AtliQo Bank Credit Card Launch ¶

Problem Statement

AtliQo Bank, a new banking company wants to launch a credit card in the highly competitive Indian market.The company needed to identify the most promising target market segment and tailor its credit card offering to meet the specific needs and preferences of that segment.The objective is to make data-driven decisions regarding the target market segment and ensure the successful launch of the new credit card within that segment, enabling the banking company to gain a competitive edge in the Indian market.

Phase 1: AtliQ0 Bank Credit Card Project

Objective: Analyze customers' transactions and credit profiles to figure out a target group for the launch of AtliQo bank credit card

Data Import

In [153]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

In [154]:
```
df_transact = pd.read_csv('Datasets/transactions.csv')
```

In [155]:
```
df_transact.head()
```

Out[155]:

	tran_id	cust_id	tran_date	tran_amount	platform	product_category	payment_type
0	1	705	2023-01-01	63	Flipkart	Electronics	Phonepe
1	2	385	2023-01-01	99	Alibaba	Fashion & Apparel	Credit Card
2	3	924	2023-01-01	471	Shopify	Sports	Phonepe
3	4	797	2023-01-01	33	Shopify	Fashion & Apparel	Gpay
4	5	482	2023-01-01	68	Amazon	Fashion & Apparel	Net Banking

In [156]:
```
df_cust = pd.read_csv('Datasets/customers.csv')
```

In [157]:
```
df_cust.head()
```

Out[157]:

	cust_id	name	gender	age	location	occupation	annual_income	marital_status
0	1	Manya Acharya	Female	2	City	Business Owner	358211.0	Married
1	2	Anjali Pandey	Female	47	City	Consultant	65172.0	Single
2	3	Aaryan Chauhan	Male	21	City	Freelancer	22378.0	Married
3	4	Rudra Bali	Male	24	Rural	Freelancer	33563.0	Married
4	5	Advait Malik	Male	48	City	Consultant	39406.0	Married

In [158]:
```
df_credit = pd.read_csv('Datasets/credit_profiles.csv')
```

In [159]:
```
df_credit.head()
```

Out[159]:

	cust_id	credit_score	credit_utilisation	outstanding_debt	credit_inquiries_last_6_months
0	1	749	0.585171	19571.0	0.0
1	2	587	0.107928	161644.0	2.0
2	3	544	0.854807	513.0	4.0
3	4	504	0.336938	224.0	2.0
4	5	708	0.586151	18090.0	2.0

Exploring Customers Table

In [160]:
```
df_cust.describe()
```

Out[160]:

	cust_id	age	annual_income
count	1000.000000	1000.000000	950.000000
mean	500.500000	36.405000	139410.314737
std	288.819436	15.666155	112416.802007
min	1.000000	1.000000	2.000000
25%	250.750000	26.000000	47627.500000
50%	500.500000	32.000000	112218.500000
75%	750.250000	46.000000	193137.500000
max	1000.000000	135.000000	449346.000000

In [161]:
```
df_cust.isnull().sum() #50Null Values
```

Out[161]:
```
cust_id            0
name               0
gender             0
age                0
location           0
occupation         0
annual_income     50
marital_status     0
dtype: int64
```

1. Analyze Income Column

Handle Null Values: Annual income

In [162]:
```
df_cust[df_cust.annual_income.isna()].head() #now we will fill the Na value
```

Out[162]:

	cust_id	name	gender	age	location	occupation	annual_income	marital_status
14	15	Sanjana Malik	Female	25	Rural	Artist	NaN	Married
82	83	Reyansh Mukherjee	Male	27	City	Freelancer	NaN	Single
97	98	Virat Puri	Male	47	Suburb	Business Owner	NaN	Married
102	103	Aarav Shah	Male	32	City	Data Scientist	NaN	Married
155	156	Kiaan Saxena	Male	24	City	Fullstack Developer	NaN	Married

In [163]:
```
occ_wise_inc_median = df_cust.groupby('occupation')['annual_income'].median
occ_wise_inc_median
```

Out[163]:
```
occupation
Accountant              65265.0
Artist                  45794.0
Business Owner         261191.5
Consultant              58017.0
Data Scientist         135759.0
Freelancer              46759.0
Fullstack Developer     76774.0
Name: annual_income, dtype: float64
```

In [164]:
```
df_cust['annual_income'] = df_cust.apply(
    lambda row : occ_wise_inc_median[row['occupation']] if pd.isnull(row['a
```

In [165]:
```
df_cust.isnull().sum() #No null values
```

Out[165]:
```
cust_id           0
name              0
gender            0
age               0
location          0
occupation        0
annual_income     0
marital_status    0
dtype: int64
```

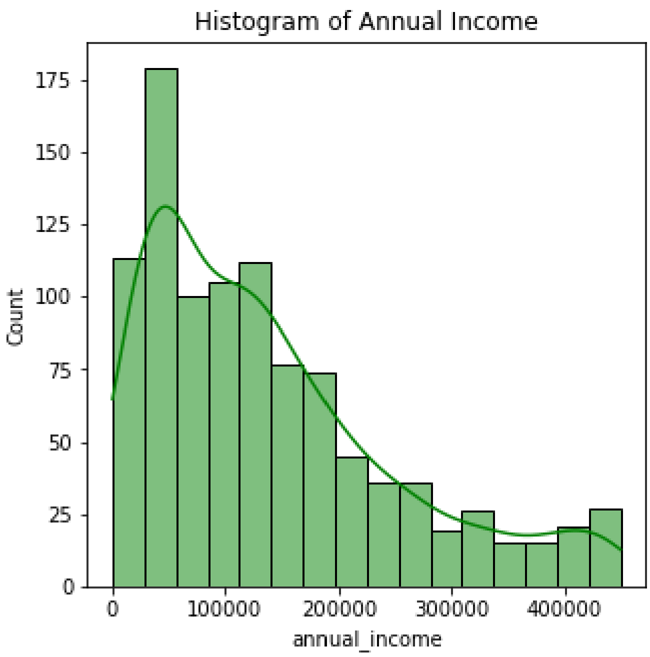
In [166]:
```
df_cust.iloc[[14,82]]
```

Out[166]:

	cust_id	name	gender	age	location	occupation	annual_income	marital_status
14	15	Sanjana Malik	Female	25	Rural	Artist	45794.0	Married
82	83	Reyansh Mukherjee	Male	27	City	Freelancer	46759.0	Single

Previously records at location 14 and 82 had null annual income. Now we have a median value per occupation

In [167]:
```
plt.figure(figsize = (5,5))
sns.histplot(df_cust['annual_income'],kde =True,color = 'green',label = 'Da
plt.title('Histogram of Annual Income')
plt.show() #rightly skewed
```



In [168]:
```
df_cust.describe() #min value is 2 its an oulier company manager told that
```

Out[168]:

	cust_id	age	annual_income
count	1000.000000	1000.000000	1000.000000
mean	500.500000	36.405000	138916.765500
std	288.819436	15.666155	110969.408643
min	1.000000	1.000000	2.000000
25%	250.750000	26.000000	48229.500000
50%	500.500000	32.000000	113416.000000
75%	750.250000	46.000000	192614.000000
max	1000.000000	135.000000	449346.000000

In [169]:
```
df_cust[df_cust.annual_income<100]
```

Out[169]:

	cust_id	name	gender	age	location	occupation	annual_income	marital_status
31	32	Veer Mistry	Male	50	City	Business Owner	50.0	Married
262	263	Vivaan Tandon	Male	53	Suburb	Business Owner	50.0	Married
316	317	Yuvraj Saxena	Male	47	City	Consultant	50.0	Married
333	334	Avani Khanna	Female	29	City	Data Scientist	50.0	Married
340	341	Priya Sinha	Female	33	Rural	Fullstack Developer	50.0	Married
543	544	Advait Batra	Male	54	City	Consultant	2.0	Married
592	593	Priya Gandhi	Female	32	City	Business Owner	50.0	Married
633	634	Rudra Mehtani	Male	26	City	Data Scientist	2.0	Married
686	687	Vihaan Jaiswal	Male	40	City	Business Owner	2.0	Married
696	697	Ishan Negi	Male	47	City	Consultant	20.0	Married

In [170]:
```
df_cust[df_cust.annual_income<100].shape
```

Out[170]:
```
(10, 8)
```

Outlier Treatment: Annual income

Above records (with <100$ income) are outliers. We have following options to treat them,

1. **Remove them**: After discussion with business manager, we decided not to remove them as these are valid customers and we want to include them in our analysis
2. **Replace them with mean or median** : Mean is sensitive to outliers. It is better to use median for income values

3. **Replace them with occupation wise median**: Income level may vary based on occupation. For example median income for data scientist can be different from a median income of a business owner. It is better to use occupation wise median income for replacement

In [171]:
```
df_cust['annual_income'] = df_cust.apply(
    lambda row : occ_wise_inc_median[row['occupation']] if row['annual_inco
```

In [172]:
```
df_cust.iloc[[31,262,316]]
```

Out[172]:

	cust_id	name	gender	age	location	occupation	annual_income	marital_status
31	32	Veer Mistry	Male	50	City	Business Owner	261191.5	Married
262	263	Vivaan Tandon	Male	53	Suburb	Business Owner	261191.5	Married
316	317	Yuvraj Saxena	Male	47	City	Consultant	58017.0	Married

Record at 31,262, and 316 location had annual income of < 100$. Now you can see it is replaced by a median income per occupation

In [173]:
```
df_cust[df_cust.annual_income<100]
```

Out[173]:

cust_id	name	gender	age	location	occupation	annual_income	marital_status

successfully manged outliers values

Data Visualization: Annual Income

In [174]:
```
df_cust.head()
```

Out[174]:

	cust_id	name	gender	age	location	occupation	annual_income	marital_status
0	1	Manya Acharya	Female	2	City	Business Owner	358211.0	Married
1	2	Anjali Pandey	Female	47	City	Consultant	65172.0	Single
2	3	Aaryan Chauhan	Male	21	City	Freelancer	22378.0	Married
3	4	Rudra Bali	Male	24	Rural	Freelancer	33563.0	Married
4	5	Advait Malik	Male	48	City	Consultant	39406.0	Married

In [175]:
```
df_occupation_mean = df_cust.groupby('occupation').annual_income.mean().sor
```

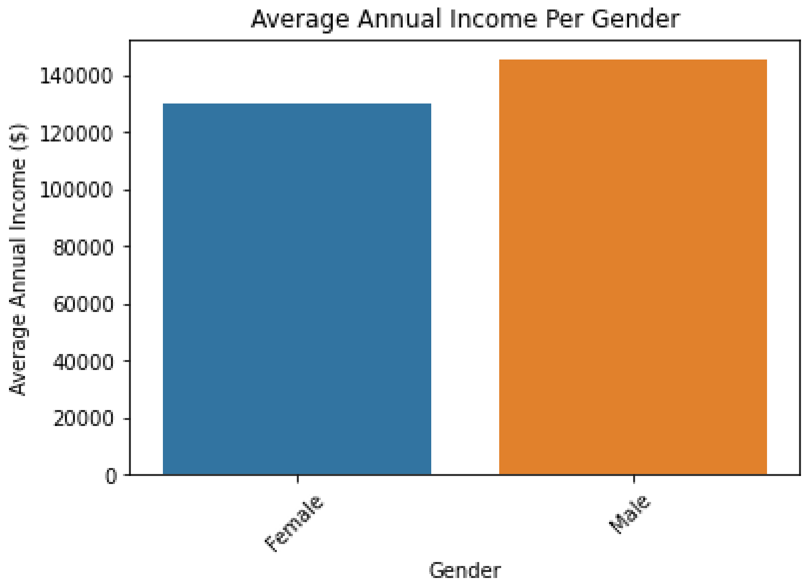
In [176]:
```
df_occupation_mean
```

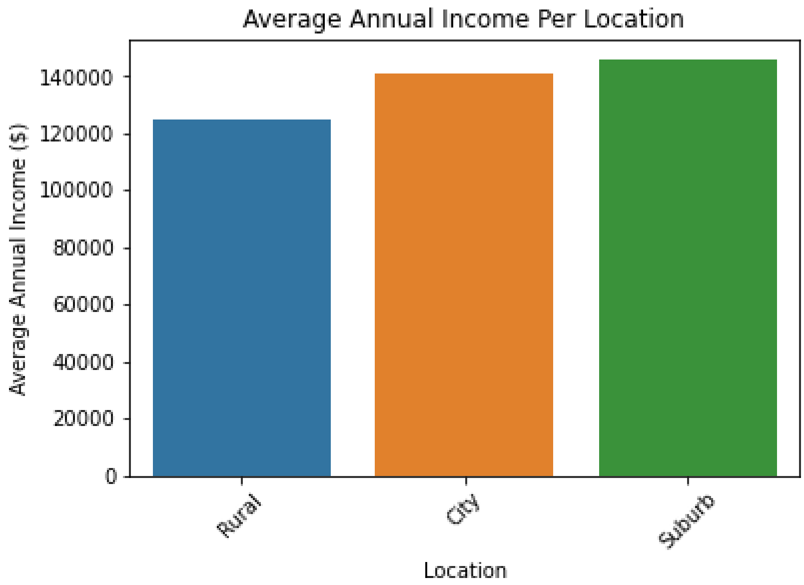
Out[176]:
```
occupation
Artist                 45309.236842
Consultant             60703.154639
Accountant             64123.562500
Freelancer             76327.508772
Fullstack Developer    78727.972973
Data Scientist        137021.266304
Business Owner        268447.368512
Name: annual_income, dtype: float64
```

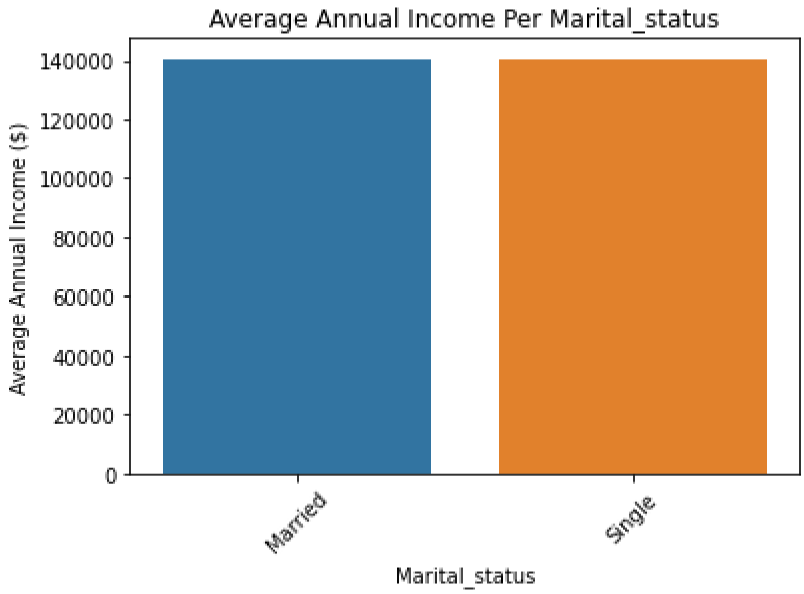
In [177]:
```
df_cust.columns
```

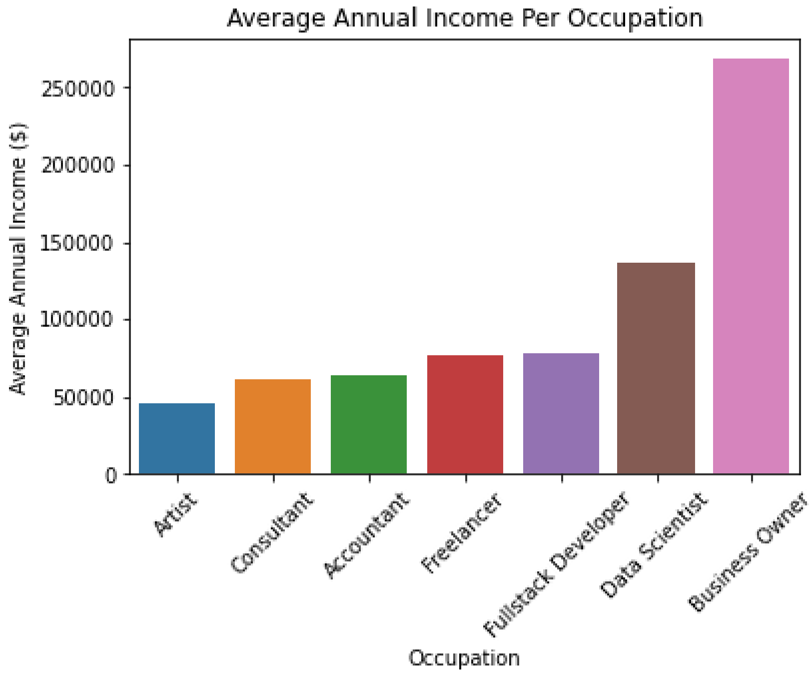
Out[177]:
```
Index(['cust_id', 'name', 'gender', 'age', 'location', 'occupation',
       'annual_income', 'marital_status'],
      dtype='object')
```

In [178]:
```
categories = ['gender','location','marital_status','occupation']

for col in categories:
    df_occupation_mean = df_cust.groupby(col).annual_income.mean().sort_val
    sns.barplot(df_occupation_mean.index,df_occupation_mean.values,palette
    plt.xticks(rotation = 45)
    plt.title(f'Average Annual Income Per {col.capitalize()}')
    plt.xlabel(col.capitalize())
    plt.ylabel('Average Annual Income ($)')
    plt.show()
```









2. Analyze Age Column

Handle Null Values: Age Column

First let us check if there are any NULL values in the Age column

In [179]:
```
df_cust.age.isnull().sum()
```

Out[179]: 0

No null values are found in age column.

In [180]:
```
df_cust.describe() #outliers in age
```

Out[180]:

	cust_id	age	annual_income
count	1000.000000	1000.000000	1000.000000
mean	500.500000	36.405000	140483.548500
std	288.819436	15.666155	110463.002934
min	1.000000	1.000000	5175.000000
25%	250.750000	26.000000	49620.500000
50%	500.500000	32.000000	115328.000000
75%	750.250000	46.000000	195514.250000
max	1000.000000	135.000000	449346.000000

Outlier Treatment: Age

Above we see that min age is 1 and max age is 135. These seem to be outliers. So let's find out age distribution.

In [181]:
```
df_outliers = df_cust[(df_cust.age<15) | (df_cust.age>80)]
```

In [182]:
```
df_outliers
```

Out[182]:

	cust_id	name	gender	age	location	occupation	annual_income	marital_status
0	1	Manya Acharya	Female	2	City	Business Owner	358211.0	Married
41	42	Aaryan Shah	Male	110	City	Artist	7621.0	Married
165	166	Sia Dutta	Female	1	City	Freelancer	39721.0	Single
174	175	Rohan Sharma	Male	110	City	Freelancer	23723.0	Married
222	223	Arjun Batra	Male	110	Suburb	Freelancer	210987.0	Married
277	278	Aarav Tandon	Male	110	City	Consultant	96522.0	Single
295	296	Ayush Pandey	Male	1	Rural	Accountant	55254.0	Married
325	326	Virat Goel	Male	110	City	Accountant	61021.0	Single
610	611	Rehan Verma	Male	135	Rural	Business Owner	444776.0	Married
692	693	Dhruv Jha	Male	1	City	Business Owner	83045.0	Married
703	704	Aanya Sharma	Female	110	City	Freelancer	43404.0	Single
709	710	Anika Verma	Female	110	City	Data Scientist	98417.0	Married
728	729	Rehan Yadav	Male	135	City	Business Owner	382836.0	Married
832	833	Ridhi Raj	Female	110	City	Fullstack Developer	95379.0	Single
845	846	Rohan Jaiswal	Male	1	City	Consultant	20838.0	Married
855	856	Aanya Taneja	Female	2	City	Fullstack Developer	30689.0	Married
895	896	Krishna Goswami	Male	1	City	Freelancer	31533.0	Married
923	924	Kunal Patel	Male	110	City	Freelancer	51629.0	Married
951	952	Virat Shetty	Male	135	City	Data Scientist	49677.0	Married
991	992	Arya Dube	Male	135	City	Fullstack Developer	93267.0	Single

In [183]:
```
df_outliers.shape
```

Out[183]: (20, 8)

we cannot remove 20 rows as they are important. So to treat these outliers we will use median age for each of the occupation

In [184]:
```
age_median = df_cust.groupby('occupation')['age'].median()
```

In [185]:
```
age_median
```

Out[185]:
```
occupation
Accountant              31.5
Artist                  26.0
Business Owner          51.0
Consultant              46.0
Data Scientist          32.0
Freelancer              24.0
Fullstack Developer     27.5
Name: age, dtype: float64
```

In [186]:
```
df_cust['age'] = df_cust.apply(
    lambda row : age_median[row['occupation']] if (row['age'] <15) | (row['
```

In [187]:
```
df_cust[(df_cust.age<15) | (df_cust.age>80)]
```

Out[187]:

cust_id	name	gender	age	location	occupation	annual_income	marital_status

In [188]:
```
df_cust.iloc[[0,41]]
```

Out[188]:

	cust_id	name	gender	age	location	occupation	annual_income	marital_status
0	1	Manya Acharya	Female	51.0	City	Business Owner	358211.0	Married
41	42	Aaryan Shah	Male	26.0	City	Artist	7621.0	Married

In [189]:
```
df_cust.describe()
```

Out[189]:

	cust_id	age	annual_income
count	1000.000000	1000.000000	1000.000000
mean	500.500000	35.541500	140483.548500
std	288.819436	12.276634	110463.002934
min	1.000000	18.000000	5175.000000
25%	250.750000	26.000000	49620.500000
50%	500.500000	32.000000	115328.000000
75%	750.250000	44.250000	195514.250000
max	1000.000000	64.000000	449346.000000

As you can see above, now we don't have any outliers left. min age is 18 and max is 64

Data Visualization: Age Column

In [190]:
```
bin_edges = [17,25,48,65]
bin_labels = ['18-25','26-48','49-65']
df_cust['age_group'] = pd.cut(df_cust['age'],bins=bin_edges,labels = bin_la
df_cust.head()
```

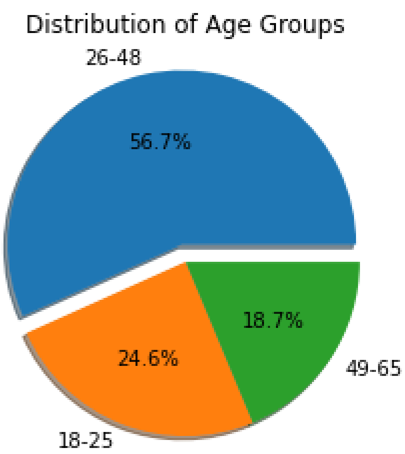
Out[190]:

	cust_id	name	gender	age	location	occupation	annual_income	marital_status	age_
0	1	Manya Acharya	Female	51.0	City	Business Owner	358211.0	Married	
1	2	Anjali Pandey	Female	47.0	City	Consultant	65172.0	Single	
2	3	Aaryan Chauhan	Male	21.0	City	Freelancer	22378.0	Married	
3	4	Rudra Bali	Male	24.0	Rural	Freelancer	33563.0	Married	
4	5	Advait Malik	Male	48.0	City	Consultant	39406.0	Married	

In [191]:
```
age_group_pct = df_cust.age_group.value_counts(normalize =True) *100
age_group_pct
```

Out[191]:
```
26-48    56.7
18-25    24.6
49-65    18.7
Name: age_group, dtype: float64
```

In [192]:
```
plt.pie(age_group_pct,labels=age_group_pct.index ,autopct = '%1.1f%%',explo
plt.title('Distribution of Age Groups')
plt.show()
```



3. Analyze Gender and Location Distribution

In [193]:
```
#to create stack bar chart
df_cust.location.value_counts()
```

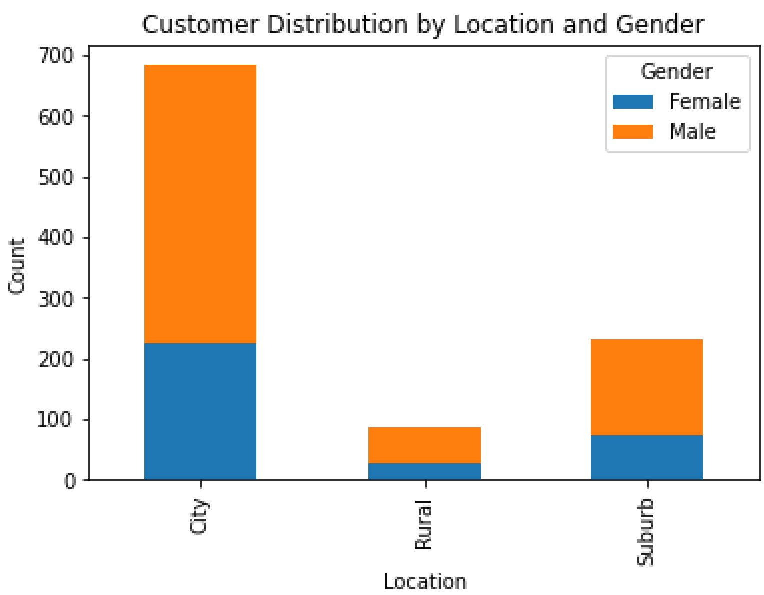
Out[193]:
```
City      683
Suburb    232
Rural      85
Name: location, dtype: int64
```

In [194]:
```
df_cust.gender.value_counts()
```

Out[194]:
```
Male      674
Female    326
Name: gender, dtype: int64
```

In [195]:
```
cus_location_gen =df_cust.groupby(['location','gender']).size().unstack() #
```

In [196]:
```
cus_location_gen.plot(kind='bar',stacked = True)
plt.title('Customer Distribution by Location and Gender')
plt.legend(title = "Gender")
plt.xlabel('Location')
plt.ylabel('Count')
plt.show()
```



Explore Credit Score Table

In [197]:
```
df_credit.head()
```

Out[197]:

	cust_id	credit_score	credit_utilisation	outstanding_debt	credit_inquiries_last_6_months
0	1	749	0.585171	19571.0	0.0
1	2	587	0.107928	161644.0	2.0
2	3	544	0.854807	513.0	4.0
3	4	504	0.336938	224.0	2.0
4	5	708	0.586151	18090.0	2.0

In [198]:
```
df_credit.shape
```

Out[198]: (1004, 6)

Credit table should have same records as customers table, so there are 4 extra records

In [199]:
```
df_credit.cust_id.nunique() #so some records have duplicates
```

Out[199]: 1000

In [200]:
```
#lets print out duplicates
df_credit[df_credit.cust_id.duplicated(keep = False)]
```

Out[200]:

	cust_id	credit_score	credit_utilisation	outstanding_debt	credit_inquiries_last_6_months
516	517	308	NaN	NaN	NaN
517	517	308	0.113860	33.0	3.0
569	569	344	NaN	NaN	NaN
570	569	344	0.112599	37.0	0.0
607	606	734	NaN	NaN	NaN
608	606	734	0.193418	4392.0	1.0
664	662	442	NaN	NaN	NaN
665	662	442	0.856039	266.0	2.0

In [201]:
```
df_credit_clean = df_credit.drop_duplicates(subset = 'cust_id',keep= 'last'
```

In [202]:
```
df_credit_clean.shape
```

Out[202]: (1000, 6)

In [203]:
```
df_credit_clean[df_credit_clean.cust_id.duplicated(keep = False)]
```

Out[203]:

cust_id	credit_score	credit_utilisation	outstanding_debt	credit_inquiries_last_6_months

looks clean now after cleaning duplicates.

Next step would be to see if there are any null values

Data Cleaning Step 2: Handle Null Values

In [204]:
```
df_credit_clean.isnull().sum() #Nullvalues are there
```

Out[204]:
```
cust_id                         0
credit_score                    0
credit_utilisation              0
outstanding_debt                0
credit_inquiries_last_6_months  0
credit_limit                   65
dtype: int64
```

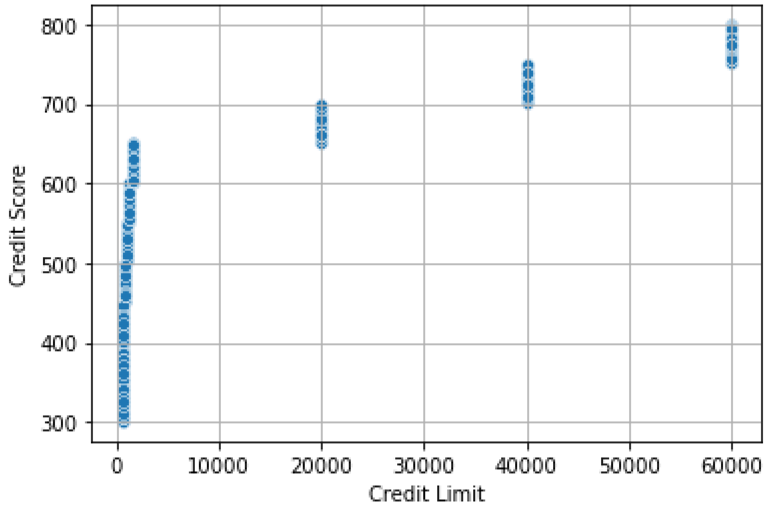
In [205]:
```
df_credit_clean[df_credit_clean.credit_limit.isna()]
```

Out[205]:

	cust_id	credit_score	credit_utilisation	outstanding_debt	credit_inquiries_last_6_months
10	11	679	0.557450	9187.0	2.0
35	36	790	0.112535	4261.0	1.0
37	38	514	0.296971	238.0	2.0
45	46	761	0.596041	24234.0	2.0
64	65	734	0.473715	13631.0	0.0
...	...	...	...	...	...
912	909	479	0.487555	320.0	3.0
931	928	311	0.832244	316.0	2.0
948	945	526	0.272734	227.0	1.0
954	951	513	0.175914	131.0	3.0
957	954	783	0.867421	46451.0	0.0

65 rows × 6 columns

In [206]:
```
sns.scatterplot(x=df_credit_clean.credit_limit, y=df_credit.credit_score)
plt.xlabel('Credit Limit')
plt.ylabel('Credit Score')
plt.grid(True)  # Add gridlines
plt.show()
```



Here we can see clear relationship between credit score and credit limit. Where there are levels for example, upto 650 score is getting a very minor credit limit (<1000$) where as a score between 650 to 700 is getting around 20000. Score between 700 to 750 is getting around 40K etc.

In [207]:
```
bin_ranges = [300, 450, 500, 550, 600, 650, 700, 750, 800]

# Create labels for the bins
bin_labels = [f'{start}-{end-1}' for start, end in zip(bin_ranges, bin_rang

# Use pd.cut to assign data to bins
df_credit_clean['credit_score_range'] = pd.cut(df_credit_clean['credit_scor
```

In [208]:
```
df_credit_clean.shape
```

Out[208]:
```
(1000, 7)
```

In [209]:
```
mode_df = df_credit_clean.groupby('credit_score_range')['credit_limit'].agg
mode_df
#iloc because if 10 rows have 5 same other 5 also same so it will return on
```

Out[209]:

	credit_score_range	credit_limit
0	300-449	500.0
1	450-499	750.0
2	500-549	1000.0
3	550-599	1250.0
4	600-649	1500.0
5	650-699	20000.0
6	700-749	40000.0
7	750-799	60000.0

In [210]:
```
df_credit_clean2 = pd.merge(df_credit_clean,mode_df, on='credit_score_range
```

In [211]:
```
df_credit_clean2.shape
```

Out[211]: (1000, 8)

In [212]:
```
df_credit_clean2[df_credit_clean2.credit_limit.isna()]
```

Out[212]:

	cust_id	credit_score	credit_utilisation	outstanding_debt	credit_inquiries_last_6_months
9	65	734	0.473715	13631.0	0.0
10	84	733	0.525567	16663.0	1.0
19	160	709	0.759795	18244.0	0.0
20	168	737	0.489797	12421.0	2.0
37	279	741	0.352932	10846.0	1.0
...	...	...	...	...	...
944	758	783	0.801201	28920.0	3.0
951	780	787	0.681978	24711.0	1.0
962	850	787	0.293520	11195.0	3.0
981	899	775	0.487290	21548.0	0.0
988	954	783	0.867421	46451.0	0.0

65 rows × 8 columns

Above we can simple replace NaN value in credit_limit column with credit_limit_mode value. This value indicates most frequently occuring credit limit for a given credit_score_range. Hence it can be used as a replacement value.

We will create a new copy of the dataframe so that we have reproducibility and access of the older dataframe in this notebook

In [213]:
```
df_cs_clean_3 = df_credit_clean2.copy()
df_cs_clean_3['credit_limit'].fillna(df_cs_clean_3['credit_limit_mode'], in
df_cs_clean_3.shape
```

Out[213]: (1000, 8)

Data Cleaning Step 3: Handle Outliers: outstanding_debt

In [214]:
```
df_cs_clean_3.describe()
```

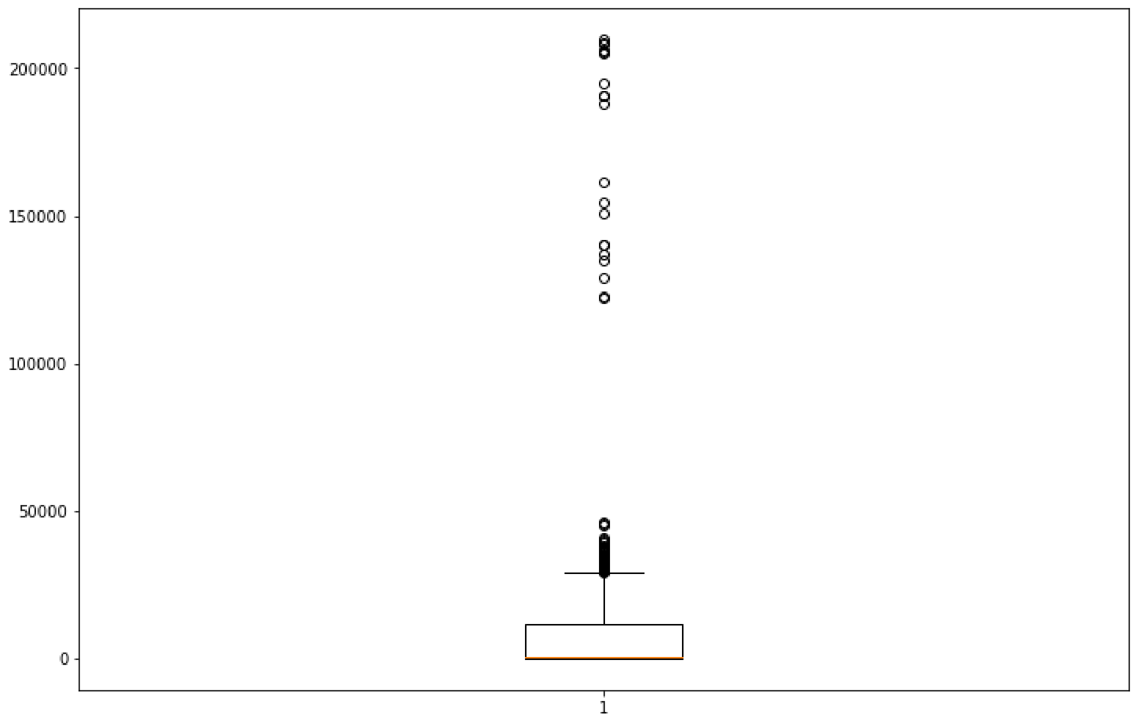
Out[214]:

	cust_id	credit_score	credit_utilisation	outstanding_debt	credit_inquiries_last_6_r
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.
mean	500.500000	589.182000	0.498950	9683.597000	1.
std	288.819436	152.284929	0.233139	25255.893671	1.
min	1.000000	300.000000	0.103761	33.000000	0.
25%	250.750000	460.000000	0.293917	221.000000	1.
50%	500.500000	601.500000	0.487422	550.000000	2.
75%	750.250000	738.000000	0.697829	11819.500000	3.
max	1000.000000	799.000000	0.899648	209901.000000	4.

Outliers are there as max outstanding debt is more than credit limit which is not possible

In [215]:
```
plt.figure(figsize=(12, 8))
plt.boxplot(df_cs_clean_3.outstanding_debt)
plt.show
```

Out[215]: <function matplotlib.pyplot.show(close=None, block=None)>



Instead of using any statistical approach (such as standard deviation or IQR), here too we will use a business knowledge. We will mark any outstanding debt that is greater than credit limit as an outlier

In [216]:
```
df_cs_clean_3[df_cs_clean_3.outstanding_debt > df_cs_clean_3.credit_limit]
```

Out[216]:

	cust_id	credit_score	credit_utilisation	outstanding_debt	credit_inquiries_last_6_months
6	39	734	0.573023	122758.0	3.0
12	94	737	0.739948	137058.0	2.0
35	272	703	0.446886	154568.0	1.0
41	302	722	0.608076	122402.0	4.0
101	726	737	0.136048	205404.0	4.0
142	2	587	0.107928	161644.0	2.0
363	205	303	0.364360	187849.0	0.0
406	351	320	0.285081	150860.0	0.0
474	637	420	0.323984	140063.0	4.0
604	647	498	0.658087	128818.0	3.0
609	724	465	0.658173	140008.0	3.0
615	767	473	0.611750	195004.0	1.0
684	20	647	0.439132	205014.0	3.0
759	731	626	0.762245	209901.0	2.0
788	26	758	0.250811	190838.0	2.0
858	331	799	0.363420	208898.0	4.0
877	447	754	0.178394	206191.0	2.0
903	545	764	0.337769	135112.0	2.0
930	699	775	0.385100	190717.0	2.0
968	863	792	0.399555	208406.0	3.0

We will replace these outliers with credit_limit. We can assume that there was some data processing error due to we got these high numbers and it is ok to replace them with a credit_limit

In [217]:
```
df_cs_clean_3['outstanding_debt'] = df_cs_clean_3.apply(
    lambda row: row['credit_limit'] if row['outstanding_debt'] > row['credi
```

In [218]:
```
df_cs_clean_3.iloc[[6,12]]
```

Out[218]:

	cust_id	credit_score	credit_utilisation	outstanding_debt	credit_inquiries_last_6_months
6	39	734	0.573023	40000.0	3.0
12	94	737	0.739948	40000.0	2.0

In [219]:
```
df_cs_clean_3[df_cs_clean_3.outstanding_debt > df_cs_clean_3.credit_limit]
```

Out[219]:

cust_id	credit_score	credit_utilisation	outstanding_debt	credit_inquiries_last_6_months	cı

Outliers managed!

Data Exploration: Visualizing Correlation in Credit Score Table

In [220]:
```
df_cust.head()
```

Out[220]:

	cust_id	name	gender	age	location	occupation	annual_income	marital_status	age_
0	1	Manya Acharya	Female	51.0	City	Business Owner	358211.0	Married	
1	2	Anjali Pandey	Female	47.0	City	Consultant	65172.0	Single	
2	3	Aaryan Chauhan	Male	21.0	City	Freelancer	22378.0	Married	
3	4	Rudra Bali	Male	24.0	Rural	Freelancer	33563.0	Married	
4	5	Advait Malik	Male	48.0	City	Consultant	39406.0	Married	

In [221]:
```
df_merged = df_cust.merge(df_cs_clean_3,on='cust_id',how='inner')
df_merged.head()
```

Out[221]:

	cust_id	name	gender	age	location	occupation	annual_income	marital_status	age_
0	1	Manya Acharya	Female	51.0	City	Business Owner	358211.0	Married	
1	2	Anjali Pandey	Female	47.0	City	Consultant	65172.0	Single	
2	3	Aaryan Chauhan	Male	21.0	City	Freelancer	22378.0	Married	
3	4	Rudra Bali	Male	24.0	Rural	Freelancer	33563.0	Married	
4	5	Advait Malik	Male	48.0	City	Consultant	39406.0	Married	

In [222]:
```
df_merged[['outstanding_debt','credit_limit']].corr() #strongly correlated
```

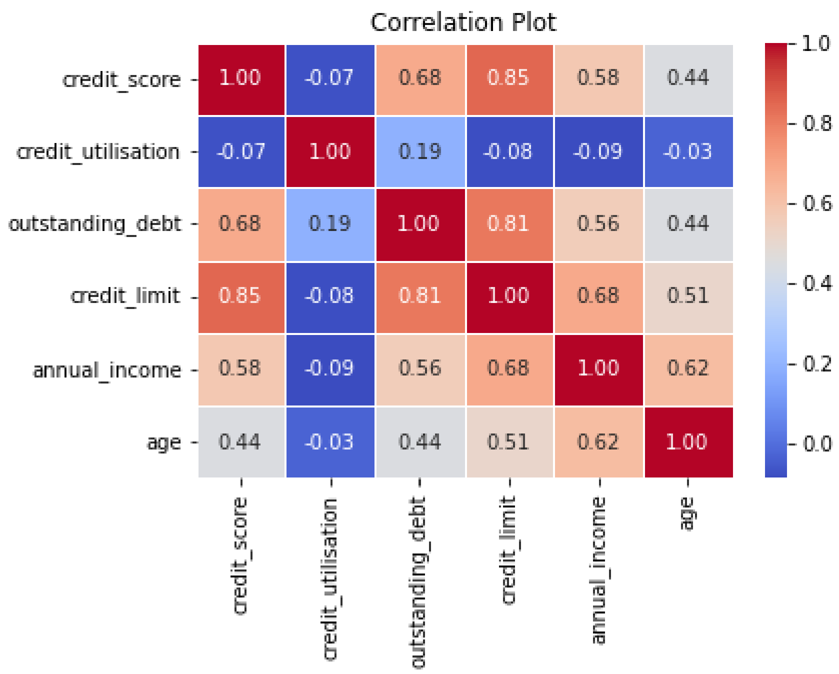
Out[222]:

	outstanding_debt	credit_limit
outstanding_debt	1.000000	0.810581
credit_limit	0.810581	1.000000

Now we will caluclate the correlations between all the numeric columns using heatmap

In [223]:
```
numeric_columns = ['credit_score','credit_utilisation','outstanding_debt','
correlation_matrix = df_merged[numeric_columns].corr()
```

In [224]:
```
sns.heatmap(correlation_matrix,annot = True,fmt = '.2f',cmap = 'coolwarm',
plt.title('Correlation Plot')
plt.show()
```



You can see a high correlation between credit limit and credit score (~0.85)

Also credit limit and annual income has a high correlation.

This correlation table can be used for further analysis. It shows if one variable has relationship with the other variable

Transactions Table

In [225]:
```
df_transact.head()
```

Out[225]:

	tran_id	cust_id	tran_date	tran_amount	platform	product_category	payment_type
0	1	705	2023-01-01	63	Flipkart	Electronics	Phonepe
1	2	385	2023-01-01	99	Alibaba	Fashion & Apparel	Credit Card
2	3	924	2023-01-01	471	Shopify	Sports	Phonepe
3	4	797	2023-01-01	33	Shopify	Fashion & Apparel	Gpay
4	5	482	2023-01-01	68	Amazon	Fashion & Apparel	Net Banking

In [226]:
```
df_transact.describe()
```

Out[226]:

	tran_id	cust_id	tran_amount
count	500000.000000	500000.000000	500000.00000
mean	250000.500000	501.400428	3225.20733
std	144337.711634	288.641924	13098.74276
min	1.000000	1.000000	0.00000
25%	125000.750000	252.000000	64.00000
50%	250000.500000	502.000000	141.00000
75%	375000.250000	752.000000	397.00000
max	500000.000000	1000.000000	69999.00000

Data Cleaning Step 1: Handle NULL Values: platform column

In [227]:
```
df_transact.isnull().sum()
```

Out[227]:
```
tran_id                0
cust_id                0
tran_date              0
tran_amount            0
platform            4941
product_category       0
payment_type           0
dtype: int64
```

platform has a lot of null values. Let's check them further

In [228]:
```
df_transact[df_transact.platform.isna()]
```

Out[228]:

	tran_id	cust_id	tran_date	tran_amount	platform	product_category	payment_type
355	356	58	2023-01-01	237	NaN	Electronics	Net Banking
418	419	383	2023-01-01	338	NaN	Electronics	Credit Card
607	608	421	2023-01-01	700	NaN	Electronics	Phonepe
844	845	945	2023-01-01	493	NaN	Sports	Credit Card
912	913	384	2023-01-01	85	NaN	Fashion & Apparel	Phonepe
...	...	...	...	...	...	...	...
499579	499580	924	2023-09-05	31	NaN	Fashion & Apparel	Gpay
499646	499647	944	2023-09-05	58445	NaN	Fashion & Apparel	Phonepe
499725	499726	620	2023-09-05	15	NaN	Sports	Net Banking
499833	499834	616	2023-09-05	97	NaN	Fashion & Apparel	Credit Card
499997	499998	57	2023-09-05	224	NaN	Garden & Outdoor	Phonepe

4941 rows × 7 columns

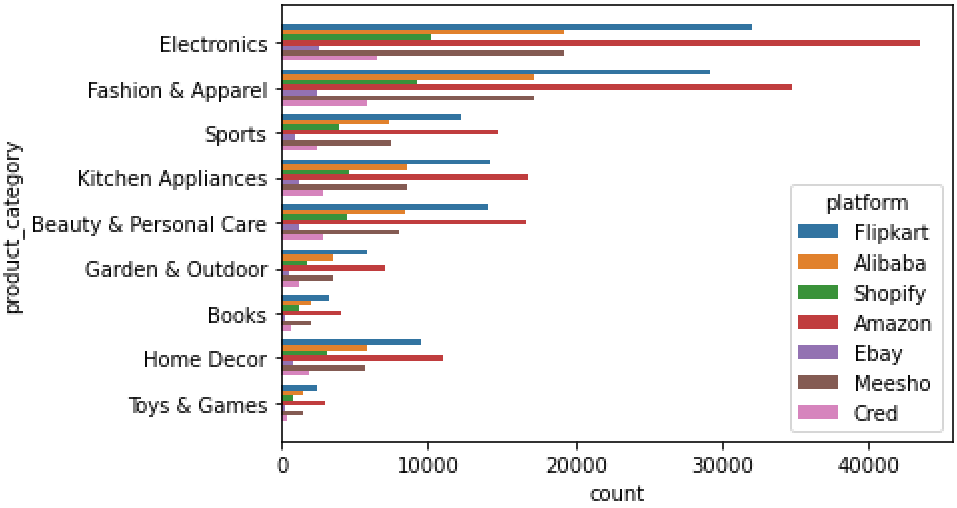
In [229]:
```
df_transact.platform.value_counts()
```

Out[229]:
```
Amazon      151443
Flipkart    122660
Alibaba      73584
Meesho       73271
Shopify      39416
Cred         24741
Ebay          9944
Name: platform, dtype: int64
```

We know that Amazon is the platform that users use the most. but still we will see for each category which platform is used the most with the help of count plot

In [230]:
```
sns.countplot(y = 'product_category',hue = 'platform',data = df_transact)
plt.plot() #Amazon is the highestselling in each platform sowe will replace
```

Out[230]: []



In [231]:
```
df_transact.platform.fillna(df_transact.platform.mode()[0],inplace = True)
```

In [232]:
```
df_transact.isnull().sum()
```

Out[232]:
```
tran_id             0
cust_id             0
tran_date           0
tran_amount         0
platform            0
product_category    0
payment_type        0
dtype: int64
```

Data Cleaning Step 2: Treat Outliers: tran_amount

In [233]:
```
df_transact.describe()#minimum transaction amount cannot be 0
```

Out[233]:

	tran_id	cust_id	tran_amount
count	500000.000000	500000.000000	500000.00000
mean	250000.500000	501.400428	3225.20733
std	144337.711634	288.641924	13098.74276
min	1.000000	1.000000	0.00000
25%	125000.750000	252.000000	64.00000
50%	250000.500000	502.000000	141.00000
75%	375000.250000	752.000000	397.00000
max	500000.000000	1000.000000	69999.00000

In [234]:
```
df_transact_zero = df_transact[df_transact.tran_amount == 0]
```

In [235]:
```
df_transact_zero.shape
```

Out[235]:
```
(4734, 7)
```

In [236]:
```
df_transact_zero.head()
```

Out[236]:

	tran_id	cust_id	tran_date	tran_amount	platform	product_category	payment_type
120	121	440	2023-01-01	0	Amazon	Electronics	Credit Card
141	142	839	2023-01-01	0	Amazon	Electronics	Credit Card
517	518	147	2023-01-01	0	Amazon	Electronics	Credit Card
533	534	891	2023-01-01	0	Amazon	Electronics	Credit Card
586	587	108	2023-01-01	0	Amazon	Electronics	Credit Card

In [237]:
```
df_transact_zero[['platform','product_category','payment_type']].value_coun
```

Out[237]:
```
platform  product_category  payment_type
Amazon    Electronics       Credit Card     4734
dtype: int64
```

It appears that when platform=Amazon, product_category=Eletronics and payment_type=Credit Card, at that time we get all these zero transactions. We need to find other transactions in this group and find its median to replace these zero values. We are not using mean because we can see some outliers as well in this column

In [238]:
```
df_transact1= df_transact[(df_transact.platform == 'Amazon') & (df_transact
```

In [239]:
```
median_value =df_transact1[df_transact1.tran_amount > 0].tran_amount.median
median_value
```

Out[239]:
```
554.0
```

In [240]:
```
df_transact.tran_amount.replace(0,median_value,inplace = True)
```

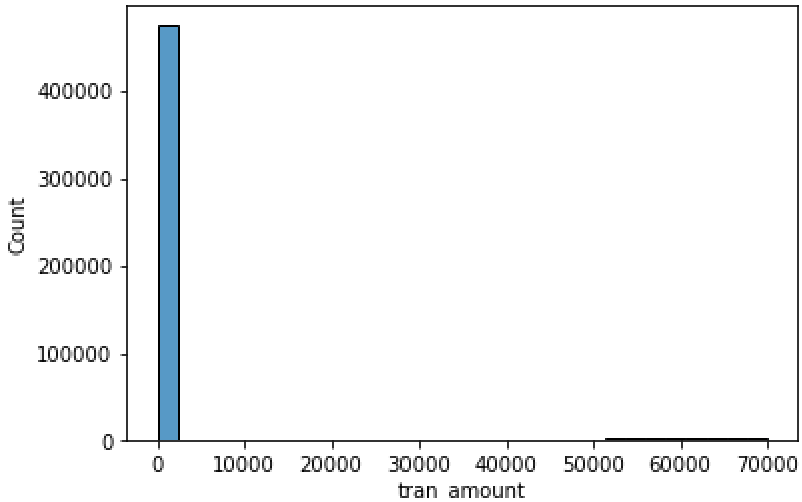
In [241]:
```
df_transact.describe()
```

Out[241]:

	tran_id	cust_id	tran_amount
count	500000.000000	500000.000000	500000.000000
mean	250000.500000	501.400428	3230.452602
std	144337.711634	288.641924	13097.561071
min	1.000000	1.000000	2.000000
25%	125000.750000	252.000000	66.000000
50%	250000.500000	502.000000	146.000000
75%	375000.250000	752.000000	413.000000
max	500000.000000	1000.000000	69999.000000

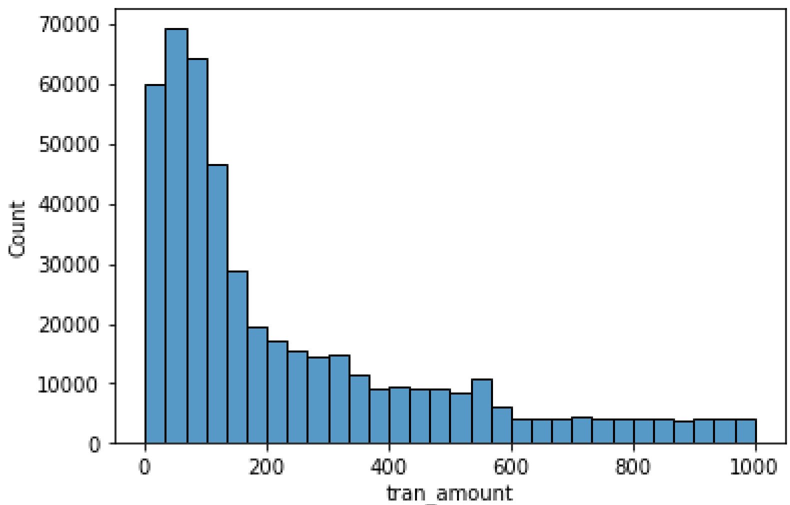
In [242]:
```
sns.histplot(df_transact.tran_amount,bins =30) #rightly skewed
```

Out[242]: <AxesSubplot:xlabel='tran_amount', ylabel='Count'>



In [243]:
```
sns.histplot(df_transact[df_transact.tran_amount<10000].tran_amount,bins=30
```

Out[243]: <AxesSubplot:xlabel='tran_amount', ylabel='Count'>



In [244]:
```
Q1,Q3 = df_transact.tran_amount.quantile([0.25,0.75])
```

In [245]:
```
IQR = Q3 - Q1
IQR
```

Out[245]: 347.0

SO THE BUSINESS MANAGER TOLD TO USE 2 INSTEAD OF 1.5 FOR IQR

In [246]:
```
upper = Q3 + 2*IQR
lower = Q1 - 2*IQR
upper,lower
```

Out[246]: (1107.0, -628.0)

In [247]:
```
df_transact_outlier =df_transact[df_transact.tran_amount >= upper]
```

In [248]:
```
df_transact_outlier.shape #25000 is outliers so we have to deal with outlie
```

Out[248]: (25000, 7)

In [249]:
```
df_transact_outlier.head()
```

Out[249]:

	tran_id	cust_id	tran_date	tran_amount	platform	product_category	payment_type
26	27	380	2023-01-01	61963	Shopify	Beauty & Personal Care	Credit Card
49	50	287	2023-01-01	57869	Amazon	Toys & Games	Gpay
94	95	770	2023-01-01	52881	Ebay	Kitchen Appliances	Credit Card
104	105	549	2023-01-01	58574	Flipkart	Fashion & Apparel	Gpay
113	114	790	2023-01-01	51669	Shopify	Kitchen Appliances	Credit Card

In [250]:
```
df_transact.head()
```

Out[250]:

	tran_id	cust_id	tran_date	tran_amount	platform	product_category	payment_type
0	1	705	2023-01-01	63	Flipkart	Electronics	Phonepe
1	2	385	2023-01-01	99	Alibaba	Fashion & Apparel	Credit Card
2	3	924	2023-01-01	471	Shopify	Sports	Phonepe
3	4	797	2023-01-01	33	Shopify	Fashion & Apparel	Gpay
4	5	482	2023-01-01	68	Amazon	Fashion & Apparel	Net Banking

In [251]:
```
df_transact_normal = df_transact[df_transact.tran_amount <= upper]
```

In [252]:
```
category_mean = df_transact_normal.groupby('product_category')['tran_amount
category_mean
```

Out[252]:
```
product_category
Beauty & Personal Care     92.167205
Books                      29.553515
Electronics               510.172685
Fashion & Apparel          64.553463
Garden & Outdoor          125.630277
Home Decor                302.487561
Kitchen Appliances        176.773288
Sports                    269.181631
Toys & Games               50.333298
Name: tran_amount, dtype: float64
```

In [253]:
```
df_transact['tran_amount'] = df_transact.apply(
    lambda row : category_mean[row['product_category']] if row['tran_amount
```

In [254]:
```
df_transact.iloc[[26]]
```

Out[254]:

	tran_id	cust_id	tran_date	tran_amount	platform	product_category	payment_type
26	27	380	2023-01-01	92.167205	Shopify	Beauty & Personal Care	Credit Card

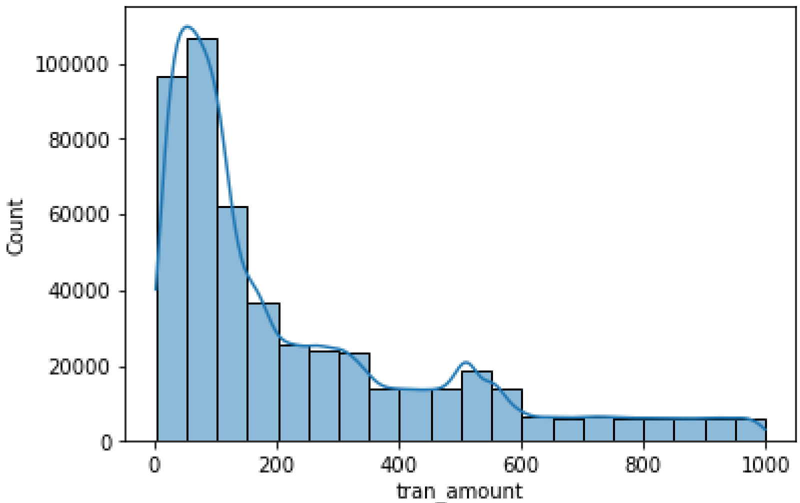
In [255]:
```
df_transact.head()
```

Out[255]:

	tran_id	cust_id	tran_date	tran_amount	platform	product_category	payment_type
0	1	705	2023-01-01	63.0	Flipkart	Electronics	Phonepe
1	2	385	2023-01-01	99.0	Alibaba	Fashion & Apparel	Credit Card
2	3	924	2023-01-01	471.0	Shopify	Sports	Phonepe
3	4	797	2023-01-01	33.0	Shopify	Fashion & Apparel	Gpay
4	5	482	2023-01-01	68.0	Amazon	Fashion & Apparel	Net Banking

In [256]:
```
sns.histplot(df_transact.tran_amount,kde = True, bins =20)
```

Out[256]: <AxesSubplot:xlabel='tran_amount', ylabel='Count'>



Without removing outliers we managed it and now the graph is good (rightly skewed)

In [257]:
```
df_transact.shape
```

Out[257]:
```
(500000, 7)
```

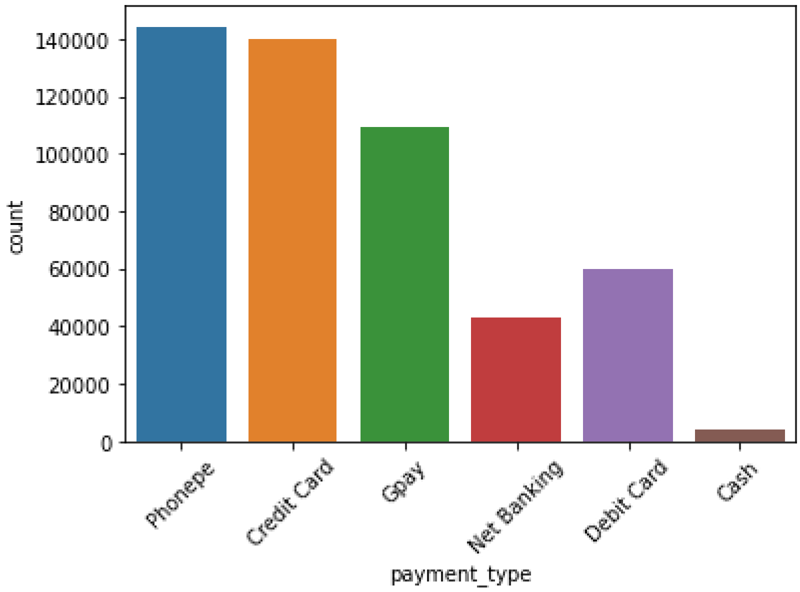
Data Visualization: Payment Type Distribution

In [258]:
```
df_transact.head()
```

Out[258]:

	tran_id	cust_id	tran_date	tran_amount	platform	product_category	payment_type
0	1	705	2023-01-01	63.0	Flipkart	Electronics	Phonepe
1	2	385	2023-01-01	99.0	Alibaba	Fashion & Apparel	Credit Card
2	3	924	2023-01-01	471.0	Shopify	Sports	Phonepe
3	4	797	2023-01-01	33.0	Shopify	Fashion & Apparel	Gpay
4	5	482	2023-01-01	68.0	Amazon	Fashion & Apparel	Net Banking

In [259]:
```
sns.countplot(x='payment_type', data=df_transact)
plt.xticks(rotation=45)
plt.show()
```

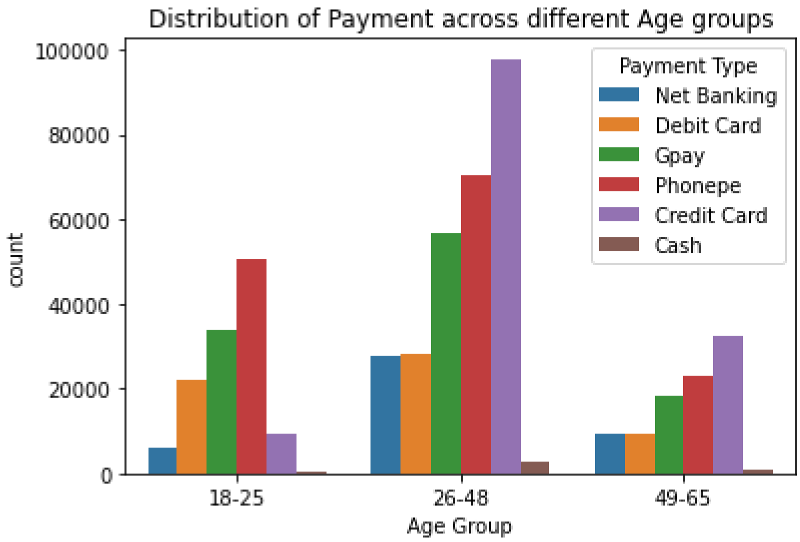


In [260]:
```
df_merged_2 = pd.merge(df_cust,df_transact,on='cust_id',how ='inner')
df_merged_2.head()
```

Out[260]:

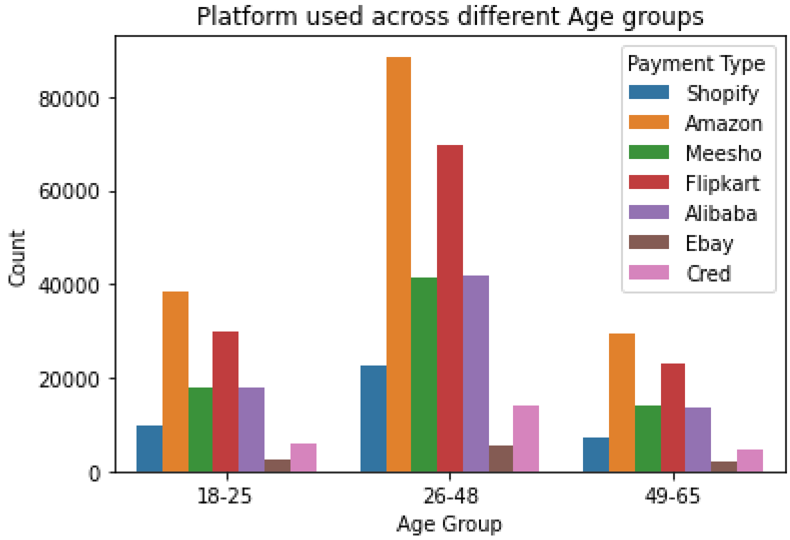
	cust_id	name	gender	age	location	occupation	annual_income	marital_status	age_
0	1	Manya Acharya	Female	51.0	City	Business Owner	358211.0	Married	
1	1	Manya Acharya	Female	51.0	City	Business Owner	358211.0	Married	
2	1	Manya Acharya	Female	51.0	City	Business Owner	358211.0	Married	
3	1	Manya Acharya	Female	51.0	City	Business Owner	358211.0	Married	
4	1	Manya Acharya	Female	51.0	City	Business Owner	358211.0	Married	

In [261]:
```
sns.countplot(x= 'age_group',hue = 'payment_type', data =df_merged_2)
plt.title('Distribution of Payment across different Age groups')
plt.xlabel('Age Group')
plt.ylabel('count')
plt.legend(title= 'Payment Type',loc = 'upper right')
plt.show()
```

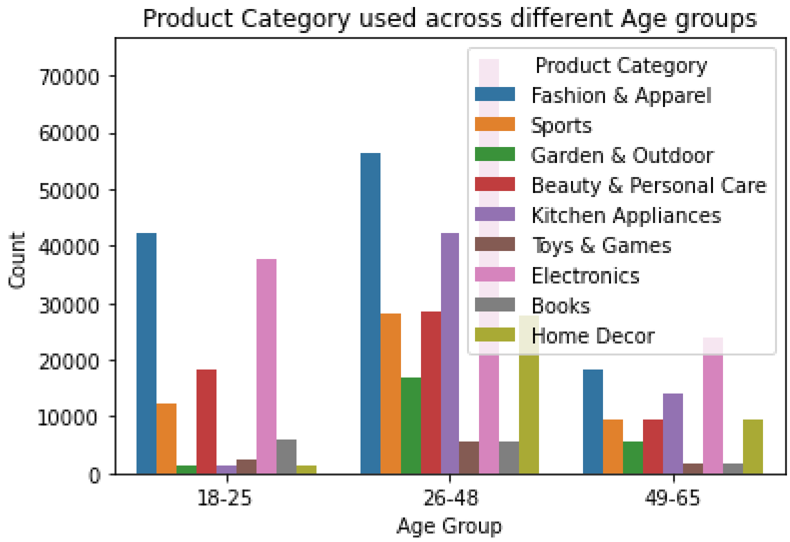


From above analysis, we can see that age group 18-25 has less exposure to credit cards compared to other groups

In [262]:
```
sns.countplot(x= 'age_group',hue = 'platform', data =df_merged_2)
plt.title('Platform used across different Age groups')
plt.xlabel('Age Group')
plt.ylabel('Count')
plt.legend(title= 'Payment Type',loc = 'upper right')
plt.show()
```



In [263]:
```
sns.countplot(x= 'age_group',hue = 'product_category', data =df_merged_2)
plt.title('Product Category used across different Age groups')
plt.xlabel('Age Group')
plt.ylabel('Count')
plt.legend(title= 'Product Category',loc = 'upper right')
plt.show()
```

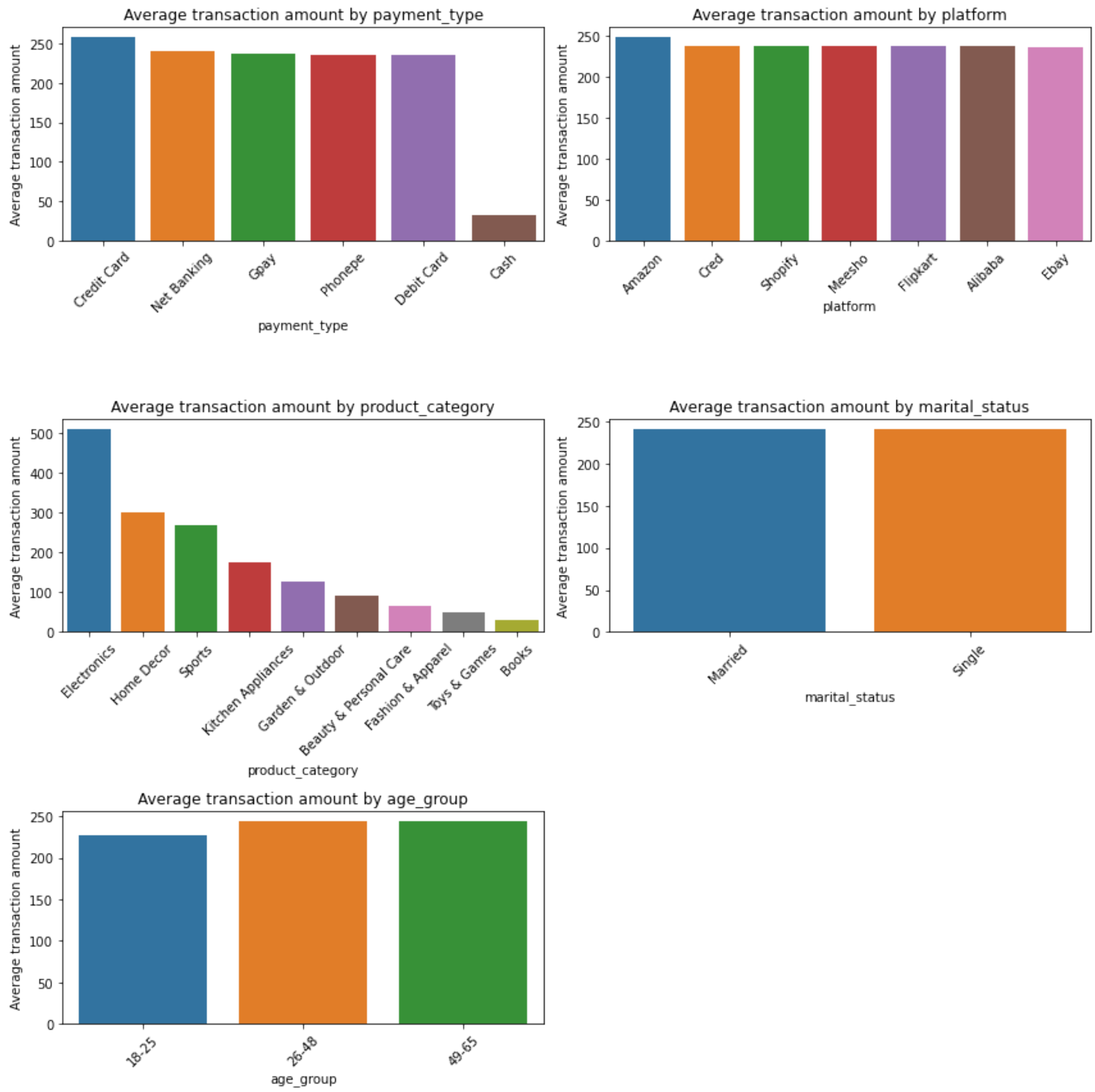


Observations:

1. Top 3 purchasing categories of customers in age group (18 -25) : Electronics, Fashion & Apparel, Beauty & personal care
2. Top platforms : Amazon, Flipkart, Alibaba

Data Visualization: Average Transaction Amount

In [264]:
```
# List of categorical columns
cat_cols = ['payment_type', 'platform', 'product_category', 'marital_status

num_rows = 3
# Create subplots
fig, axes = plt.subplots(num_rows, 2, figsize=(12, 4 * num_rows))

# Flatten the axes array to make it easier to iterate
axes = axes.flatten()

# Create subplots for each categorical column
for i, cat_col in enumerate(cat_cols):
    # Calculate the average annual income for each category
    avg_tran_amount_by_category = df_merged_2.groupby(cat_col)['tran_amount

    # Sort the data by 'annual_income' before plotting
    sorted_data = avg_tran_amount_by_category.sort_values(by='tran_amount',

    sns.barplot(x=cat_col, y='tran_amount', data=sorted_data, ci=None, ax=a
    axes[i].set_title(f'Average transaction amount by {cat_col}')
    axes[i].set_xlabel(cat_col)
    axes[i].set_ylabel('Average transaction amount')

    # Rotate x-axis labels for better readability
    axes[i].set_xticklabels(axes[i].get_xticklabels(), rotation=45)

# Hide any unused subplots
for i in range(len(cat_cols), len(axes)):
    fig.delaxes(axes[i])
plt.tight_layout()
plt.show()
```



Further Analysis On Age Group

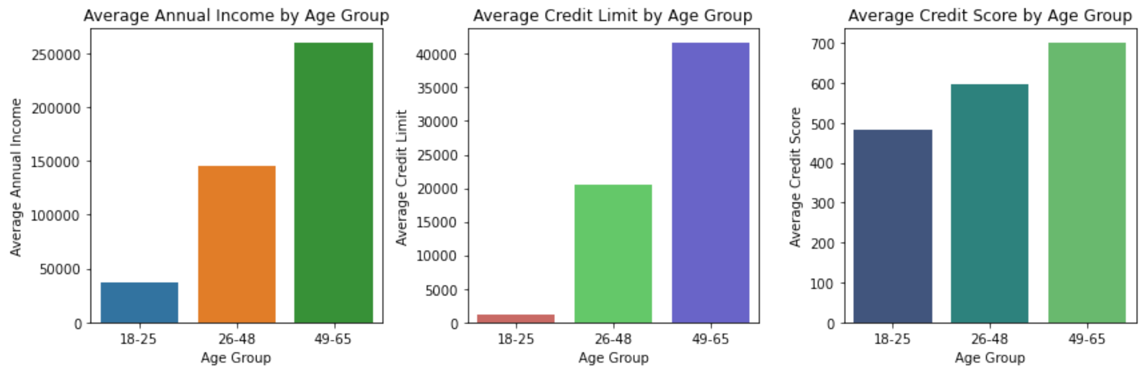
Let us do further analysis on age group to figure out their average income, credit limit, credit score etc

In [265]:
```
# Group the data by age group and calculate the average credit_limit and cr
age_group_metrics = df_merged.groupby('age_group')[['annual_income', 'credi
age_group_metrics
```

Out[265]:

	age_group	annual_income	credit_limit	credit_score
0	18-25	37091.235772	1130.081301	484.451220
1	26-48	145869.623457	20560.846561	597.569665
2	49-65	260165.925134	41699.197861	701.524064

In [266]:
```
# Create subplots
fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(12, 4))

# Plot 1: Average annual income by age group
sns.barplot(x='age_group', y='annual_income', data=age_group_metrics, palet
ax1.set_title('Average Annual Income by Age Group')
ax1.set_xlabel('Age Group')
ax1.set_ylabel('Average Annual Income')
ax1.tick_params(axis='x', rotation=0)

# Plot 2: Average Max Credit Limit by Age Group
sns.barplot(x='age_group', y='credit_limit', data=age_group_metrics, palett
ax2.set_title('Average Credit Limit by Age Group')
ax2.set_xlabel('Age Group')
ax2.set_ylabel('Average Credit Limit')
ax2.tick_params(axis='x', rotation=0)

# Plot 3: Average Credit Score by Age Group
sns.barplot(x='age_group', y='credit_score', data=age_group_metrics, palett
ax3.set_title('Average Credit Score by Age Group')
ax3.set_xlabel('Age Group')
ax3.set_ylabel('Average Credit Score')
ax3.tick_params(axis='x', rotation=0)

plt.tight_layout()
plt.show()
```



Finalize Target Market For a Trial Credit Card Launch

Targeting Untapped market

1. People with age group of 18 -25 accounts to ~26% of customer base in the data
2. Avg annual income of this group is less than 50k
3. They don't have much credit history which is getting reflected in their credit score and credit limit
4. Usage of credit cards as payment type is relatively low compared to other groups
5. Top 3 most shopping products categories : Electronics, Fashion & Apparel, Beauty & Personal care

Phase 2: AtliQ0 Bank Credit Card Project

Business Analysis and launch of AB testing: Targeting Untapped Market (18 - 25 age group)

In [267]:
```
import statsmodels.stats.api as sms
import statsmodels.api as sm
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
from scipy import stats as st
import seaborn as sns
```

In [268]:
```
alpha = 0.05 # 5% significance
power = 0.8 #statistical power
effect_size = 0.2

sms.tt_ind_solve_power(
effect_size = effect_size,
alpha=alpha,
power = power,
ratio = 1,
alternative = 'two-sided')  #for finding the sample size with the parameter
```

Out[268]:
```
393.4056989990322
```

For effect size 2 we need 393 customers. We have to keep in mind budgeting restrictions while running this campaign hence let us run this for different effect sizes and discuss with business to find out which sample size would be optimal

But the product manager wants less number of people as there are some budget constraints as well

In [269]:
```
alpha = 0.05 # 5% significance
power = 0.8 #statistical power

effect_sizes = [0.2,0.3,0.4,0.5,1]
for effect in effect_sizes:
    sample_size = sms.tt_ind_solve_power(
        effect_size=effect,
        alpha=alpha,
        power=power,
        ratio=1,
        alternative='two-sided'
    )
    print(f"Effect Size {effect} has {sample_size:.2f} customers")
```

```
Effect Size 0.2 has 393.41 customers
Effect Size 0.3 has 175.38 customers
Effect Size 0.4 has 99.08 customers
Effect Size 0.5 has 63.77 customers
Effect Size 1 has 16.71 customers
```

Based on business requirements, the test should be capable of detecting a minimum 0.4 standard deviation difference between the control and test groups. For the effect size 0.4, we need 100 customers and when we discussed with business, 100 customers is ok in terms of their budgeting constraints for this trail run

Forming control and test groups

1.We have identified approximately 246 customers within the age group of 18 to 25. From this pool, we will select 100 customers for the initial campaign launch.

2.The campaign is launched for 100 customers, as determined by the effective size calculation and by considering budgeting costs, and will run campaign for a duration of 2 months

3.Got a conversion rate of ~40% (implies 40 out of 100 customers in test group started using credit card)

4.To maintain a similar sample size, a control group consisting of 40 customers will be created. Importantly, this control group will be completely exclusive of initial 100 customers used as test group.

5.So now we have 40 customers in each of control and test groups

At the end of the 2-month campaign period (from 09-10-23 to 11-10-23), we obtained daily data showing the average transaction amounts made by the entire group of 40 customers in both the control and test groups using existing and newly launched credit cards respectively

The key performance indicator (KPI) for this AB test aims to enhance average transaction amounts facilitated by the new card

(2) Post-Campaign

Two Sample Z Test for Our Hypothesis Testing

In [270]:
```
df_post = pd.read_csv('Datasets/avg_transactions_after_campaign.csv')
```

In [271]:
```
df_post.head()
```

Out[271]:

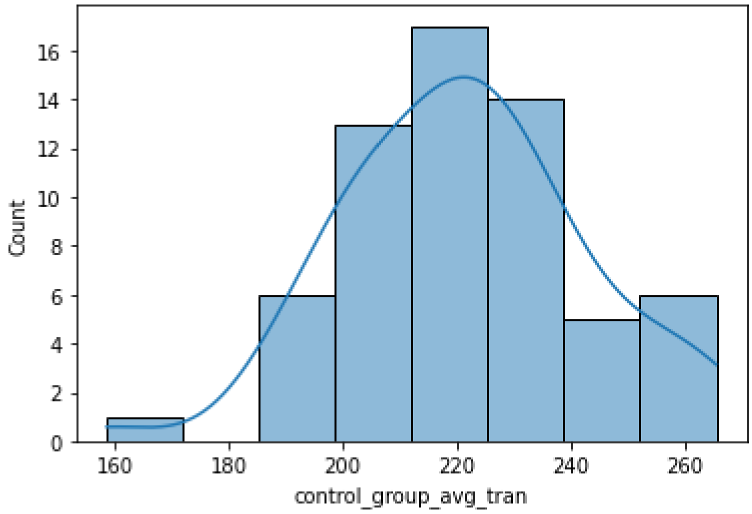
	campaign_date	control_group_avg_tran	test_group_avg_tran
0	2023-09-10	259.83	277.32
1	2023-09-11	191.27	248.68
2	2023-09-12	212.41	286.61
3	2023-09-13	214.92	214.85
4	2023-09-14	158.55	344.08

In [272]:
```
df_post.shape
```

Out[272]: (62, 3)

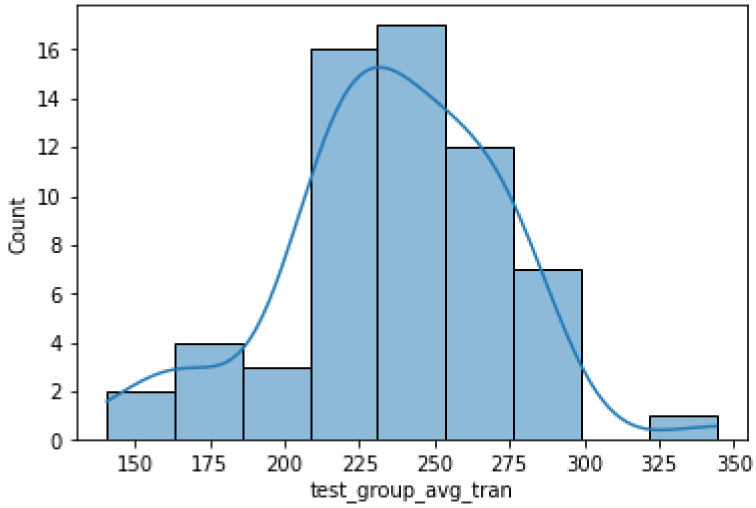
In [273]:
```
sns.histplot(df_post.control_group_avg_tran ,kde=True)
```

Out[273]: <AxesSubplot:xlabel='control_group_avg_tran', ylabel='Count'>



In [274]:
```
sns.histplot(df_post.test_group_avg_tran ,kde=True)
```

Out[274]: <AxesSubplot:xlabel='test_group_avg_tran', ylabel='Count'>



Definiing hypothesis :

1.)Null Hypothesis: our old credit card has more transactions and performing well(meanof c > mean of t).

2.)Alternate hypothesis : our new credit card has more transactions and performing well (mean of t > mean of c),

In [275]:
```
#for control group
control_mean1 = df_post["control_group_avg_tran"].mean()
control_std = df_post.control_group_avg_tran.std()
shape = df_post.shape[0]
control_mean1,control_std,shape
```

Out[275]: (221.1751612903226, 21.359192112027014, 62)

In [276]:
```
#for test_group
test_mean = df_post.test_group_avg_tran.mean()
test_std = df_post.test_group_avg_tran.std()

test_mean,test_std
```

Out[276]: (235.98354838709682, 36.65808210918637)

In [277]:
```
a = control_std**2/ shape
b = test_std **2/ shape
a,b
```

Out[277]: (7.358307865781887, 21.67443522457822)

In [278]:
```
z_score =( test_mean - control_mean1) / np.sqrt(a+b)
```

In [279]:
```
z_score
```

Out[279]: 2.748297374569119

In [280]:
```
alpha = 0.05
z_critical = st.norm.ppf(1 - alpha)
z_critical
```

Out[280]: 1.6448536269514722

In [281]:
```
z_score>z_critical # null hypothesis is rejected
```

Out[281]: True

The analysis validated the new credit card's performance, and can now be confidently introduced to the market.