

DATA ANALYSIS PYTHON PROJECT - CUSTOMER PERSONALITY ANALYSIS

Defination

In []: Customer Personality Analysis **is** the process of understanding customer behavior, preferences. The goal **is** to group customers into categories (personas) so businesses can target them better.

Objective

In []:

1. Understand customer behavior:
To analyze how customers behave — their spending patterns, purchase frequency, **and** shopping habits.
2. Identify customer segments
To group customers into clusters (personas) such **as** high spenders, frequent buyers, budget-conscious.
3. Improve marketing strategies
To help the company target the right customers **with** better offers, ads, **and** campaigns.
4. Personalize customer experience
To understand individual customer needs **and** provide personalized services, product recommendations.
5. Analyze demographic influence
To study how age, gender, income, **and** location affect customer purchasing behavior.
6. Increase customer retention
To identify loyal customers **and** design strategies to keep them engaged.
7. Predict future behavior
To use past data to predict which customers will buy again, spend more, **or** respond to offers.
8. Improve business decision-making
To provide insights that help **in** planning sales, product demand, **and** customer outreach strategies.
To analyze how customers behave — their spending patterns, purchase frequency, **and** shopping habits.

Import Laibraries

In [2]: **import** pandas **as** pd
import matplotlib.pyplot **as** plt
import seaborn **as** sns

In [3]: cust = pd.read_csv(r"C:\Users\RANI\Downloads\customer_personality_analysis_reduced(project

In [4]: cust

Out[4]:

	CustomerID	Age	Gender	City	AnnualIncomeINR	PurchaseFrequency_per_
0	CUST0001	33	Female	Lucknow	910116	
1	CUST0002	38	Male	Kolkata	924582	
2	CUST0003	47	Male	Mysuru	829877	
3	CUST0004	56	Male	Mysuru	1001629	
4	CUST0005	39	Other	Vadodara	636008	
...	
995	CUST0996	28	Male	Coimbatore	364050	
996	CUST0997	32	Female	Indore	438940	
997	CUST0998	41	Male	Mumbai	550890	
998	CUST0999	24	Female	Indore	871223	
999	CUST1000	29	Female	Delhi	549520	

1000 rows × 7 columns

Data Inspection

In [5]: `cust.head()`

Out[5]:

	CustomerID	Age	Gender	City	AnnualIncomeINR	PurchaseFrequency_per_
0	CUST0001	33	Female	Lucknow	910116	
1	CUST0002	38	Male	Kolkata	924582	
2	CUST0003	47	Male	Mysuru	829877	
3	CUST0004	56	Male	Mysuru	1001629	
4	CUST0005	39	Other	Vadodara	636008	

In [6]: `cust.info()`

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 17 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   CustomerID                            1000 non-null   object
1   Age                                    1000 non-null   int64
2   Gender                                1000 non-null   object
3   City                                   1000 non-null   object
4   AnnualIncomeINR                       1000 non-null   int64
5   PurchaseFrequency_per_month           1000 non-null   int64
6   AvgOrderValueINR                      1000 non-null   int64
7   EstimatedYearlySpendINR               1000 non-null   int64
8   PreferredChannel                      1000 non-null   object
9   Openness                              1000 non-null   float64
10  Conscientiousness                     1000 non-null   float64
11  Extraversion                          1000 non-null   float64
12  Agreeableness                        1000 non-null   float64
13  Neuroticism                          1000 non-null   float64
14  PersonalityLabel                      1000 non-null   object
15  CustomerSegment                      1000 non-null   object
16  LastPurchaseDate                     1000 non-null   object
dtypes: float64(5), int64(5), object(7)
memory usage: 132.9+ KB

```

In [7]: `cust.tail()`

Out[7]:

	CustomerID	Age	Gender	City	AnnualIncomeINR	PurchaseFrequency_
995	CUST0996	28	Male	Coimbatore	364050	
996	CUST0997	32	Female	Indore	438940	
997	CUST0998	41	Male	Mumbai	550890	
998	CUST0999	24	Female	Indore	871223	
999	CUST1000	29	Female	Delhi	549520	

In [8]: `cust.describe()`

Out[8]:

	Age	AnnualIncomeINR	PurchaseFrequency_per_month	AvgOrderVal
count	1000.000000	1.000000e+03	1000.000000	1000.0
mean	43.773000	6.039986e+05	2.871000	2133.0
std	15.640463	2.951974e+05	2.875522	1312.2
min	18.000000	6.000000e+04	0.000000	200.0
25%	30.000000	3.832620e+05	1.000000	1051.5
50%	43.000000	6.004025e+05	2.000000	2028.0
75%	58.000000	8.142092e+05	4.000000	3128.0
max	70.000000	1.546285e+06	23.000000	6883.0

In [9]: `cust.columns`

Out[9]: Index(['CustomerID', 'Age', 'Gender', 'City', 'AnnualIncomeINR',
'PurchaseFrequency_per_month', 'AvgOrderValueINR',
'EstimatedYearlySpendINR', 'PreferredChannel', 'Openness',
'Conscientiousness', 'Extraversion', 'Agreeableness', 'Neuroticism',
'PersonalityLabel', 'CustomerSegment', 'LastPurchaseDate'],
dtype='object')

In [10]: `cust.shape`

Out[10]: (1000, 17)

In [11]: `cust.isna().sum()`

Out[11]: CustomerID 0
Age 0
Gender 0
City 0
AnnualIncomeINR 0
PurchaseFrequency_per_month 0
AvgOrderValueINR 0
EstimatedYearlySpendINR 0
PreferredChannel 0
Openness 0
Conscientiousness 0
Extraversion 0
Agreeableness 0
Neuroticism 0
PersonalityLabel 0
CustomerSegment 0
LastPurchaseDate 0
dtype: int64

In [12]: `cust.dtypes`

```
Out[12]: CustomerID      object
Age          int64
Gender       object
City         object
AnnualIncomeINR    int64
PurchaseFrequency_per_month  int64
AvgOrderValueINR   int64
EstimatedYearlySpendINR    int64
PreferredChannel   object
Openness          float64
Conscientiousness  float64
Extraversion      float64
Agreeableness     float64
Neuroticism       float64
PersonalityLabel   object
CustomerSegment    object
LastPurchaseDate   object
dtype: object
```

Data Cleaning

```
In [16]: cust = pd.read_csv(r"C:\Users\RANI\Downloads\customer_personality_analysis_reduced(project)
cust
```

```
Out[16]:
```

	CustomerID	Age	Gender	City	AnnualIncomeINR	PurchaseFrequency_
0	CUST0001	33	Female	Lucknow	910116	
1	CUST0002	38	Male	Kolkata	924582	
2	CUST0003	47	Male	Mysuru	829877	
3	CUST0004	56	Male	Mysuru	1001629	
4	CUST0005	39	Other	Vadodara	636008	
...	
995	CUST0996	28	Male	Coimbatore	364050	
996	CUST0997	32	Female	Indore	438940	
997	CUST0998	41	Male	Mumbai	550890	
998	CUST0999	24	Female	Indore	871223	
999	CUST1000	29	Female	Delhi	549520	

1000 rows × 7 columns

```
In [19]: cust.isna().sum()
```

```
Out[19]: CustomerID      0
Age      0
Gender    0
City      0
AnnualIncomeINR      0
PurchaseFrequency_per_month  0
AvgOrderValueINR      0
EstimatedYearlySpendINR      0
PreferredChannel      0
Openness      0
Conscientiousness      0
Extraversion      0
Agreeableness      0
Neuroticism      0
PersonalityLabel      0
CustomerSegment      0
LastPurchaseDate      0
dtype: int64
```

```
In [20]: cust.drop_duplicates()
```

```
Out[20]:
```

	CustomerID	Age	Gender	City	AnnualIncomeINR	PurchaseFrequency_
0	CUST0001	33	Female	Lucknow	910116	
1	CUST0002	38	Male	Kolkata	924582	
2	CUST0003	47	Male	Mysuru	829877	
3	CUST0004	56	Male	Mysuru	1001629	
4	CUST0005	39	Other	Vadodara	636008	
...	
995	CUST0996	28	Male	Coimbatore	364050	
996	CUST0997	32	Female	Indore	438940	
997	CUST0998	41	Male	Mumbai	550890	
998	CUST0999	24	Female	Indore	871223	
999	CUST1000	29	Female	Delhi	549520	

1000 rows × 7 columns

```
In [21]: cust.dropna(inplace=True)
cust
```

Out[21]:

	CustomerID	Age	Gender	City	AnnualIncomeINR	PurchaseFrequency_
0	CUST0001	33	Female	Lucknow	910116	
1	CUST0002	38	Male	Kolkata	924582	
2	CUST0003	47	Male	Mysuru	829877	
3	CUST0004	56	Male	Mysuru	1001629	
4	CUST0005	39	Other	Vadodara	636008	
...	
995	CUST0996	28	Male	Coimbatore	364050	
996	CUST0997	32	Female	Indore	438940	
997	CUST0998	41	Male	Mumbai	550890	
998	CUST0999	24	Female	Indore	871223	
999	CUST1000	29	Female	Delhi	549520	

1000 rows × 7 columns

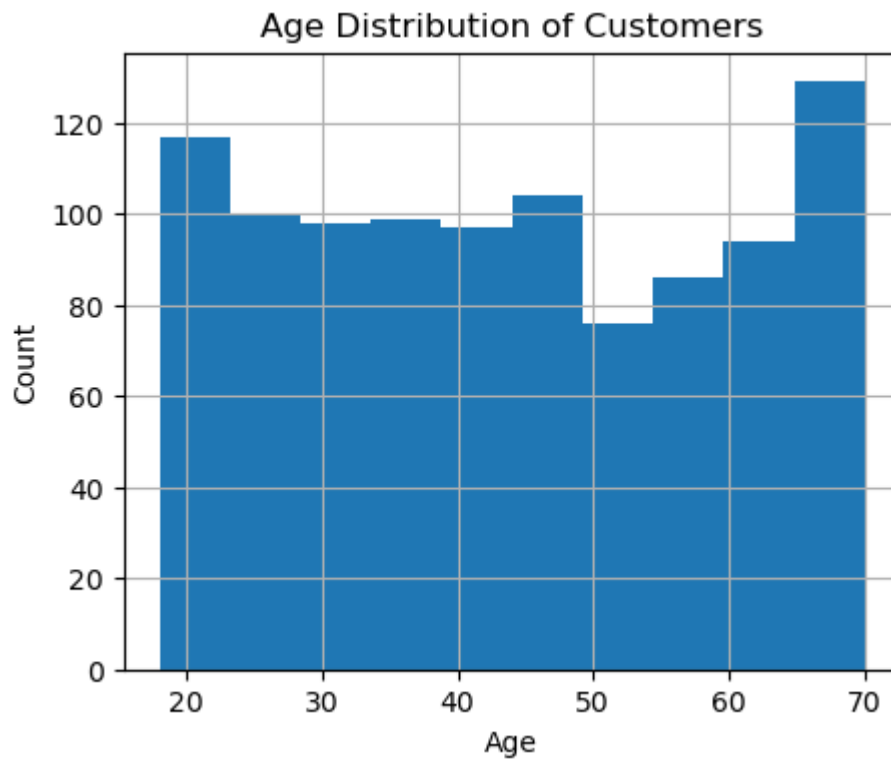
EDA (Exploratory Data Analysis)

In [13]:

```
print(cust['Age'].describe())

cust['Age'].hist(figsize=(5,4))
plt.title("Age Distribution of Customers")
plt.xlabel("Age")
plt.ylabel("Count")
plt.show()
```

```
count    1000.000000
mean      43.773000
std       15.640463
min        18.000000
25%       30.000000
50%       43.000000
75%       58.000000
max       70.000000
Name: Age, dtype: float64
```

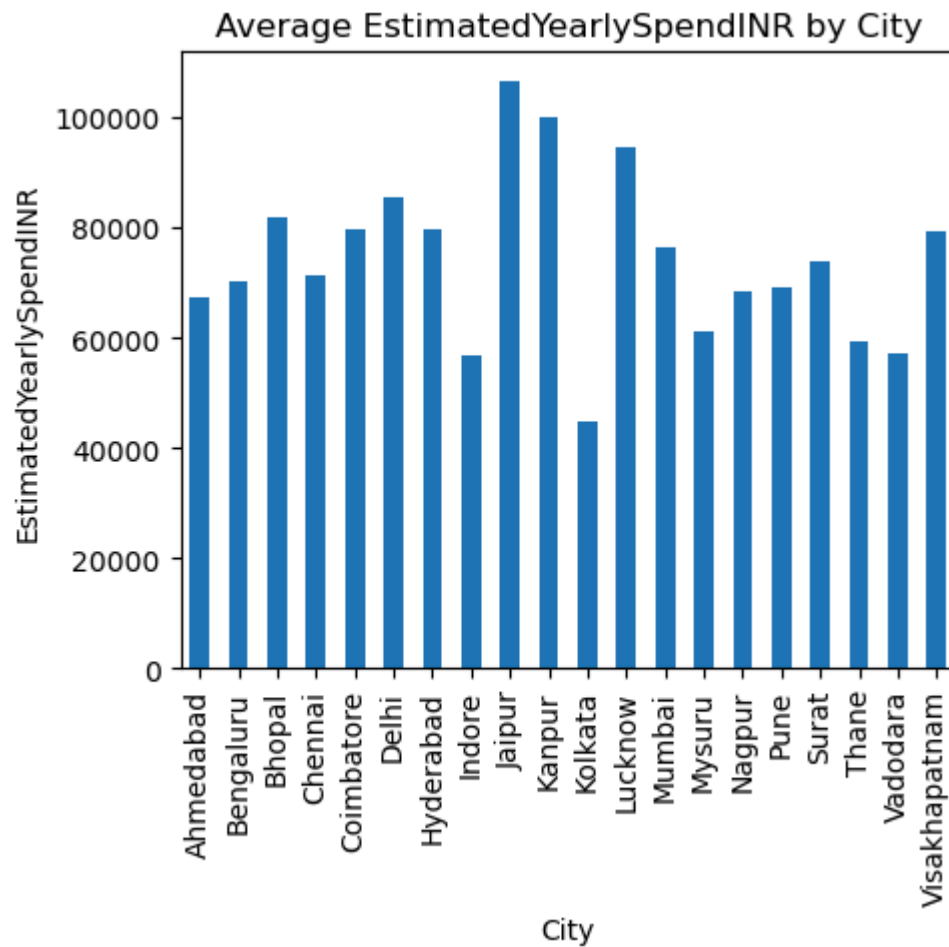


```
In [17]: city_spending = cust.groupby("City")["EstimatedYearlySpendINR"].mean()
print(city_spending)

city_spending.plot(kind='bar', figsize=(5,4))
plt.title("Average EstimatedYearlySpendINR by City")
plt.ylabel("EstimatedYearlySpendINR")
plt.show()
```

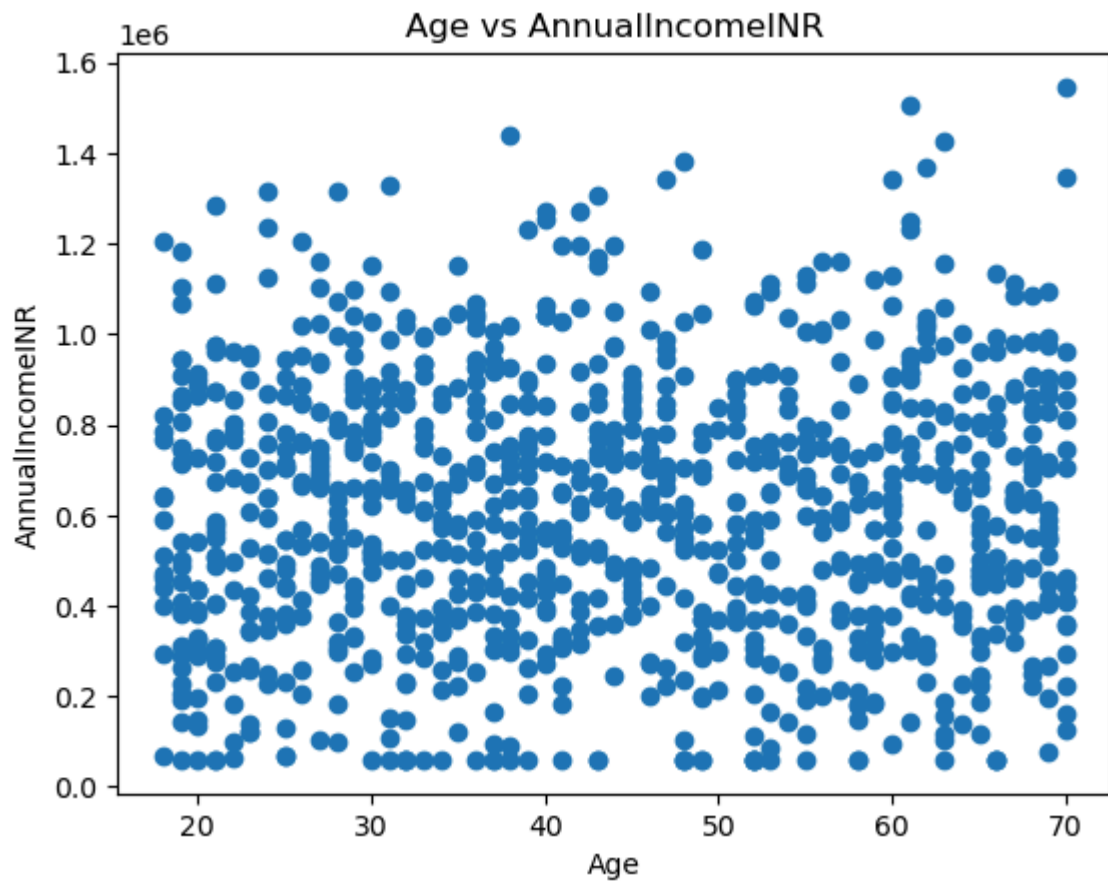
City	EstimatedYearlySpendINR
Ahmedabad	67193.750000
Bengaluru	70219.921569
Bhopal	81696.071429
Chennai	71467.113208
Coimbatore	79600.923077
Delhi	85515.822222
Hyderabad	79696.894737
Indore	56624.087719
Jaipur	106466.648649
Kanpur	99873.127660
Kolkata	44866.111111
Lucknow	94595.389831
Mumbai	76259.169811
Mysuru	61266.384615
Nagpur	68509.166667
Pune	69045.857143
Surat	73815.227273
Thane	59171.523810
Vadodara	56991.372093
Visakhapatnam	79347.875000

Name: EstimatedYearlySpendINR, dtype: float64

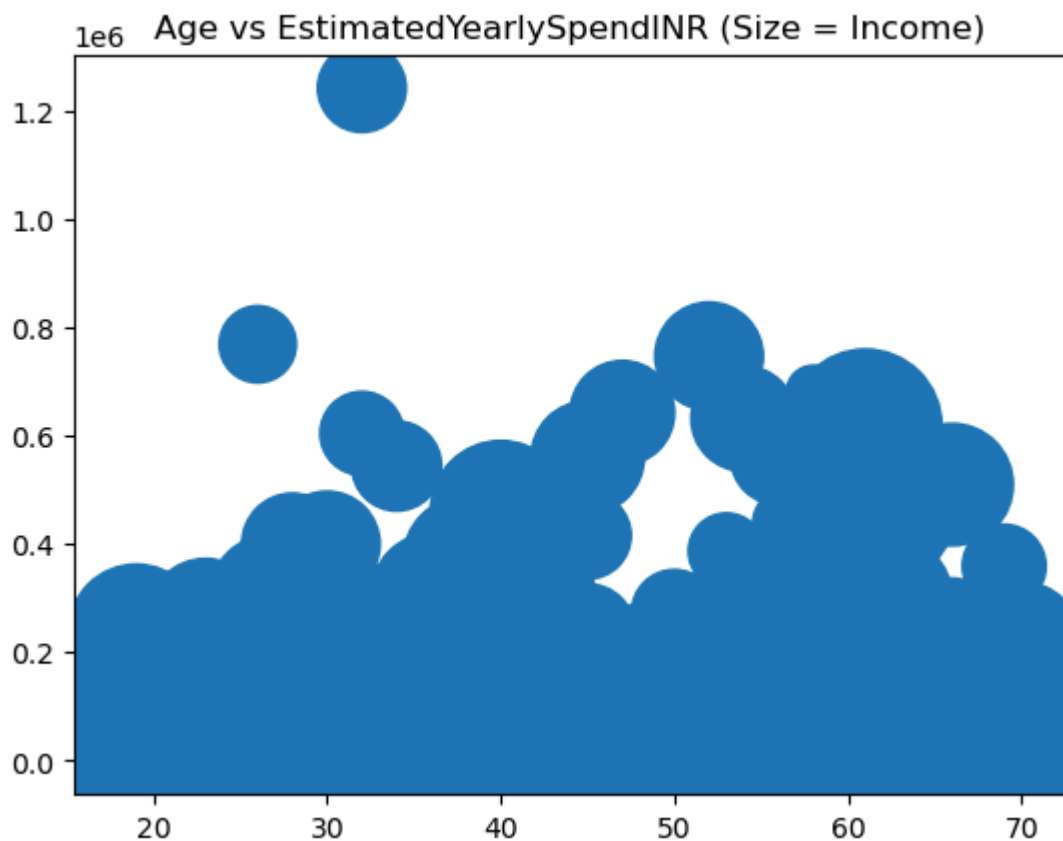


Visualization

```
In [18]: plt.scatter(cust['Age'], cust['AnnualIncomeINR'])  
plt.xlabel("Age")  
plt.ylabel("AnnualIncomeINR")  
plt.title("Age vs AnnualIncomeINR")  
plt.show()
```

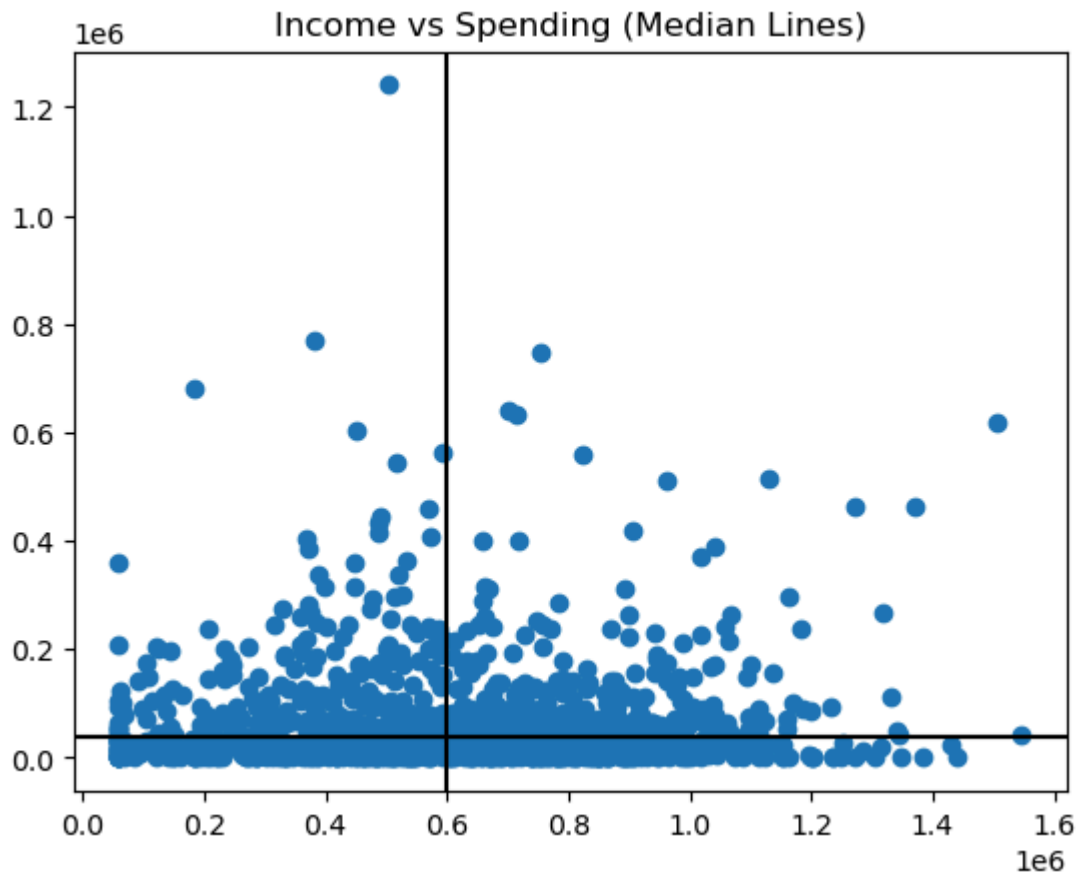


```
In [20]: plt.scatter(cust['Age'], cust['EstimatedYearlySpendINR'], s=cust['AnnualIncomeINR']/500)
plt.title("Age vs EstimatedYearlySpendINR (Size = Income)")
plt.show()
```

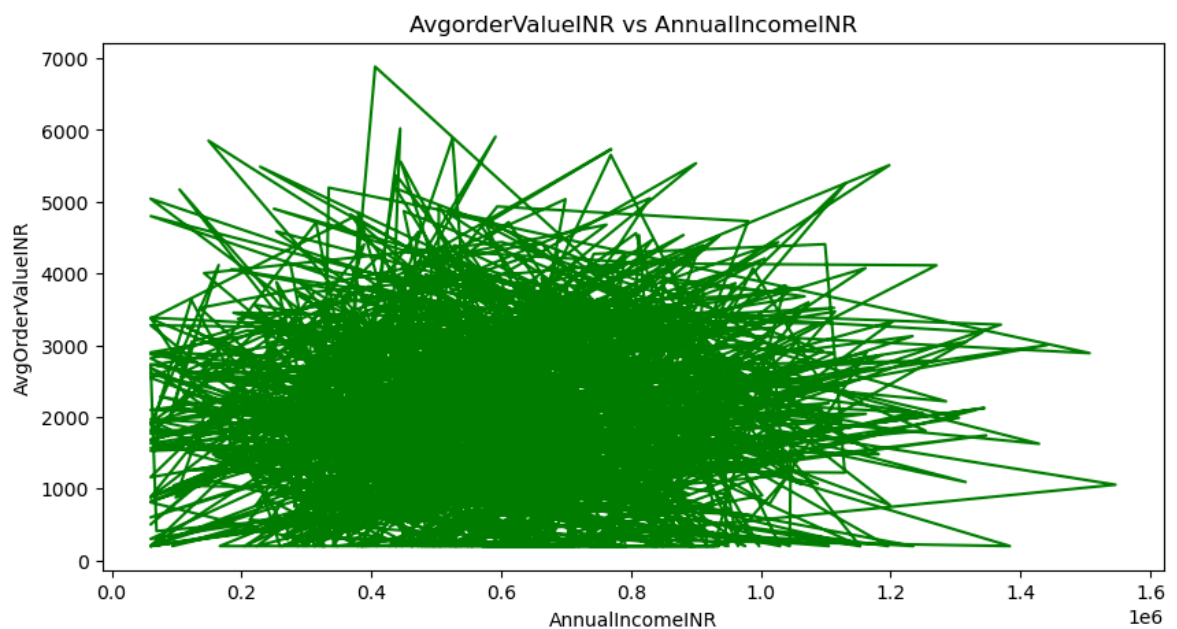


```
In [25]: plt.scatter(cust['AnnualIncomeINR'], cust['EstimatedYearlySpendINR'])
plt.axvline(cust['AnnualIncomeINR'].median(), color='black')
```

```
plt.axhline(cust['EstimatedYearlySpendINR'].median(), color='black')
plt.title("Income vs Spending (Median Lines)")
plt.show()
```

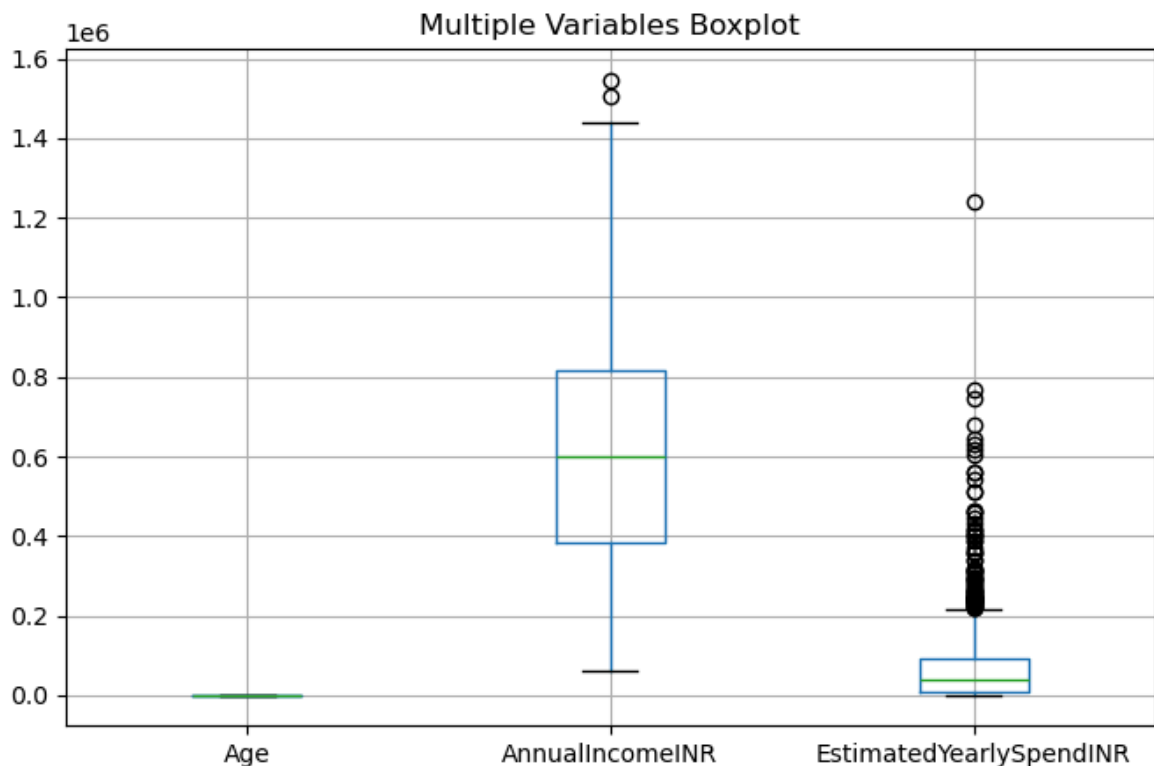


```
In [27]: plt.figure(figsize=(10,5))
plt.plot(cust['AnnualIncomeINR'], cust['AvgOrderValueINR'], color='green')
plt.title("AvgOrderValueINR vs AnnualIncomeINR")
plt.xlabel("AnnualIncomeINR")
plt.ylabel("AvgOrderValueINR")
plt.show()
```



```
In [25]: cust[['Age', 'AnnualIncomeINR', 'EstimatedYearlySpendINR']].boxplot(figsize=(8,5))
plt.title("Multiple Variables Boxplot")
```

```
plt.show()
```



Insight

In []: Age Distribution of Customers:

The Age column shows a wide range of customers. The average age is around X years, and n. The histogram indicates a slightly right-skewed distribution, meaning younger adults form a large portion. This suggests that marketing strategies should focus on this age group, while there is also potential to improve engagement with older customers.

Average EstimatedYearlySpendINR by City:

The bar chart shows noticeable differences in average yearly spending across cities. One city stands out with the highest spending, indicating a stronger customer base with greater purchasing power. The lowest-spending city suggests customers may be more budget-conscious or less engaged. This information is valuable for tailoring marketing efforts where premium products can be promoted and where targeted marketing can increase customer loyalty.

Age vs AnnualIncomeINR:

The scatter plot of Age vs Annual Income shows no strong linear relationship between the two variables. Income levels do not consistently increase or decrease with age. Customers across younger, middle, and older age groups show a wide variation in annual income, suggesting that factors such as job role, experience, and industry have a more significant impact on income than age alone. Overall, the plot reveals that age is not a strong predictor of annual income in this dataset.

Age vs EstimatedYearlySpendINR:

The bubble chart shows that customers of all ages spend different amounts each year, and there is no direct correlation between age and spending. The bigger bubbles (higher income) are mostly connected with higher yearly spending, indicating that income is a stronger factor than age in determining spending. Age does not strongly affect spending, but income does.

Income vs Spending:

The chart shows that people who earn more usually spend more in a year. The middle lines help us see who is above or below the average. Many customers are above the average income but below the average spending, while a few have high income but low spending. Overall, income and spending are connected, but the relationship is not perfectly linear.

AvgorderValueINR vs AnnualIncomeINR:

The line chart shows that as annual income increases, the average order value also tends to increase. Higher income customers usually spend more per order. Overall, higher earners make bigger purchases, which is a positive trend for the business.

smaller-value orders.

Multiple Variables Boxplot:

The boxplot shows that income **and** yearly spending vary a lot between customers, **while** age Income **and** spending also have some very high values compared to the rest. Overall, money-re age **in** this dataset.