation")

plt.xticks(rotation=45)

plt.savefig(r"E:/Personal_Finance_Advisor/output/graphs/Savings_By_Occupation.png", bbox_inches='tight')

plt.show()

plt.clf()




# City-wise Savings Performance

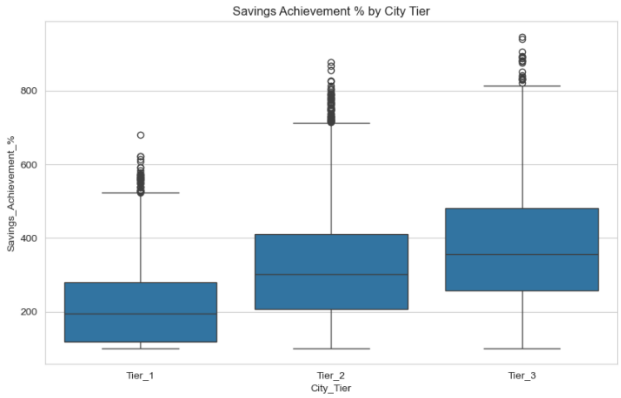
sns.boxplot(x='City_Tier', y='Savings_Achievement_%', data=df)

plt.title("Savings Achievement % by City Tier")

plt.savefig(r"E:/Personal_Finance_Advisor/output/graphs/Savings_By_City.png", bbox_inches='tight')

plt.show()

plt.clf()



# Potential Savings Correlation Heatmap

potential_cols = [col for col in df.columns if 'Potential_Savings' in col]

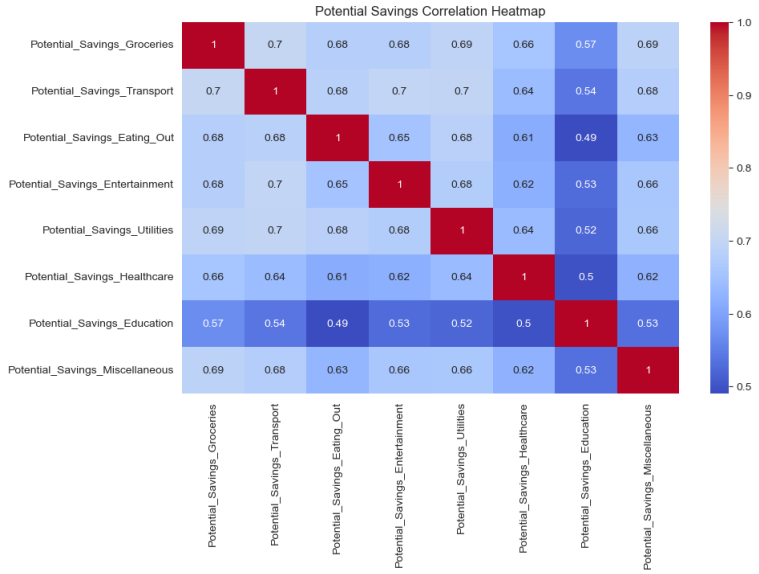
sns.heatmap(df[potential_cols].corr(), annot=True, cmap='coolwarm')

plt.title("Potential Savings Correlation Heatmap")

plt.savefig(r"E:/Personal_Finance_Advisor/output/graphs/Potential_Savings_Heatmap.png", bbox_inches='tight')

plt.show()

plt.clf()




# Spending Distribution Pie Chart

df[expense_cols].sum().sort_values(ascending=False).plot.pie(autopct='%1.1f%%', startangle=140)

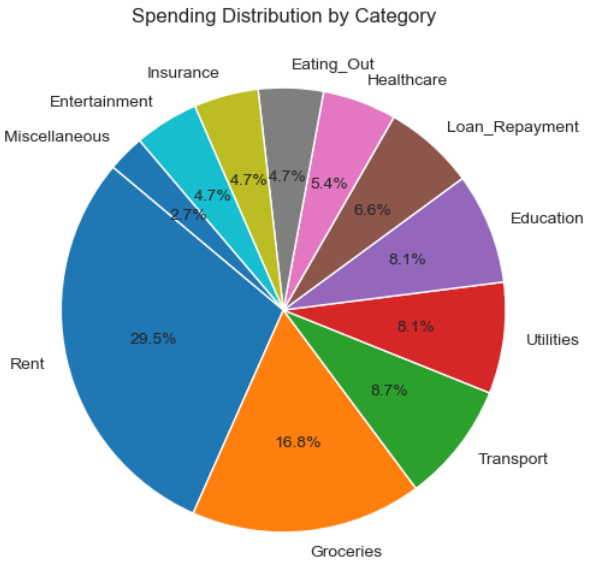
plt.title("Spending Distribution by Category")

plt.ylabel("")

plt.savefig(r"E:/Personal_Finance_Advisor/output/graphs/Spending_Distribution.png", bbox_inches='tight')

plt.show()

plt.clf()




# Desired vs Actual Savings Distribution

sns.kdeplot(df['Desired_Savings'], label='Desired Savings', fill=True)

sns.kdeplot(df['Actual_Savings'], label='Actual Savings', fill=True)

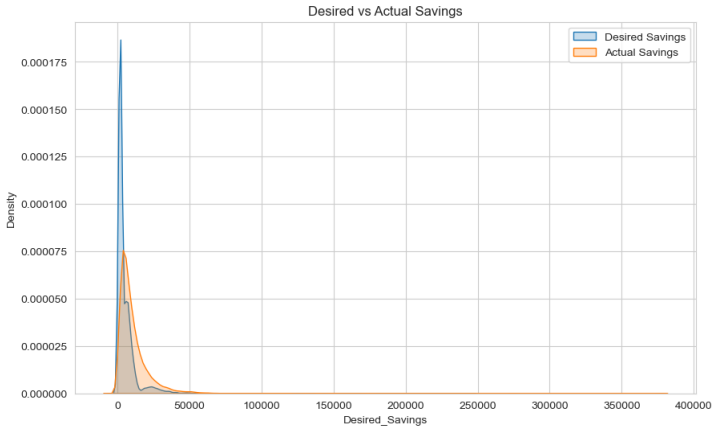
plt.title("Desired vs Actual Savings")

plt.legend()

plt.savefig(r"E:/Personal_Finance_Advisor/output/graphs/Desired_vs_Actual_Savings.png", bbox_inches='tight')

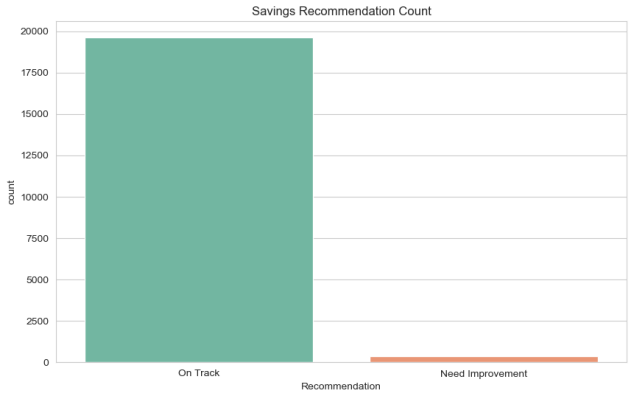
plt.show()

plt.clf()



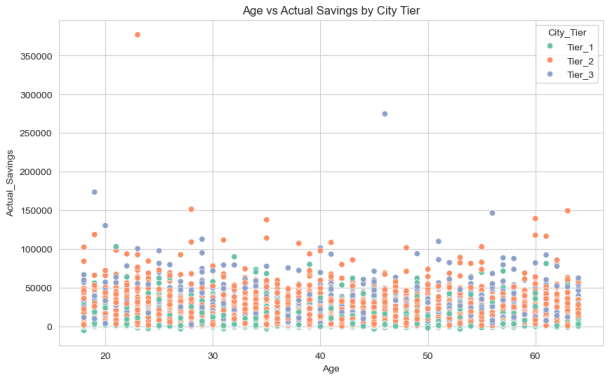
# Savings Status Count

```
sns.countplot(x='Recommendation', data=df, palette='Set2')

plt.title("Savings Recommendation Count")

plt.savefig(r"E:/Personal_Finance_Advisor/output/graphs/Savings_Recommendation_Count.png", bbox_inches='tight')

plt.show()

plt.clf()
```




# Age vs Actual Savings Scatter Plot

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

sns.scatterplot(x='Age', y='Actual_Savings', hue='City_Tier', data=df, palette='Set2')

plt.title("Age vs Actual Savings by City Tier")

plt.savefig(r"E:/Personal_Finance_Advisor/output/graphs/Age_vs_Actual_Savings.png", bbox_inches='tight')

plt.show()

plt.clf()
```



# Category-wise Potential Savings Distribution

potential_cols = [col for col in df.columns if 'Potential_Savings' in col]

df[potential_cols].sum().sort_values(ascending=False).plot(kind='bar', color='orange')

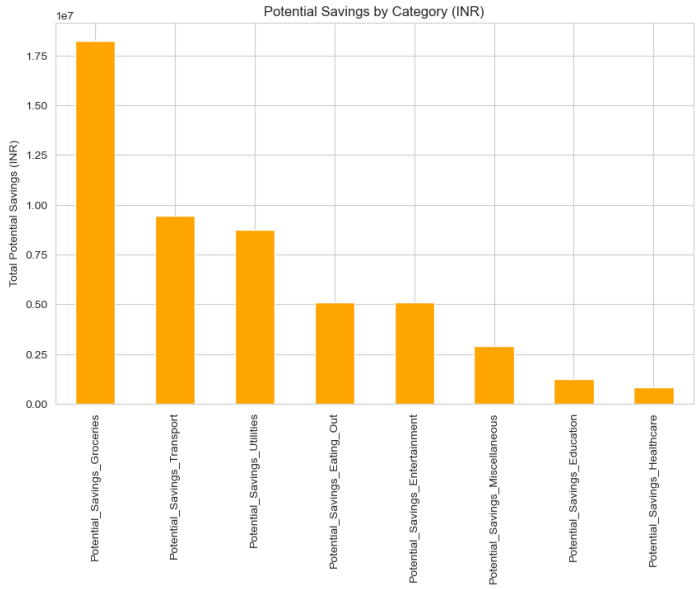
plt.title("Potential Savings by Category (INR)")

plt.ylabel("Total Potential Savings (INR)")

plt.savefig(r"E:/Personal_Finance_Advisor/output/graphs/Potential_Savings_By_Category.png", bbox_inches='tight')

plt.show()

plt.clf()




# City Tier-wise Average Income vs Average

city_avg = df.groupby('City_Tier')[['Income', 'Total_Expense']].mean().reset_index()

city_avg.plot(x='City_Tier', kind='bar', figsize=(8,6), color=['green', 'red'])

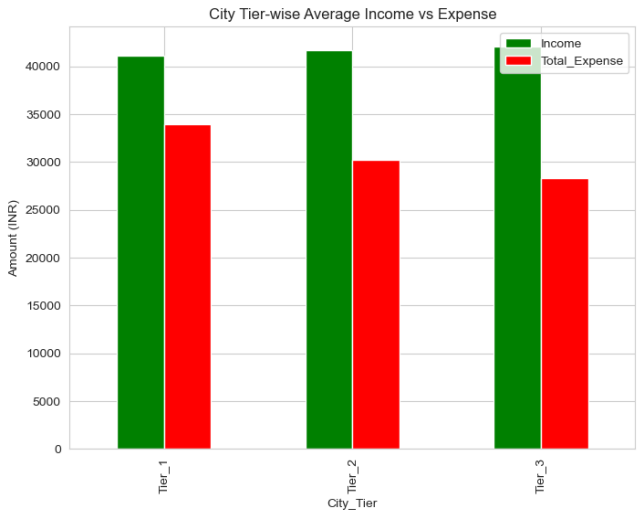
plt.title("City Tier-wise Average Income vs Expense")

plt.ylabel("Amount (INR)")

plt.savefig(r"E:/Personal_Finance_Advisor/output/graphs/City_Avg_Income_Expense.png", bbox_inches='tight')

plt.show()

plt.clf()

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**Summary**

The project analyzed income, expenses, and savings patterns to understand why individuals fail to meet their desired savings targets.

**Key takeaways:**

- High discretionary spending impacts savings
- Savings vary by occupation and city tier
- Clear potential to reduce expenses in specific categories

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**Conclusion**

Data-driven insights can help individuals control expenses and improve savings.

- Monitor savings regularly
- Reduce unnecessary spending
- Tailored financial planning improves savings performance

The project emphasizes how simple analysis can drive better financial decisions.