Problem Statement

Walmart is an American multinational retail corporation that operates a chain of supercenters, discount departmental stores, and grocery stores from the United States. Walmart has more than 100 million customers worldwide.

The Management team at Walmart Inc. wants to analyze the customer purchase behavior (specifically, purchase amount) against the customer's gender and the various other factors to help the business make better decisions.

They want to understand if the spending habits differ between male and female customers: Do women spend more on Black Friday than men? (Assume 50 million customers are male and 50 million are female).

Dataset Definition

The company collected the transactional data of customers who purchased products from the Walmart Stores during Black Friday. The dataset has the following features:

Dataset link: Walmart_data.csv

Column Name	Description
User_ID	User ID
Product_ID	Product ID
Gender	Sex of User
Age	Age in bins
Occupation	Occupation(Masked)
City_Category	Category of the City (A,B,C)
Stay_In_Current_City_Years	Number of years stay in current city
Marital_Status	Marital Status
ProductCategory	Product Category (Masked)
Purchase	Purchase Amount

Methodology

1. Import the dataset and do usual data analysis steps like checking the structure & characteristics of the dataset.

2. Detect Null values & Outliers (using boxplot, "describe" method by checking the difference between mean and median, isnull etc.)

3. Do some data exploration steps like:

    - Tracking the amount spent per transaction of all the 50 million female customers, and all the 50 million male customers, calculate the average, and conclude the results.
    - Inference after computing the average female and male expenses.

- Use the sample average to find out an interval within which the population average will lie. Using the sample of female customers you will calculate the interval within which the average spending of 50 million male and female customers may lie.

4. Use the Central limit theorem to compute the interval. Change the sample size to observe the distribution of the mean of the expenses by female and male customers.

   - The interval that you calculated is called Confidence Interval. The width of the interval is mostly decided by the business: Typically 90%, 95%, or 99%. Play around with the width parameter and report the observations.

5. Conclude the results and check if the confidence intervals of average male and female spends are overlapping or not overlapping. How can Walmart leverage this conclusion to make changes or improvements?

6. Perform the same activity for Married vs Unmarried and Age

   - For Age, you can try bins based on life stages: 0-17, 18-25, 26-35, 36-50, 51+ years.

7. Give recommendations and action items to Walmart.

Exploratory Analysis

Import statements

In [66]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import scipy.stats as st
import statsmodels.api as sm
import math as mt
import random as rd
import time as tm
```

Data Loading

In [67]:
```
file_link = "https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/001/293/original/w

raw_data = pd.read_csv(file_link)
raw_data.head()
```

Out[67]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_S
0	1000001	P00069042	F	0-17	10	A	2	
1	1000001	P00248942	F	0-17	10	A	2	
2	1000001	P00087842	F	0-17	10	A	2	
3	1000001	P00085442	F	0-17	10	A	2	
4	1000002	P00285442	M	55+	16	C	4+	

In [68]:
```python
raw_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 10 columns):
 #   Column                      Non-Null Count   Dtype 
---  ------                      --------------   ----- 
 0   User_ID                     550068 non-null  int64 
 1   Product_ID                  550068 non-null  object
 2   Gender                      550068 non-null  object
 3   Age                         550068 non-null  object
 4   Occupation                  550068 non-null  int64 
 5   City_Category               550068 non-null  object
 6   Stay_In_Current_City_Years  550068 non-null  object
 7   Marital_Status              550068 non-null  int64 
 8   Product_Category            550068 non-null  int64 
 9   Purchase                    550068 non-null  int64 
dtypes: int64(5), object(5)
memory usage: 42.0+ MB
```

In [69]:
```python
raw_data.describe(include='all')
```

Out[69]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City
count	5.500680e+05	550068	550068	550068	550068.000000	550068	5
unique	NaN	3631	2	7	NaN	3	
top	NaN	P00265242	M	26-35	NaN	B	
freq	NaN	1880	414259	219587	NaN	231173	1
mean	1.003029e+06	NaN	NaN	NaN	8.076707	NaN	
std	1.727592e+03	NaN	NaN	NaN	6.522660	NaN	
min	1.000001e+06	NaN	NaN	NaN	0.000000	NaN	
25%	1.001516e+06	NaN	NaN	NaN	2.000000	NaN	
50%	1.003077e+06	NaN	NaN	NaN	7.000000	NaN	
75%	1.004478e+06	NaN	NaN	NaN	14.000000	NaN	
max	1.006040e+06	NaN	NaN	NaN	20.000000	NaN	

Observations:

1. There are 5.5 lakh records of transaction data
2. User ID and Product ID columns identify the product purchased by a user in the current transaction
3. User ID is of int data type and should be changed to string
4. There does not seem to be an unique identifier for each transaction
5. There are 3631 unique products
6. There are not any null values in the data
7. The category columns such as Occupation, City_Category, Marital_Status, Product_Category are of int data type and are masked so need to change to category type

Next Steps:

1. Convert User ID to type string (so no numerical operations may be performed)
2. Create a unique id for each transaciton using the row number and cast it as string

3. Convert the masked int category columns to type category with appropriate prefix
4. Check for outliers in the numerical and categorical columns
5. Check the different types of categories and their frequencies in each categorical column

Data Cleaning

1. Changing Data Types
2. Checking Missing values
3. Outlier Detection

In [70]:
```
clean_data = raw_data.reset_index().copy()

clean_data['User_ID'] = clean_data['User_ID'].astype('str')
clean_data['Product_ID'] = clean_data['Product_ID'].astype('str')
clean_data.rename(columns={'index': 'Transaction_ID'}, inplace=True, errors='ignore')
clean_data['Transaction_ID'] = clean_data['Transaction_ID'].astype('str')

clean_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 11 columns):
 #   Column                      Non-Null Count   Dtype
---  ------                      --------------   -----
 0   Transaction_ID              550068 non-null  object
 1   User_ID                     550068 non-null  object
 2   Product_ID                  550068 non-null  object
 3   Gender                      550068 non-null  object
 4   Age                         550068 non-null  object
 5   Occupation                  550068 non-null  int64
 6   City_Category               550068 non-null  object
 7   Stay_In_Current_City_Years  550068 non-null  object
 8   Marital_Status              550068 non-null  int64
 9   Product_Category            550068 non-null  int64
 10  Purchase                    550068 non-null  int64
dtypes: int64(4), object(7)
memory usage: 46.2+ MB
```

In [71]:
```
clean_data.isna().sum()
```

Out[71]:
```
Transaction_ID                0
User_ID                       0
Product_ID                    0
Gender                        0
Age                           0
Occupation                    0
City_Category                 0
Stay_In_Current_City_Years    0
Marital_Status                0
Product_Category              0
Purchase                      0
dtype: int64
```

In [72]:
```
value_counts = pd.DataFrame()

columns_to_check = [
    'Gender', 'Age', 'Occupation',
    'City_Category', 'Stay_In_Current_City_Years',
    'Marital_Status', 'Product_Category'
    ]

for column in columns_to_check:
```

```python
    column_value_counts = (
        clean_data[column]
        .value_counts()
        .reset_index()
        .rename(columns={column:'value'})
        )
    column_value_counts['pct'] = column_value_counts['count'] * 100 / clean_data.shape[0]
    column_value_counts['column'] = column
    value_counts = pd.concat([value_counts, column_value_counts], ignore_index=True)

value_counts[['column', 'value', 'count', 'pct']]
```

Out[72]:

	column	value	count	pct
0	Gender	M	414259	75.310507
1	Gender	F	135809	24.689493
2	Age	26-35	219587	39.919974
3	Age	36-45	110013	19.999891
4	Age	18-25	99660	18.117760
5	Age	46-50	45701	8.308246
6	Age	51-55	38501	6.999316
7	Age	55+	21504	3.909335
8	Age	0-17	15102	2.745479
9	Occupation	4	72308	13.145284
10	Occupation	0	69638	12.659889
11	Occupation	7	59133	10.750125
12	Occupation	1	47426	8.621843
13	Occupation	17	40043	7.279645
14	Occupation	20	33562	6.101427
15	Occupation	12	31179	5.668208
16	Occupation	14	27309	4.964659
17	Occupation	2	26588	4.833584
18	Occupation	16	25371	4.612339
19	Occupation	6	20355	3.700452
20	Occupation	3	17650	3.208694
21	Occupation	10	12930	2.350618
22	Occupation	5	12177	2.213726
23	Occupation	15	12165	2.211545
24	Occupation	11	11586	2.106285
25	Occupation	19	8461	1.538173
26	Occupation	13	7728	1.404917
27	Occupation	18	6622	1.203851
28	Occupation	9	6291	1.143677
29	Occupation	8	1546	0.281056
30	City_Category	B	231173	42.026259
31	City_Category	C	171175	31.118880
32	City_Category	A	147720	26.854862
33	Stay_In_Current_City_Years	1	193821	35.235825
34	Stay_In_Current_City_Years	2	101838	18.513711
35	Stay_In_Current_City_Years	3	95285	17.322404

	column	value	count	pct
36	Stay_In_Current_City_Years	4+	84726	15.402823
37	Stay_In_Current_City_Years	0	74398	13.525237
38	Marital_Status	0	324731	59.034701
39	Marital_Status	1	225337	40.965299
40	Product_Category	5	150933	27.438971
41	Product_Category	1	140378	25.520118
42	Product_Category	8	113925	20.711076
43	Product_Category	11	24287	4.415272
44	Product_Category	2	23864	4.338373
45	Product_Category	6	20466	3.720631
46	Product_Category	3	20213	3.674637
47	Product_Category	4	11753	2.136645
48	Product_Category	16	9828	1.786688
49	Product_Category	15	6290	1.143495
50	Product_Category	13	5549	1.008784
51	Product_Category	10	5125	0.931703
52	Product_Category	12	3947	0.717548
53	Product_Category	7	3721	0.676462
54	Product_Category	18	3125	0.568112
55	Product_Category	20	2550	0.463579
56	Product_Category	19	1603	0.291419
57	Product_Category	14	1523	0.276875
58	Product_Category	17	578	0.105078
59	Product_Category	9	410	0.074536

Assumption: Marital Status 1 means married and 0 means unmarried

In [73]:
```
columns_to_convert = {
    'Gender', 'Age','Occupation',
    'Marital_Status', 'Product_Category',
    'City_Category', 'Stay_In_Current_City_Years'
}

for column in columns_to_convert:
    if column in {'Marital_Status'}:
        clean_data[column] = clean_data[column].apply(lambda x: 'Married' if x == 1 else 'Unm
    elif column in {'Product_Category', 'Occupation'}:
        clean_data[column] = clean_data[column].apply(lambda x: f'{column}_{str(x)}')
    clean_data[column] = clean_data[column].astype('category')

clean_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 11 columns):
 #   Column                      Non-Null Count   Dtype   
---  ------                      --------------   -----   
 0   Transaction_ID              550068 non-null  object  
 1   User_ID                     550068 non-null  object  
 2   Product_ID                  550068 non-null  object  
 3   Gender                      550068 non-null  category
 4   Age                         550068 non-null  category
 5   Occupation                  550068 non-null  category
 6   City_Category               550068 non-null  category
 7   Stay_In_Current_City_Years  550068 non-null  category
 8   Marital_Status              550068 non-null  category
 9   Product_Category            550068 non-null  category
 10  Purchase                    550068 non-null  int64   
dtypes: category(7), int64(1), object(3)
memory usage: 20.5+ MB
```

In [74]:
```
clean_data.describe()
```

Out[74]:

	Purchase
count	550068.000000
mean	9263.968713
std	5023.065394
min	12.000000
25%	5823.000000
50%	8047.000000
75%	12054.000000
max	23961.000000

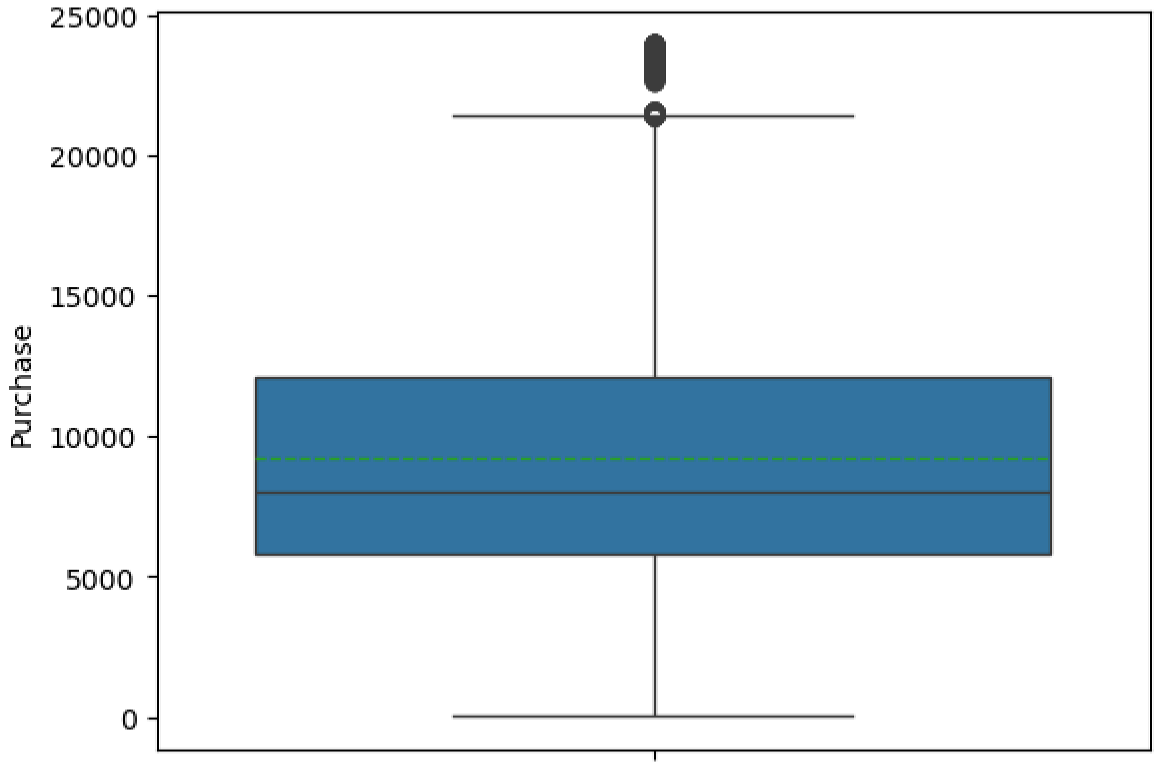
In [75]:
```
clean_data.describe(include='category')
```

Out[75]:

	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Prod
count	550068	550068	550068	550068	550068	550068	
unique	2	7	21	3	5	2	
top	M	26-35	Occupation_4	B	1	Unmarried	Produ
freq	414259	219587	72308	231173	193821	324731	

In [76]:
```
sns.boxplot(y=clean_data['Purchase'], meanline=True, showmeans=True)
```

Out[76]: <Axes: ylabel='Purchase'>



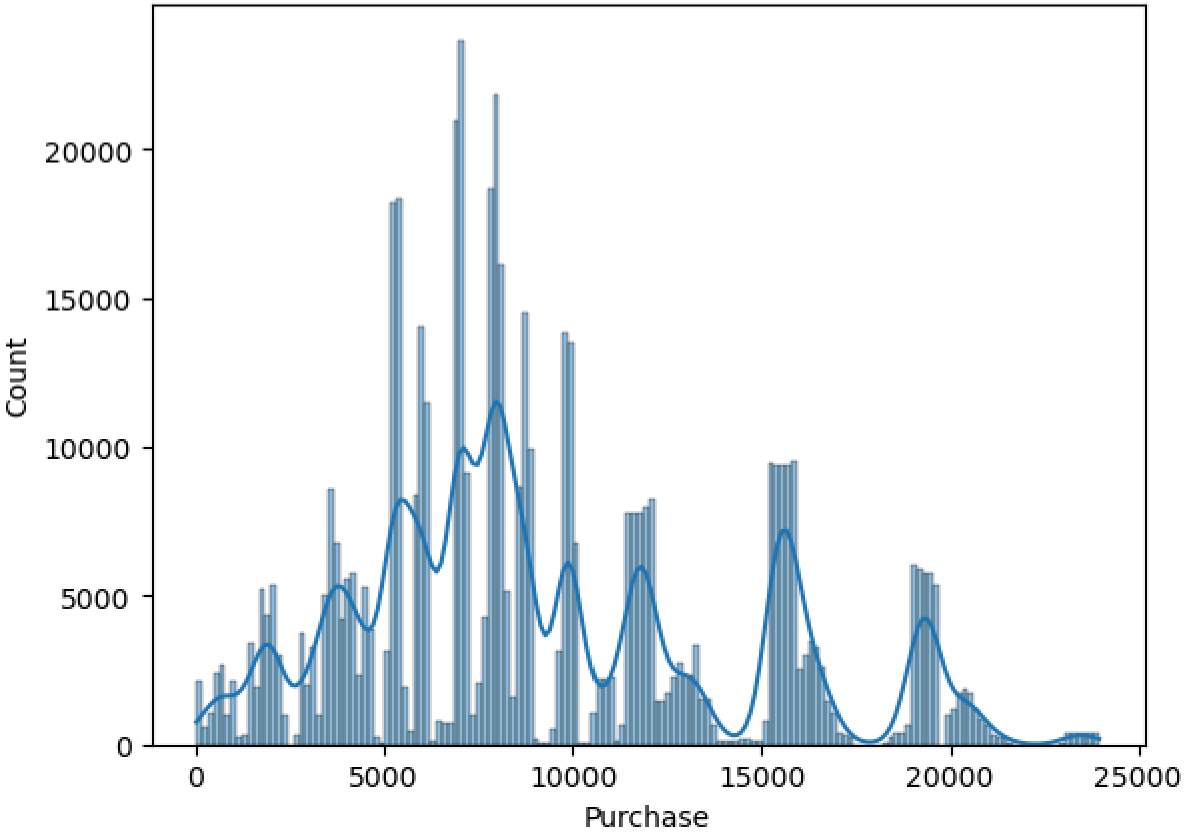
In [77]:
```
iqr = clean_data['Purchase'].quantile(0.75) - clean_data['Purchase'].quantile(0.25)
lower_bound = clean_data['Purchase'].quantile(0.25) - 1.5 * iqr
upper_bound = clean_data['Purchase'].quantile(0.75) + 1.5 * iqr

total_count = clean_data.shape[0]
lower_count = clean_data[clean_data['Purchase'] < lower_bound].shape[0]
upper_count = clean_data[clean_data['Purchase'] > upper_bound].shape[0]
inner_count = total_count - lower_count - upper_count

outlier_distribution = pd.DataFrame({
    'Bound': [f'< {lower_bound}', f'{lower_bound} - {upper_bound}', f'> {upper_bound}'],
    'Count': [lower_count, inner_count, upper_count],
    'Percentage': [lower_count*100/total_count, inner_count*100/total_count, upper_count*100/
    }
)
outlier_distribution
```

Out[77]:

	Bound	Count	Percentage
0	< -3523.5	0	0.000000
1	-3523.5 - 21400.5	547391	99.513333
2	> 21400.5	2677	0.486667

In [78]:
```
sns.histplot(clean_data['Purchase'], kde=True)
```

Out[78]: <Axes: xlabel='Purchase', ylabel='Count'>



In [79]:
```
clean_data['Purchase'].mean(), clean_data['Purchase'].median()
```

Out[79]: (9263.968712959126, 8047.0)

Observations:

1. There are no missing values in the data as confirmed earlier
2. All the categorical variables have a significant size of samples except for occupation 8 and product category 9 which have less than 1% of samples, since there will not be much analysis of these columns for the current problem statement, it can be ignored
3. There are 0.5% outliers in the purchase amount column which are above upper limit of 21400 but are still less than 25000, hence there is no need to remove these outliers
4. The mean purchase amount is greater than the median which means the distribution is right skewed as confirmed by the hist plot
5. The product category and occupation columns are masked with each containing around 20 unique values which will make it hard to analyse since we cannot bin it or infer business insight directly from it, hence these columns can be dropped from here including the product id column

Next Steps:

1. Remove the outliers based on the purchase column
2. Drop the product category and occupation columns
3. Perform univariate exploratory analysis of all columns
4. Perform bivariate exploratory analysis of all columns

In [80]:
```
analysis_data = (
    clean_data
    .drop(columns=['Occupation', 'Product_Category', 'Product_ID'])
    )
analysis_data.head()
```

Out[80]:

	Transaction_ID	User_ID	Gender	Age	City_Category	Stay_In_Current_City_Years	Marital_Status	Pu
0	0	1000001	F	0-17	A	2	Unmarried	
1	1	1000001	F	0-17	A	2	Unmarried	
2	2	1000001	F	0-17	A	2	Unmarried	
3	3	1000001	F	0-17	A	2	Unmarried	
4	4	1000002	M	55+	C	4+	Unmarried	

Univariate Analysis

Types of columns:

Categorical	ID Columns	Numerical
Gender	Transaction_ID	Purchase
Age	User_ID	
City_Category		
Stay_In_Current_City_Years		
Marital_Status		

In [81]:

```
id_columns = ['User_ID', 'Transaction_ID']
categorical_columns = analysis_data.select_dtypes(include='category').columns.tolist()
numerical_columns = analysis_data.select_dtypes(include='number').columns.tolist()

categorical_columns, numerical_columns
```

Out[81]:

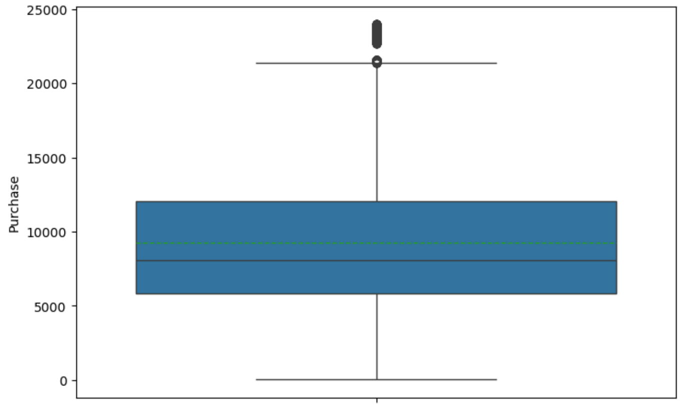
```
(['Gender',
  'Age',
  'City_Category',
  'Stay_In_Current_City_Years',
  'Marital_Status'],
 ['Purchase'])
```

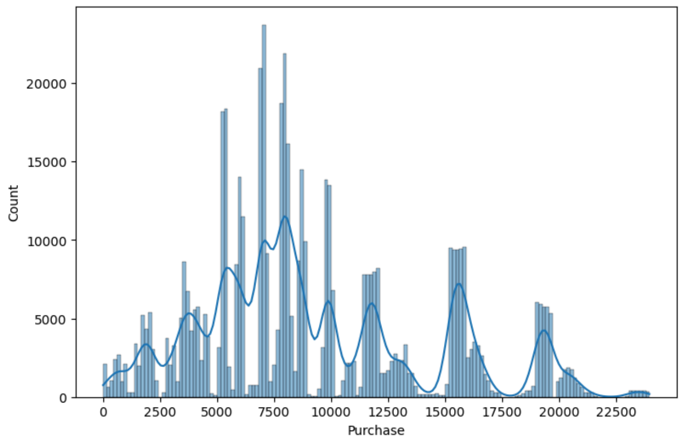
For numerical variables

Numerical	Metric	Visualisation
Purchase	Distribution	Box Plot
		Hist Plot

In [82]:

```
fig, axes = plt.subplots(1, 2, figsize=(15, 5))

sns.boxplot(data= analysis_data, y= 'Purchase', meanline= True, showmeans= True, ax= axes[0])
sns.histplot(data= analysis_data, x= 'Purchase', kde= True, ax= axes[1])

axes[1].set_xticks(range(0,25000,2500))
plt.tight_layout()
plt.show()
```





In [83]:
```
bins = [0, 1000, 2500, 5000, 7500, 10000, 12500, 15000, 17500, 20000, 22500, 25000]
labels = [f'{bins[i]} - {bins[i+1]}' for i in range(len(bins)-1)]

analysis_data['Purchase_Bucket'] = pd.cut(analysis_data['Purchase'], bins= bins, labels= labe

numerical_bucketed_columns = ['Purchase_Bucket']
```

In [84]:
```
def get_difference(left, right, mode= 'relative'):
    if mode == 'absolute':
        return left - right
    if mode == 'relative':
        return (left - right)/right

get_difference(analysis_data['Purchase'].mean(), analysis_data['Purchase'].median())
```

Out[84]: 0.1512325976089382

Observations:

- The mean purchase amount per transaction is 15% more than median amount, which indicates a right skew in the purchase amount distribution
- The purchase amount distribution does not seem to be a normal distribution, a normality check is required before selecting a test statistic for any subsequent hypothesis testing
- The transactions seems to cluster around ranges of purchase amount, which may be due to prices being discounted down from a round figure

For categorical variables

Category	Metric	Visualisation
Gender	% Customers	Column Chart
Age	% Transactions	
City_Category	% Revenue	
Stay_In_Current_City_Years	# Transaction per User	
Marital_Status	Avg Purchase Amount per Transaction	
Purchase Amount Bucket	Avg Purchase Amount per User	

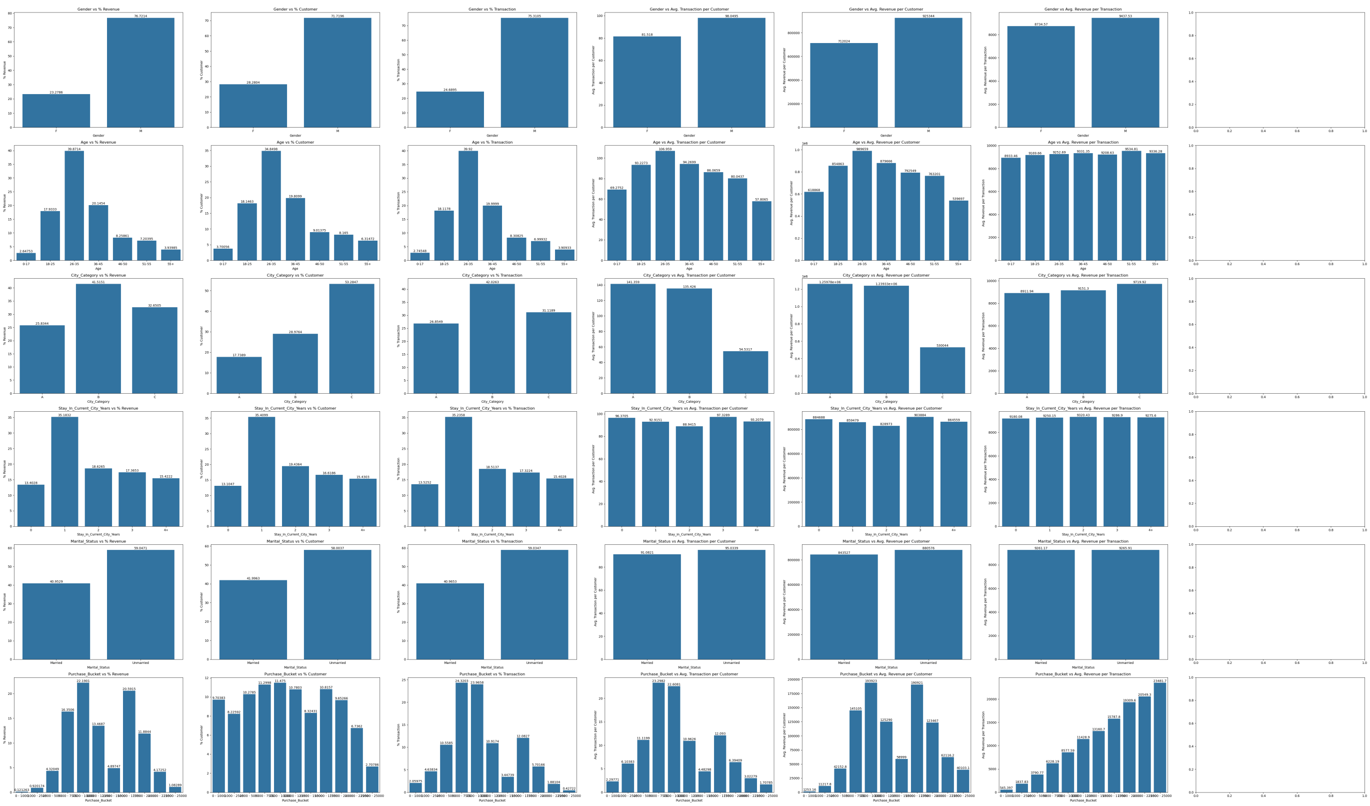
In [85]:
```
base_aggs = {
    '# Customer': ('User_ID', 'nunique'),
    '# Transaction': ('Transaction_ID', 'count'),
    '$ Revenue': ('Purchase', 'sum')
}
```

```python
custom_aggs = {
    '%': {'# Customer', '# Transaction', '$ Revenue'},
    'Avg.': {
        '# Transaction': ['# Customer'],
        '$ Revenue': ['# Customer', '# Transaction']
    }
}
```

In [86]:
```python
def get_size(collection):
    if type(collection) in {str, int, float}:
        return 1
    elif type(collection) in {list, set, dict}:
        n = 0
        collections = collection.values() if type(collection) == dict else collection
        for sub_collection in collections:
            n += get_size(sub_collection)
        return n
    else:
        return 0

def remove_agg_prefixes(name, prefixes, trim= True):
    for prefix in prefixes:
        name = name.replace(prefix, '')

    name = name.strip()

    return name


def get_agg_data(data, groupby_coulmns, base_aggs, custom_aggs, include= 'custom', ret_agg_nai
    base_agg_data = data.groupby(groupby_coulmns, observed= True).agg(**base_aggs)
    base_agg_names = list(base_aggs.keys())
    if include == 'base':
        if ret_agg_names:
            return base_agg_data.reset_index(), base_agg_names
        return base_agg_data.reset_index()

    custom_agg_names = []
    agg_data = base_agg_data.copy()
    for agg_type, agg_columns in custom_aggs.items():
        if agg_type == '%':
            for column in agg_columns:
                new_column = remove_agg_prefixes(column, ['#', '$'])
                agg_data[f'% {new_column}'] = agg_data[column] * 100 / agg_data[column].sum()
                custom_agg_names.append(f'% {new_column}')
        elif agg_type == 'Avg.':
            for numerator, denominators in agg_columns.items():
                new_numerator = remove_agg_prefixes(numerator, ['#', '$'])
                for denominator in denominators:
                    new_denominator = remove_agg_prefixes(denominator, ['#', '$'])
                    agg_data[f'Avg. {new_numerator} per {new_denominator}'] = agg_data[numerat
                    custom_agg_names.append(f'Avg. {new_numerator} per {new_denominator}')

    if include == 'both':
        if ret_agg_names:
            return agg_data.reset_index(), base_agg_names + custom_agg_names
        return agg_data.reset_index()

    if ret_agg_names:
        return agg_data.drop(columns= base_agg_data.columns.tolist()).reset_index(), custom_a
    return agg_data.drop(columns= base_agg_data.columns.tolist()).reset_index()
```

In [87]:
```python
r, c = get_size(categorical_columns + numerical_bucketed_columns), get_size(custom_aggs) + 1

fig, axes = plt.subplots(r, c, figsize=(r*10, c*5))
```

```
for i, column in enumerate(categorical_columns + numerical_bucketed_columns):
    agg_data, agg_columns = get_agg_data(analysis_data, column, base_aggs, custom_aggs, ret_a
    for j, agg_column in enumerate(agg_columns):
        sns.barplot(data=agg_data, x=column, y=agg_column, ax=axes[i][j])
        axes[i][j].set_title(f'{column} vs {agg_column}')
        axes[i][j].set_xlabel(column)
        axes[i][j].set_ylabel(agg_column)
        axes[i][j].bar_label(axes[i][j].containers[0])

# for i in range(r):
#     fig.delaxes(axes[i][c-1])

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



In [88]:
```
print(
    get_difference(
        analysis_data[analysis_data['Gender']=='M']['Purchase'].mean(),
        analysis_data[analysis_data['Gender']=='F']['Purchase'].mean()
    )
)

print(get_difference(98.045, 81.518))

print(get_difference(925.344, 712.024))

print(get_difference(0.53, 1.26))

print(get_difference(9719, 9151))

print(get_difference(54.5, 135.4))

print(get_difference(8986, 9591))
```

```
0.08048027735060238
0.2027404990308889
0.299596642809793
-0.5793650793650793
0.06206971915637635
-0.5974889217134417
-0.06307997080596392
```

Observations:

- Gender:
  - 72% of purchasing customers are male and 28% customers are female
  - The same is reflected in transaction and revenue which is distributed as 75% male and 25% female
  - The male customers made 98 transactions on average which is 20% more than 81 transactions made by female customers
  - Average revenue per customer is 925K for males which is 30% more than 712K for females
  - Average order value is 9.5K for males which is 8% more than 8.7K for females
  - The metrics seems to be high for males compared to females, need to test significance of the same
  - It is also possible that only a few customers are generating most of the revenue, need to check revenue distribution as the user level
- Age:
  - 40% of customers are in the age range of 26-35 while 20% in 36-45 and 18% in 18-25, a total of 78% of customers are in the age range 18-45
  - The same is the case for revenue contribution and transaction volume across the given age ranges, which can indicate that the revenue may be uniformly distributed across customers atleast across age ranges
  - The average revenue per user and the average no. of transactions per user seem to be ranked similary with age ranges (26-35, 36-45, 18-25) ranking at the top and age ranges (0-17 and 55+) ranking at the bottom, need to check the significance for the same
  - The average order value seems to be similar across the given age ranges, need to check significance of the same
- Marital Status
  - 58% of customers are unmarried and 42% of customers are married
  - The transaction count and revenue are distributed in the same way with 59% from unmarried and 41% from married
  - The average revenue per user and average order value seem to be similar for married and unmarried customers, need to check the same
- City Category
  - 53% of the customers are from City C which is the majority compared to other two cities which have 29% and 18% from City B and City C respectively
  - Unlike age, gender and marital status the transaction volume and revenue is not distributed similar to the no of customers, with City B contributing 41% of revenue/transaction and then City C with 31% of revenue/transaction
  - The average revenue per customer across city seems to also behave unlike age, gender and marital status, with City A and City B being similar at 1.26M (1.6% more than) and 1.24M while City C is 58% low at 530K revenue per user. The same is reflected with average transaciton volume per customer.

- The average order value looks similar across cities with City C leading by a small margin of 6%. Need to check significance of the same.
- Need to also check the distribution average order value and total revenue at user level across city, age, gender and marital status

Next Steps:

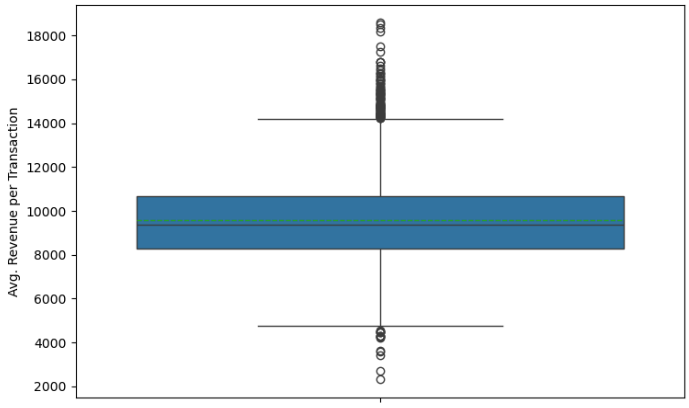
1. Check the customer level distribution of average order value (avg revenue per transaction) and total revenue across city, age, gender and marital status
2. Test the hypotheses that average order value is same across gender, age, marital status and city

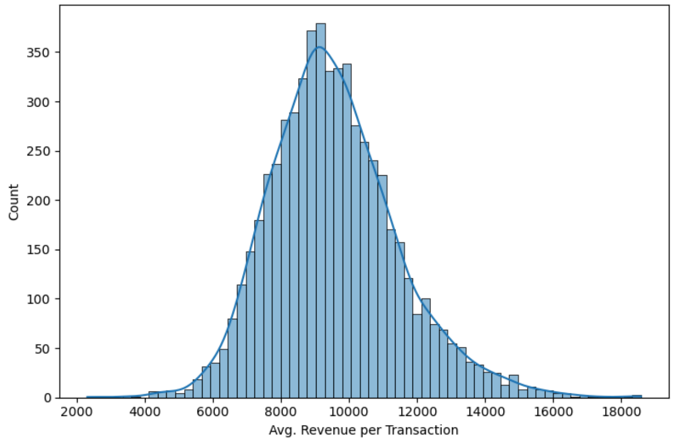
In [89]:
```
user_base_aggs = {
    '# Transaction': ('Transaction_ID', 'count'),
    '$ Revenue': ('Purchase', 'sum')
}

user_custom_aggs = {
    'Avg.': {
        '$ Revenue': ['# Transaction']
    }
}

user_agg_data, user_agg_columns = get_agg_data(analysis_data, ['User_ID'] + categorical_colum

user_agg_data.head()
```

Out[89]:

	User_ID	Gender	Age	City_Category	Stay_In_Current_City_Years	Marital_Status	# Transaction	Rever
0	1000001	F	0-17	A	2	Unmarried	35	334
1	1000002	M	55+	C	4+	Unmarried	77	810
2	1000003	M	26-35	A	3	Unmarried	29	341
3	1000004	M	46-50	B	2	Married	14	206
4	1000005	M	26-35	A	1	Married	106	821

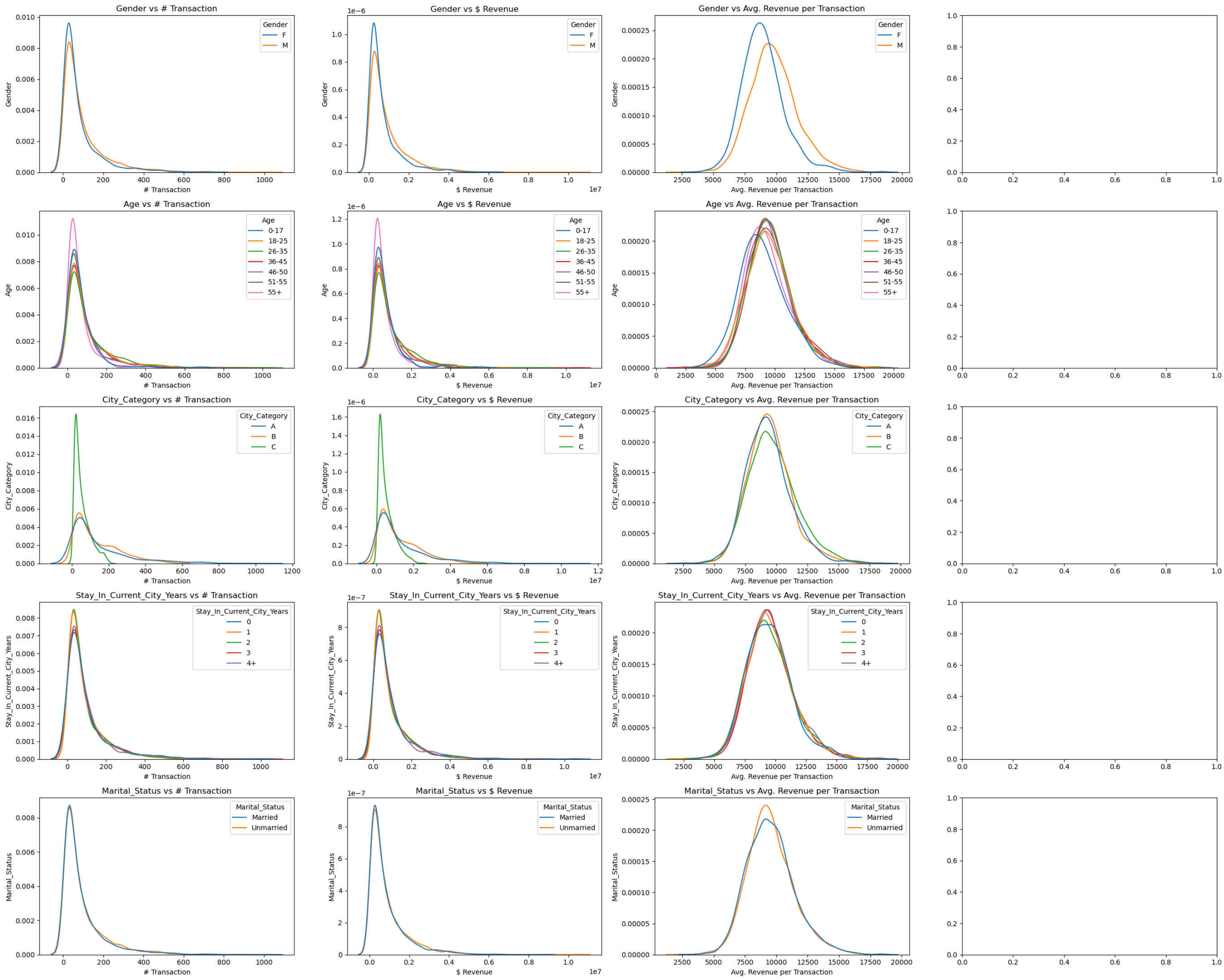
In [90]:
```
fig, axes = plt.subplots(1, 2, figsize=(15, 5))

sns.boxplot(data= user_agg_data, y= 'Avg. Revenue per Transaction', meanline= True, showmeans
sns.histplot(data= user_agg_data, x= 'Avg. Revenue per Transaction', kde= True, ax= axes[1])

# axes[1].set_xticks(range(0,25000,2500))
plt.tight_layout()
plt.show()
```





In [91]:

```
r, c = get_size(categorical_columns), get_size(user_base_aggs) + get_size(user_agg_columns) +

fig, axes = plt.subplots(r, c, figsize=(r*5, c*5))

for i, column in enumerate(categorical_columns):
    for j, agg_column in enumerate(user_agg_columns):
        sns.kdeplot(data= user_agg_data, x= agg_column, hue= column, common_norm= False, ax=
        axes[i][j].set_title(f'{column} vs {agg_column}')
        axes[i][j].set_xlabel(agg_column)
        axes[i][j].set_ylabel(column)

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



Observations

- The average revenue per transaction seems to approximately follow a normal distribution, need to check for the same
- Gender
  - There seems to be more female customers who make low order value transactions
  - The same trend seems to appear for Transaction volume and Revenue
- Age
  - The avg order value seems to be distributed similarly across age
  - There are more customers in the age group 55+ who contributed low revenue with low transaction volume
- City
  - Though the average order value is same across cities, there seems to be more customers with higher average order value in City C compared to others
  - There are very large no of customers with low revenue and transaction volume in City C compared to other cities
  - The trend here seems to be that most of users from City C make very few transactions of slightly high average order value
- Marital Status
  - The distribution of transaction volume and revenue seems to be exactly overlapping across marital status
  - The same is the case for average order value with the exception that there are slightly more customers at the mean avg purchase per transaction

Next Steps

1. Test the hypthesis that average purchase per transaction is similar across age, gender, marital status, city
2. Identify the confidence intervals and check for overlap for the population across the above categories
   A. Observe the distribution of sample means at different sample sizes
   B. Calculate the confidence intervals at different confidence levels: 90%, 95%, 99%

Hypothesis Testing

Test Hypothesis Framework

Metric: Avg purchase amount per transaction

Null Hypothesis: There is no significant difference between the variables

Variable	Variable Type	Cardinality	Alternate Hypothesis
Gender	Categorical	2	Greater for Male
Marital_Status	Categorical	2	Greater for Unmarried
Age	Categorical	6	Greater for (26-35 / 18-45)
City_Category	Categorical	3	Lesser for City C

Choice of Test Framework

```
Variable Type
├── Numerical vs Categorical:
│   ├── Cardinality = 2:
```

```
│    │    ├── Normal: Yes → Two Sample T-Test Independent
│    │    └── Normal: No → Two Sample KS-Test
│    └── Cardinality > 2: No  → Outcome B
│         ├── Normal and Homoscedastic: Yes → Two Sample ANOVA
│         └── Normal and Homoscedastic: No → Kruskal-Wallis Test
├── Categorical vs Categorical:
└── Numerical vs Numerical:
```

Gender

Metric: Avg purchase amount per transaction

Null Hypothesis (H0): There is no significant difference between the male vs female customers

Alternate Hypothesis(Ha): Male avg purchase amount per transaction is greater than female

In [92]:
```
# Checking for data types and cardinality and sample size

print(user_agg_data['Avg. Revenue per Transaction'].dtype, user_agg_data['Gender'].dtype)

print(user_agg_data['Avg. Revenue per Transaction'].shape, user_agg_data['Gender'].nunique())

user_agg_data['Gender'].value_counts()
```

```
float64 category
(5891,) 2
```

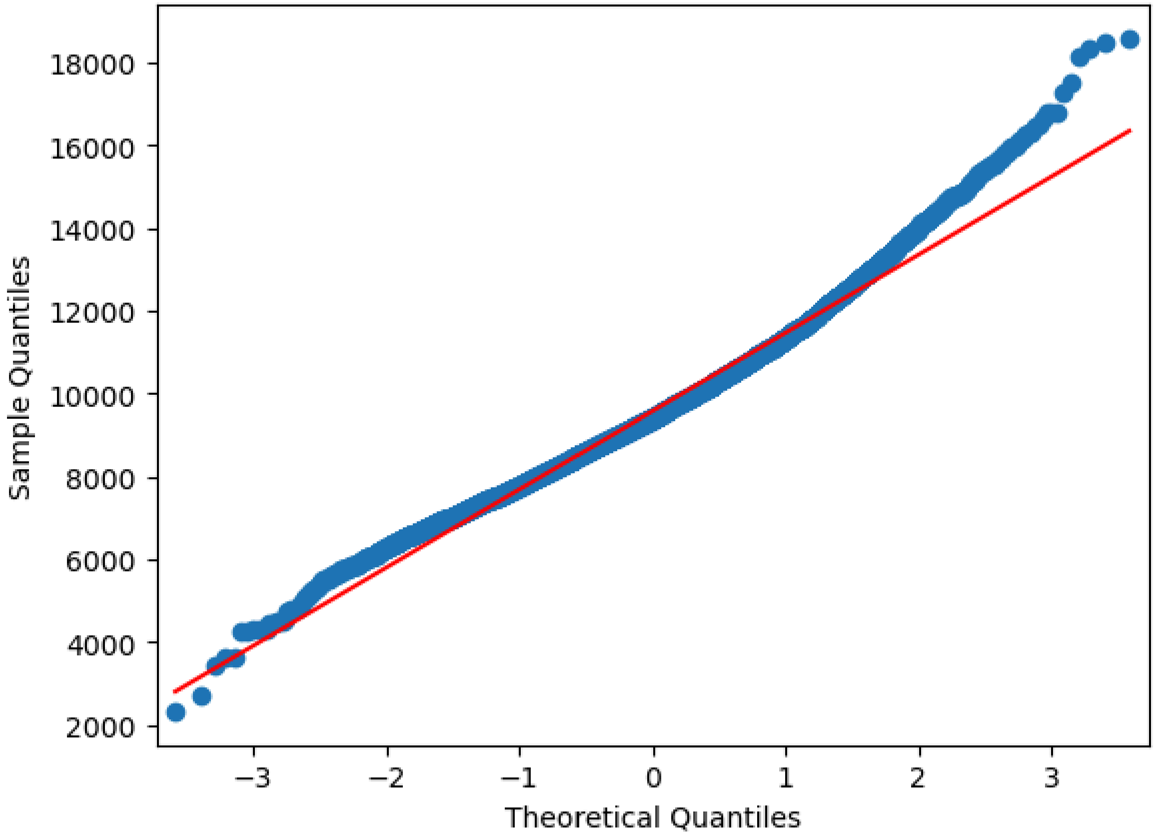
Out[92]:
```
Gender
M    4225
F    1666
Name: count, dtype: int64
```

Sample size: 5891 (no. of customers)

Data Types: Avg Revenue per Transaction is Numerical and Gender is categorical

Cardinality: Gender has 2 values M (male: 4225) and F (female: 1666)

In [93]:
```
# Checking for Normality of the metric using QQ plot and KS Test (one sample - theoretical no

sm.qqplot(user_agg_data['Avg. Revenue per Transaction'], line= 's')
plt.show()

ks_stat, p_val = st.kstest(user_agg_data['Avg. Revenue per Transaction'], 'norm')

alpha = 0.05
if p_val > alpha:
    print(f"The sample data follows a normal distribution at {int((1 - alpha)*100)}% confiden
else:
    print(f"The sample data not follow a normal distribution at {int((1 - alpha)*100)}% confi
```




```
The sample data not follow a normal distribution at 95% confidence level with ks_stat: 1.0, p_
val: 0.0
```

Observations:

- The qq plot looks mostly linear with outliers towards the right,
- The ks test shows that the sample is not following a normal distribution

In [94]:
```
male_purchase_data = user_agg_data[user_agg_data['Gender'] == 'M']['Avg. Revenue per Transact
female_purchase_data = user_agg_data[user_agg_data['Gender'] == 'F']['Avg. Revenue per Transa
```

Assumption: Average spending does not follow a normal distribution as per the ks test

Checking for the null hypothesis using Two Sample KS Test with two tailed alternative hypothesis

In [95]:
```
ks_stat, p_val = st.kstest(male_purchase_data, female_purchase_data, alternative= 'two-sided'

print(f"ks_stat: {ks_stat:4f}, p_val: {p_val:4f}")


alpha = 0.05
if p_val > alpha:
    print(f"There is not significant difference between Male and Female purchase distribution
else:
    print(f"There is a significant difference between Male and Female purchase distributions 
```

```
ks_stat: 0.219469, p_val: 0.000000
There is a significant difference between Male and Female purchase distributions at 95% confid
ence level
```

Observations:

- The average spending amount **is significantly different** for male vs female customers

Assumption: Average spending follows almost normal distribution as per the qq plot, despite the ks test not showing significance

In [96]:
```
male_purchase_data.mean(), female_purchase_data.mean()
```

Out[96]:
```
(9806.867524226629, 8965.19846393646)
```

Checking for the null hypothesis using Two Sample T Test with left tailed alternative hypothesis (male spending is greater than female)

Left tailed test because mean of avg purchase amount for male is higher than female

In [97]:
```
t_stat, p_val = st.ttest_ind(male_purchase_data, female_purchase_data, alternative= 'greater'

print(f"t_stat: {t_stat:4f}, p_val: {p_val:4f}")


alpha = 0.05
if p_val > alpha:
    print(f"There is no significant difference between avg spending for Male and Female users
else:
    print(f"Male avg purchase amount is significantly greater than Female at {int((1 - alpha)
```

```
t_stat: 15.710671, p_val: 0.000000
Male avg purchase amount is significantly greater than Female at 95% confidence level
```

Observations:

- Male avg purchase amount is significantly greater than Female as per the left tailed t-test at 95% confidence level

Calculating the confidence intervals for male and female avg purchase amount

In [98]:
```
male_purchase_size, male_purchase_mean, male_purchase_std = male_purchase_data.shape[0], male_
female_purchase_size, female_purchase_mean, female_purchase_std = female_purchase_data.shape[

male_purchase_se, female_purchase_se = male_purchase_std / mt.sqrt(male_purchase_size), femal

width = 0.95

lower_width, upper_width = (1 - width)/2, width - ((1-width)/2)
male_purchase_lower, male_purchase_upper = male_purchase_mean + (st.norm.ppf(lower_width) * m
female_purchase_lower, female_purchase_upper = female_purchase_mean + (st.norm.ppf(lower_widt

print(f"Male population avg purchase amount {int(width*100)}% confidence interval: {male_purc
print(f"Female population avg purchase amount {int(width*100)}% confidence interval: {female_
```

```
Male population avg purchase amount 95% confidence interval: 9749.383406 - 9849.087789
Female population avg purchase amount 95% confidence interval: 8883.296988 - 9025.352504
```

Observations:

- There is no overlap between male (9749.4 - 9849.1) and female (8883.3 - 9025.3) avg purchase amount for the population at 95% confidence interval

Validating the overlap of confidence intervals for male and female avg purchase amount at different widths and sample sizes

In [99]:
```
def get_confidence_interval(data, sample_pct, width):
    if sample_pct < 1:
        sample_data = data.sample(frac= sample_pct)
    else:
        sample_data = data
```

```python
    sample_size, sample_mean, sample_std = sample_data.shape[0], sample_data.mean(), sample_d

    sample_se = sample_std / mt.sqrt(sample_size)

    lower_width, upper_width = (1 - width)/2, width - ((1-width)/2)
    sample_lower, sample_upper = (
        sample_mean + (st.norm.ppf(lower_width) * sample_se),
        sample_mean + (st.norm.ppf(upper_width) * sample_se)
        )

    return [sample_lower, sample_upper]

def check_overlap(left_interval, right_interval):
    if len(left_interval) != 2 or len(right_interval) != 2:
        return 'Invalid inteval size'

    if (left_interval[0] > left_interval[1]) or (right_interval[0] > right_interval[1]):
        return 'Invalid interval order'

    if left_interval[1] < right_interval[0] or right_interval[1] < left_interval[0]:
        return 'No Overlap'

    return 'Overlap'
```

In [100…

```python
params = {
    'width': [0.90, 0.95, 0.99],
    'sample_pct': [0.10, 0.25, 0.50, 0.75, 0.90]
}

confidence_intervals_data = pd.DataFrame()

for w in params['width']:
    for pct in params['sample_pct']:
        male_confidence_interval = get_confidence_interval(male_purchase_data, sample_pct= pc
        female_confidence_interval = get_confidence_interval(female_purchase_data, sample_pct

        current_confidence_intervals = pd.DataFrame(
            {
                'width': w, 'sample_pct': pct,
                'female_interval': f'[{female_confidence_interval[0]:2f}, {female_confidence_
                'female_interval_range': female_confidence_interval[1] - female_confidence_in
                'male_interval': f'[{male_confidence_interval[0]:2f}, {male_confidence_interv
                'male_interval_range': male_confidence_interval[1] - male_confidence_interval
                'overlap_status': check_overlap(male_confidence_interval, female_confidence_i
            },
            index= [0]
        )

        confidence_intervals_data = (
            pd.concat([confidence_intervals_data, current_confidence_intervals], ignore_index
        )

confidence_intervals_data
```

Out[100…]

	width	sample_pct	female_interval	female_interval_range	male_interval	male_interval_range	ove
0	0.90	0.10	[8754.445743, 9119.808351]	365.362608	[9521.854783, 9770.751725]	248.896942	
1	0.90	0.25	[8845.332585, 9053.629102]	208.296517	[9671.682889, 9827.578468]	155.895579	
2	0.90	0.50	[8819.715048, 8980.560083]	160.845034	[9763.959012, 9875.079198]	111.120185	
3	0.90	0.75	[8890.747606, 9021.451069]	130.703463	[9723.231337, 9814.179208]	90.947871	
4	0.90	0.90	[8860.428652, 8975.330489]	114.901837	[9750.803178, 9833.743059]	82.939881	
5	0.95	0.10	[8646.665229, 9044.704775]	398.039546	[9627.094196, 9924.397091]	297.302895	
6	0.95	0.25	[8733.963809, 9024.963630]	290.999821	[9632.777876, 9837.467294]	204.689419	
7	0.95	0.50	[8779.599580, 8979.507642]	199.908062	[9659.439167, 9798.734187]	139.295020	
8	0.95	0.75	[8900.138249, 9062.522383]	162.384134	[9736.325516, 9852.111118]	115.785602	
9	0.95	0.90	[8885.376300, 9036.475883]	151.099584	[9754.860999, 9860.096985]	105.235986	
10	0.99	0.10	[8864.646230, 9490.454752]	625.808522	[9554.048807, 9987.049776]	433.000970	
11	0.99	0.25	[8810.877350, 9219.545552]	408.668202	[9605.541348, 9885.384987]	279.843639	
12	0.99	0.50	[8794.961959, 9066.243344]	271.281385	[9711.286586, 9909.837979]	198.551393	
13	0.99	0.75	[8841.717378, 9068.942295]	227.224916	[9720.103331, 9880.094686]	159.991354	
14	0.99	0.90	[8846.976664, 9055.882254]	208.905589	[9717.531736, 9863.455622]	145.923885	

Observations:

- The confidence interval range increases as the sample size decreases and also as the width increases
- There is no overlap at different combinations of width and sample sizes
- Hence, it can be concluded that male avg spend amount is significantly higher than female

Marital Status

Metric: Avg purchase amount per transaction

Null Hypothesis (H0): There is no significant difference between the married vs unmarried customers

Alternate Hypothesis(Ha): Avg purchase amount per transaction is greater for Married customers than Unmarried

In [101…
```
# Checking for data types and cardinality and sample size

print(user_agg_data['Avg. Revenue per Transaction'].dtype, user_agg_data['Marital_Status'].dt

print(user_agg_data['Avg. Revenue per Transaction'].shape, user_agg_data['Marital_Status'].nu

user_agg_data['Marital_Status'].value_counts()
```

```
float64 category
(5891,) 2
```

Out[101…
```
Marital_Status
Unmarried    3417
Married      2474
Name: count, dtype: int64
```

Sample size: 5891 (no. of customers)

Data Types: Avg Revenue per Transaction is Numerical and Marital Status is categorical

Cardinality: Gender has 2 values Unmarried (3417) and Married (2474)

In [102…
```
married_purchase_data = user_agg_data[user_agg_data['Marital_Status'] == 'Married']['Avg. Rev
unmarried_purchase_data = user_agg_data[user_agg_data['Marital_Status'] == 'Unmarried']['Avg.
```

Assumption: Average spending does not follow a normal distribution as per the ks test

Checking for the null hypothesis using Two Sample KS Test with two tailed alternative hypothesis

In [103…
```
ks_stat, p_val = st.kstest(married_purchase_data, unmarried_purchase_data, alternative= 'two-

print(f"ks_stat: {ks_stat:4f}, p_val: {p_val:4f}")


alpha = 0.05
if p_val > alpha:
    print(f"There is no significant difference between Unmarried and Married customer purchase
else:
    print(f"There is a significant difference between Unmarried and Married customer purchase
```

```
ks_stat: 0.023913, p_val: 0.377029
There is no significant difference between Unmarried and Married customer purchase distributio
ns at 95% confidence level
```

Observations:

- The average spending amount **is not significantly different** for married vs unmarried customers

Assumption: Average spending follows almost normal distribution as per the qq plot, despite the ks test showing otherwise

In [104…
```
married_purchase_data.mean(), unmarried_purchase_data.mean()
```

Out[104…
```
(9574.962299031744, 9564.407141636266)
```

Checking for the null hypothesis using Two Sample T Test with left tailed alternative hypothesis (married spending is greater than unmarried)

Left tailed test because mean of avg purchase amount for married is higher than unmarried

In [105…
```
t_stat, p_val = st.ttest_ind(married_purchase_data, unmarried_purchase_data, alternative= 'gr
```

```
print(f"t_stat: {t_stat:4f}, p_val: {p_val:4f}")


alpha = 0.05
if p_val > alpha:
    print(f"There is no significant difference between avg spending for married and unmarried
else:
    print(f"Married customer avg purchase amount is significantly greater than Unmarried custo
```

```
t_stat: 0.211532, p_val: 0.416240
There is no significant difference between avg spending for married and unmarried users at 95%
confidence level
```

Observations:

- There is no significant difference between avg spending between married and unmarried customers

Calculating the confidence intervals for Married and Unmarried avg purchase amount

In [106…

```
married_purchase_size, married_purchase_mean, married_purchase_std = married_purchase_data.sh
unmarried_purchase_size, unmarried_purchase_mean, unmarried_purchase_std = unmarried_purchase_

married_purchase_se, unmarried_purchase_se = married_purchase_std / mt.sqrt(married_purchase_

width = 0.95

lower_width, upper_width = (1 - width)/2, width - ((1-width)/2)
married_purchase_lower, married_purchase_upper = married_purchase_mean + (st.norm.ppf(lower_w
unmarried_purchase_lower, unmarried_purchase_upper = unmarried_purchase_mean + (st.norm.ppf(l

print(f"Married population avg purchase amount {int(width*100)}% confidence interval: {marrie
print(f"Unmarried population avg purchase amount {int(width*100)}% confidence interval: {unma
```

```
Married population avg purchase amount 95% confidence interval: 9499.780970 - 9630.180604
Unmarried population avg purchase amount 95% confidence interval: 9501.461343 - 9610.638837
```

Observations:

- There is a full overlap of intervals between married and unmarried avg purchase amount for the population at 95% confidence interval
- The interval for unmarried customers is contained within the married population interval

Validating the overlap of confidence intervals for married and unmarried avg purchase amount at different widths and sample sizes

In [107…

```
params = {
    'width': [0.90, 0.95, 0.99],
    'sample_pct': [0.10, 0.25, 0.50, 0.75, 0.90]
}

confidence_intervals_data = pd.DataFrame()

for w in params['width']:
    for pct in params['sample_pct']:
        married_confidence_interval = get_confidence_interval(married_purchase_data, sample_p
        unmarried_confidence_interval = get_confidence_interval(unmarried_purchase_data, samp

        current_confidence_intervals = pd.DataFrame(
            {
                'width': w, 'sample_pct': pct,
                'unmarried_interval': f'[{unmarried_confidence_interval[0]:2f}, {unmarried_co
                # 'unmarried_interval_lower': unmarried_confidence_interval[0],
```

```
            # 'unmarried_interval_upper': unmarried_confidence_interval[1],
            'unmarried_interval_range': unmarried_confidence_interval[1] - unmarried_conf
            'married_interval': f'[{married_confidence_interval[0]:2f}, {married_confiden
            # 'married_interval_lower': married_confidence_interval[0],
            # 'married_interval_upper': married_confidence_interval[1],
            'married_interval_range': married_confidence_interval[1] - married_confidence
            'overlap_status': check_overlap(married_confidence_interval, unmarried_confid
        },
        index= [0]
    )

    confidence_intervals_data = (
        pd.concat([confidence_intervals_data, current_confidence_intervals], ignore_index
    )

confidence_intervals_data
```

Out[107…

	width	sample_pct	unmarried_interval	unmarried_interval_range	married_interval	married_interva
0	0.90	0.10	[9456.685682, 9724.652698]	267.967016	[9281.544505, 9602.926664]	321
1	0.90	0.25	[9537.063888, 9714.984532]	177.920645	[9448.119790, 9659.248697]	211
2	0.90	0.50	[9458.396060, 9581.247041]	122.850980	[9461.754717, 9608.028602]	146
3	0.90	0.75	[9493.321916, 9592.516179]	99.194263	[9505.769631, 9621.270724]	115
4	0.90	0.90	[9520.772718, 9611.930054]	91.157336	[9482.307615, 9589.760260]	107
5	0.95	0.10	[9380.409603, 9734.457281]	354.047678	[9235.446009, 9647.400711]	411
6	0.95	0.25	[9296.183671, 9512.353264]	216.169593	[9524.701857, 9782.034070]	257
7	0.95	0.50	[9460.214606, 9616.493799]	156.279193	[9511.058052, 9702.482770]	191
8	0.95	0.75	[9484.504851, 9611.260095]	126.755244	[9487.214988, 9639.746651]	152
9	0.95	0.90	[9490.805246, 9605.662598]	114.857352	[9509.644507, 9648.151825]	138
10	0.99	0.10	[9309.003521, 9803.924089]	494.920567	[9249.593193, 9796.015990]	546
11	0.99	0.25	[9393.318680, 9696.799411]	303.480731	[9372.049987, 9742.108205]	370
12	0.99	0.50	[9442.500827, 9659.172847]	216.672020	[9406.872337, 9665.688797]	258
13	0.99	0.75	[9443.302087, 9617.578976]	174.276889	[9432.581428, 9643.292719]	210
14	0.99	0.90	[9487.074602, 9648.108686]	161.034083	[9489.965829, 9683.530545]	193

Observations:

- The confidence interval range increases as the sample size decreases and also as the width increases
- There is a significant overlap at different combinations of width and sample sizes between confidence intervals of married and unmarried customers
- Hence, it can be concluded that there is **no significant** difference between avg spend amount for married vs unmarried customers

Age

Metric: Avg purchase amount per transaction

Null Hypothesis (H0): There is no significant difference across age groups

Alternate Hypothesis(Ha): Avg purchase amount is significantly different across age groups

In [108…

```
# Checking for data types and cardinality and sample size

print(user_agg_data['Avg. Revenue per Transaction'].dtype, user_agg_data['Age'].dtype)

print(user_agg_data['Avg. Revenue per Transaction'].shape, user_agg_data['Age'].nunique())

user_agg_data['Age'].value_counts()
```

```
float64 category
(5891,) 7
```

Out[108…

```
Age
26-35    2053
36-45    1167
18-25    1069
46-50     531
51-55     481
55+       372
0-17      218
Name: count, dtype: int64
```

Next Steps

- For simplicity and actionable result, 36-45, 46-50 can be grouped together

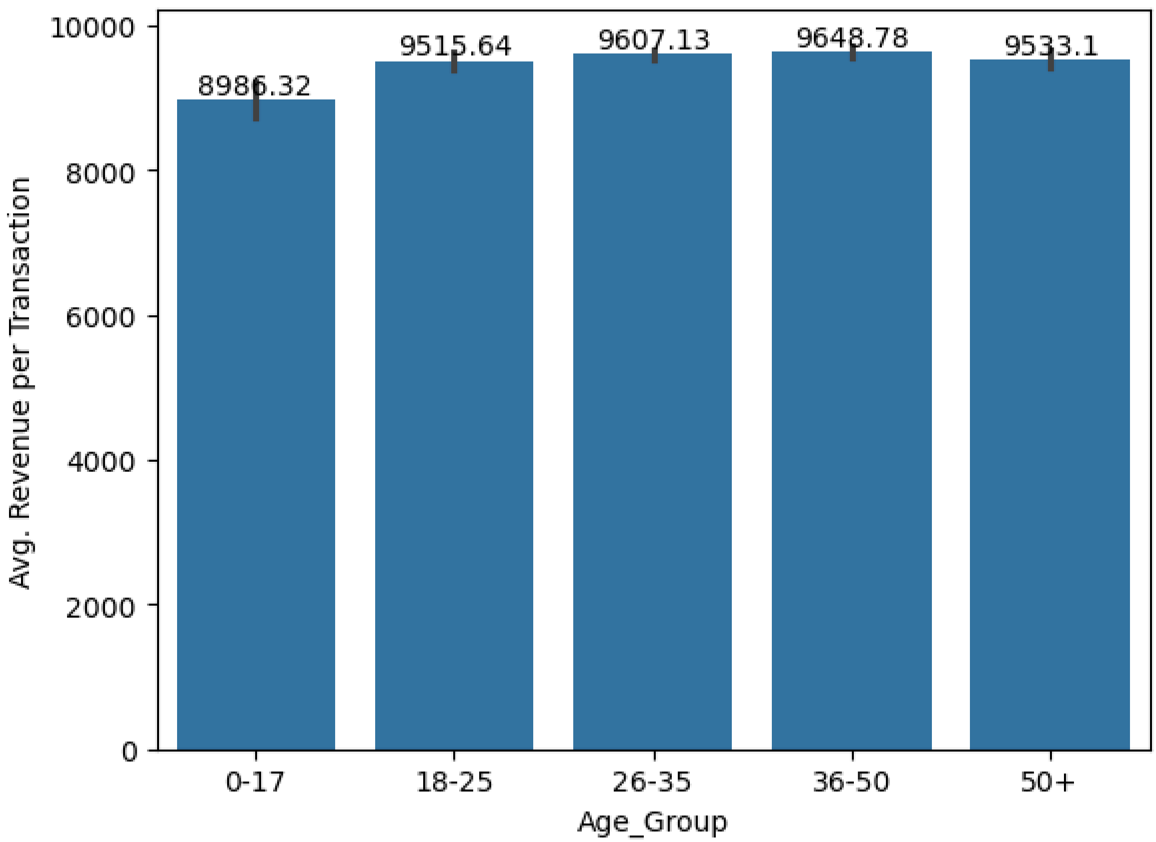
In [109…

```
age_group_mapping = {
    '0-17': '0-17',
    '18-25': '18-25',
    '26-35': '26-35',
    '36-45': '36-50',
    '46-50': '36-50',
    '51-55': '50+',
    '55+': '50+'
}

user_agg_data['Age_Group'] = user_agg_data['Age'].map(age_group_mapping).astype('category')

# Checking for data types and cardinality and sample size

print(user_agg_data['Avg. Revenue per Transaction'].dtype, user_agg_data['Age_Group'].dtype)

print(user_agg_data['Avg. Revenue per Transaction'].shape, user_agg_data['Age_Group'].nunique

user_agg_data['Age_Group'].value_counts()
```

```
float64 category
(5891,) 5
```

Out[109…
```
Age_Group
26-35    2053
36-50    1698
18-25    1069
50+       853
0-17      218
Name: count, dtype: int64
```

In [110…
```
ax = sns.barplot(data= user_agg_data, x= 'Age_Group', y= 'Avg. Revenue per Transaction')

ax.bar_label(ax.containers[0])
plt.show()
```



Sample size: 5891 (no. of customers)

Data Types: Avg Revenue per Transaction is Numerical and Age is categorical

Cardinality: Age has 4 values 0-25, 26-35, 36-45, 46+

In [111…
```
age_0_17_purchase_data = user_agg_data[user_agg_data['Age_Group'] == '0-17']['Avg. Revenue pe
age_18_25_purchase_data = user_agg_data[user_agg_data['Age_Group'] == '18-25']['Avg. Revenue 
age_26_35_purchase_data = user_agg_data[user_agg_data['Age_Group'] == '26-35']['Avg. Revenue 
age_36_50_purchase_data = user_agg_data[user_agg_data['Age_Group'] == '36-50']['Avg. Revenue 
age_50P_purchase_data = user_agg_data[user_agg_data['Age_Group'] == '50+']['Avg. Revenue per 

age_group_purchase_data_dict = {
    '0-17'  : age_0_17_purchase_data,
    '18-25'  : age_18_25_purchase_data,
    '26-35' : age_26_35_purchase_data,
    '36-50' : age_36_50_purchase_data,
    '50+'   : age_50P_purchase_data
}
```

Assumption: Average spending does not follow a normal distribution as per the ks test

Checking for the null hypothesis using Kruskal Wallis Test with two tailed alternative hypothesis

In [112…
```
ks_stat, p_val = st.kruskal(age_0_17_purchase_data, age_18_25_purchase_data, age_26_35_purcha

print(f"ks_stat: {ks_stat:4f}, p_val: {p_val:4f}")


alpha = 0.05
if p_val > alpha:
    print(f"There is no significant difference in median of avg purchase amount between age g
else:
    print(f"There is a significant difference in median of avg purchase amount between age gro
```

```
ks_stat: 27.391812, p_val: 0.000017
There is a significant difference in median of avg purchase amount between age groups at 95% c
onfidence level
```

Observations:

- The median of average spending amount **is significantly different** between age groups of customers

Assumption: Average spending follows almost normal distribution as per the qq plot, despite the ks test showing otherwise

Checking for homoscedasticity using Levene's test for applying ANOVA Test

In [113…
```
l_stat, p_val = st.levene(age_0_17_purchase_data, age_18_25_purchase_data, age_26_35_purchase_

print(f"l_stat: {l_stat:4f}, p_val: {p_val:4f}")


alpha = 0.05
if p_val > alpha:
    print(f"There is no significant difference variances of avg spending between age groups at
else:
    print(f"There is a significant difference variances of avg spending between age groups at
```

```
l_stat: 2.761620, p_val: 0.026140
There is a significant difference variances of avg spending between age groups at 95% confiden
ce level
```

Observation:

- There is a significant difference in variances across age groups at 95% confidence level
- The result would change to having equal variance at 99% confidence level
- Perform ANOVA nevertheless based on 99% confidence result to make sure again that there is no difference

Checking for the null hypothesis using ANOVA Test

In [114…
```
f_stat, p_val = st.f_oneway(age_0_17_purchase_data, age_18_25_purchase_data, age_26_35_purcha

print(f"f_stat: {f_stat:4f}, p_val: {p_val:4f}")


alpha = 0.05
if p_val > alpha:
    print(f"There is no significant difference between avg spending between age groups of cust
else:
    print(f"There is a significant difference between avg spending between age groups of custo
```

```
f_stat: 6.458619, p_val: 0.000035
There is a significant difference between avg spending between age groups of customers at 95% confidence level
```

Observations:

- ANOVA: There is a significant difference between avg spending between age groups of customers
- Kruskal Wallis: ANOVA: There is a significant difference between avg spending between age groups of customers
- Both the tests result in the same conclusion that the average spending behaviour is different across age groups

Next Steps:

- Apply ttest for all combinations to identify similar and significantly different groups
- Merge the subsequent groups that are not significantly different
- Compare the confidence intervals of the final groups and check for overlaps

In [115…

```python
def get_ttest_result(left_data, right_data, alpha):

    two_tailed_t_stat, two_tailed_p_val = st.ttest_ind(left_data, right_data, alternative= 't

    two_tailed_result = 'same' if two_tailed_p_val > alpha else 'different'

    alternative = 'less' if left_data.mean() < right_data.mean() else 'greater'

    one_tailed_t_stat, one_tailed_p_val = st.ttest_ind(left_data, right_data, alternative= al

    one_tailed_result = 'same' if one_tailed_p_val > alpha else alternative

    result = {
        'two_tailed_p_val'   : round(two_tailed_p_val, 5),
        'two_tailed_result' : two_tailed_result,
        'one_tailed_p_val'   : round(one_tailed_p_val, 5),
        'one_tailed_result' : one_tailed_result
    }

    return result
```

Calculating the ttest results and confidence intervals of avg purchase amount for all combinations of age groups

In [116…

```python
age_group_names = list(age_group_purchase_data_dict.keys())
age_group_ttest_results_data = pd.DataFrame()
alpha= 0.05; width = 1 - alpha

for i in range(len(age_group_names)):
    for j in range(i + 1, len(age_group_names)):

        result = dict()
        result['left_age_group'], result['right_age_group'] = age_group_names[i], age_group_n
        result.update(
            get_ttest_result(
                age_group_purchase_data_dict[age_group_names[i]],
                age_group_purchase_data_dict[age_group_names[j]],
                alpha
            )
        )
        left_confidence_interval = get_confidence_interval(
            age_group_purchase_data_dict[age_group_names[i]], sample_pct= 1, width= 1 - alpha
```

```
        )
        right_confidence_interval = get_confidence_interval(
            age_group_purchase_data_dict[age_group_names[j]], sample_pct= 1, width= 1 - alpha
        )

        result.update(
            {
                'left_interval': f'[{left_confidence_interval[0]:2f}, {left_confidence_interv
                'right_interval': f'[{right_confidence_interval[0]:2f}, {right_confidence_int
                'overlap_status': check_overlap(left_confidence_interval, right_confidence_in
            }
        )
        result_data = pd.DataFrame(
            data= result, index= [0]
        )

        age_group_ttest_results_data = pd.concat([age_group_ttest_results_data, result_data],

age_group_ttest_results_data
```

Out[116…

	left_age_group	right_age_group	two_tailed_p_val	two_tailed_result	one_tailed_p_val	one_tailed_resu
0	0-17	18-25	0.00034	different	0.00017	le
1	0-17	26-35	0.00000	different	0.00000	le
2	0-17	36-50	0.00000	different	0.00000	le
3	0-17	50+	0.00024	different	0.00012	le
4	18-25	26-35	0.19796	same	0.09898	sar
5	18-25	36-50	0.07354	same	0.03677	le
6	18-25	50+	0.84753	same	0.42377	sar
7	26-35	36-50	0.48896	same	0.24448	sar
8	26-35	50+	0.33008	same	0.16504	sar
9	36-50	50+	0.14401	same	0.07201	sar

Observations:

- The avg purchase amount of 0-17 age group is significantly lesses from other groups without overlap
- The other groups have similar average purchase value among each other with overlaps for exceptions
- A final grouping of 0-17, 18+ will be useful for further analysis and actionable insights

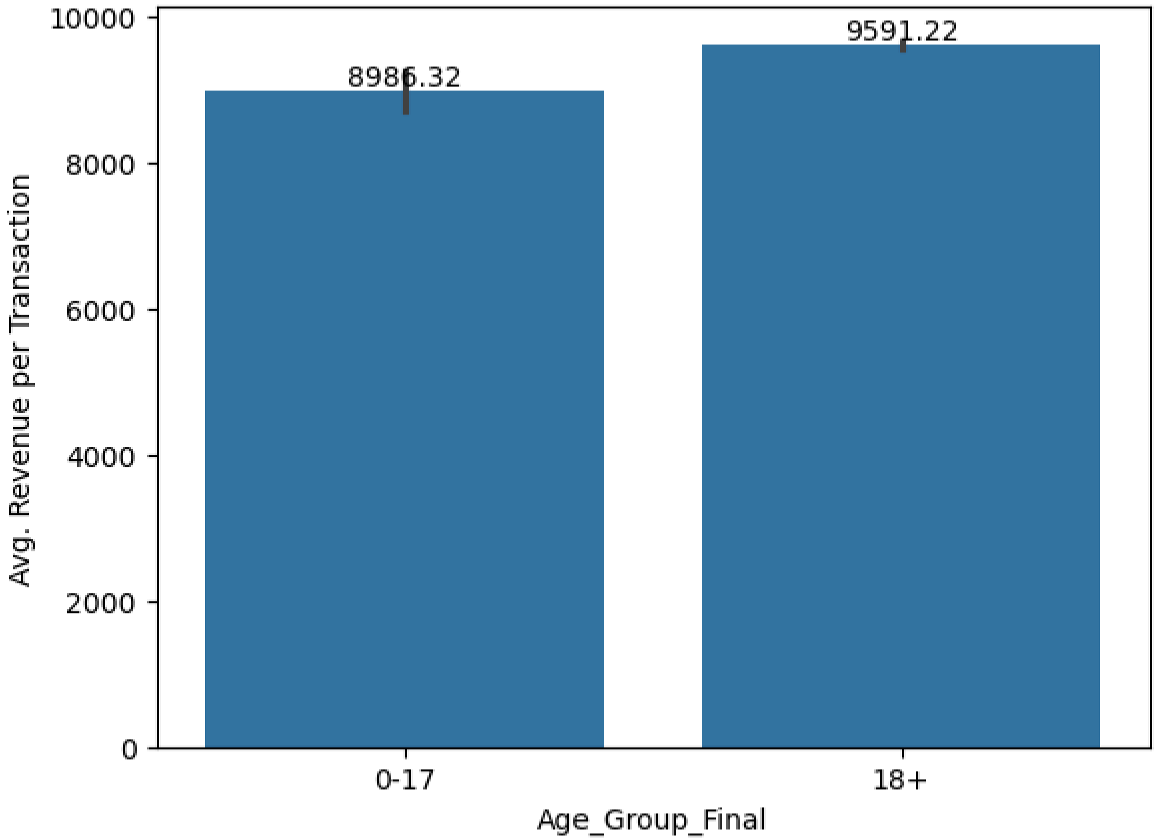
In [117…

```
age_group_final_mapping = {
    '0-17': '0-17',
    '18-25': '18+',
```

```
    '26-35': '18+',
    '36-45': '18+',
    '46-50': '18+',
    '51-55': '18+',
    '55+': '18+'
}

user_agg_data['Age_Group_Final'] = user_agg_data['Age'].map(age_group_final_mapping).astype('
```

In [118…

```
ax = sns.barplot(data= user_agg_data, x= 'Age_Group_Final', y= 'Avg. Revenue per Transaction'

ax.bar_label(ax.containers[0])
plt.show()
```



Validating the overlap of confidence intervals for age <18 and 18+ avg purchase amount at different widths and sample sizes

In [119…

```
age_final_L17_purchase_data = user_agg_data[user_agg_data['Age_Group_Final'] == '0-17']['Avg.
age_final_18P_purchase_data = user_agg_data[user_agg_data['Age_Group_Final'] == '18+']['Avg.
```

In [120…

```
params = {
    'width': [0.90, 0.95, 0.99],
    'sample_pct': [0.10, 0.50, 0.90]
}

confidence_intervals_data = pd.DataFrame()

for w in params['width']:
    for pct in params['sample_pct']:
        age_final_L17_confidence_interval = get_confidence_interval(age_final_L17_purchase_da
        age_final_18P_confidence_interval = get_confidence_interval(age_final_18P_purchase_da

        current_confidence_intervals = pd.DataFrame(
            {
                'width': w, 'sample_pct': pct,
                'age_L17_interval': f'[{age_final_L17_confidence_interval[0]:2f}, {age_final_
                'age_L17_interval_range': age_final_L17_confidence_interval[1] - age_final_L1
                'age_18P_interval': f'[{age_final_18P_confidence_interval[0]:2f}, {age_final_
```

```
            'age_18P_interval_range': age_final_18P_confidence_interval[1] - age_final_18
            'overlap_status': check_overlap(age_final_18P_confidence_interval, age_final_
        },
        index= [0]
    )

    confidence_intervals_data = (
        pd.concat([confidence_intervals_data, current_confidence_intervals], ignore_index
    )

confidence_intervals_data
```

Out[120…

	width	sample_pct	age_L17_interval	age_L17_interval_range	age_18P_interval	age_18P_interval_rang
0	0.90	0.1	[8626.351693, 9671.058646]	1044.706953	[9367.389890, 9584.341908]	216.9520
1	0.90	0.5	[8554.119611, 9042.834252]	488.714642	[9525.039897, 9619.693722]	94.6538
2	0.90	0.9	[8758.894314, 9134.207974]	375.313661	[9551.029177, 9621.774685]	70.7455
3	0.95	0.1	[8188.421046, 9349.524091]	1161.103046	[9505.330927, 9763.842919]	258.5119
4	0.95	0.5	[8622.575754, 9210.203516]	587.627762	[9521.562101, 9643.821436]	122.2593
5	0.95	0.9	[8768.593540, 9249.061785]	480.468245	[9536.814387, 9626.671802]	89.8574
6	0.99	0.1	[8156.275355, 10029.405173]	1873.129817	[9287.694276, 9646.276037]	358.5817
7	0.99	0.5	[8453.420465, 9401.643469]	948.223004	[9435.967421, 9604.875386]	168.9079
8	0.99	0.9	[8666.925469, 9314.819340]	647.893871	[9535.565178, 9661.258960]	125.6937

Observations:

- There is no overlap at most of the combinations of width and sample sizes between confidence intervals of age <17 and 18+ customers, except for 99% width and 10% sample pct
- Hence, it can be concluded that there **is a significant difference** between avg spend amount for age <17 vs 18+ customers

City Category

Metric: Avg purchase amount per transaction

Null Hypothesis (H0): There is no significant difference across city categories

Alternate Hypothesis(Ha): Avg purchase amount is significantly different across city categories

In [121…

```
# Checking for data types and cardinality and sample size

print(user_agg_data['Avg. Revenue per Transaction'].dtype, user_agg_data['City_Category'].dty

print(user_agg_data['Avg. Revenue per Transaction'].shape, user_agg_data['City_Category'].nun
```

```
user_agg_data['City_Category'].value_counts()
```

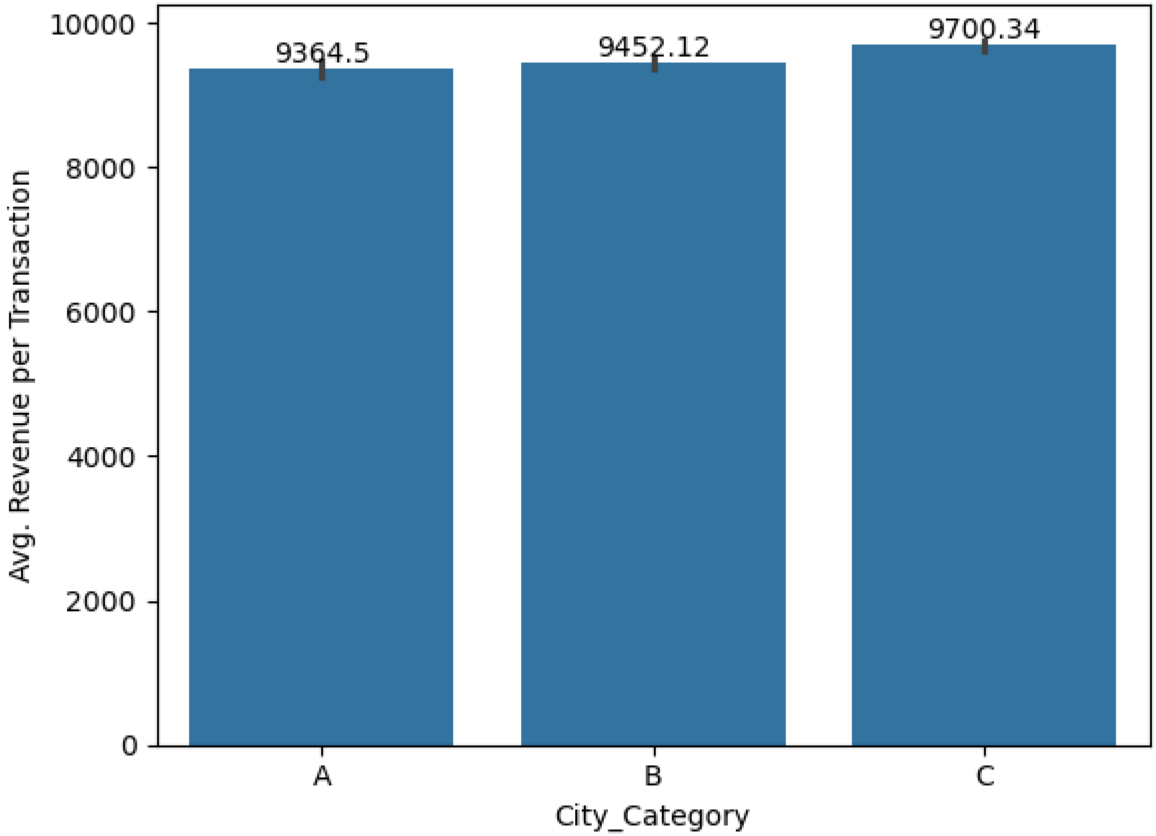
```
float64 category
(5891,) 3
```

Out[121…

```
City_Category
C    3139
B    1707
A    1045
Name: count, dtype: int64
```

In [122…

```
ax = sns.barplot(data= user_agg_data, x= 'City_Category', y= 'Avg. Revenue per Transaction')

ax.bar_label(ax.containers[0])
plt.show()
```



Sample size: 5891 (no. of customers)

Data Types: Avg Revenue per Transaction is Numerical and City Category is categorical

Cardinality: City Category has 3 values A, B, C

In [123…

```
city_A_purchase_data = user_agg_data[user_agg_data['City_Category'] == 'A']['Avg. Revenue per
city_B_purchase_data = user_agg_data[user_agg_data['City_Category'] == 'B']['Avg. Revenue per
city_C_purchase_data = user_agg_data[user_agg_data['City_Category'] == 'C']['Avg. Revenue per

city_category_purchase_data_dict = {
    'A' : city_A_purchase_data,
    'B' : city_B_purchase_data,
    'C' : city_C_purchase_data,
}
```

Assumption: Average spending does not follow a normal distribution (as per the ks test)

Checking for the null hypothesis using Kruskal Wallis Test with two tailed alternative hypothesis

In [124…

```
ks_stat, p_val = st.kruskal(city_A_purchase_data, city_B_purchase_data, city_C_purchase_data)
```

```
print(f"ks_stat: {ks_stat:4f}, p_val: {p_val:4f}")


alpha = 0.05
if p_val > alpha:
    print(f"There is no significant difference in median of avg purchase amount between city 
else:
    print(f"There is a significant difference in median of avg purchase amount between city ca
```

```
ks_stat: 32.399297, p_val: 0.000000
There is a significant difference in median of avg purchase amount between city categories at
95% confidence level
```

Observations:

- The median of average spending amount **is significantly different** between city categories of customers

Assumption: Average spending follows almost normal distribution as per the qq plot, despite the ks test showing otherwise

Checking for homoscedasticity using Levene's test for applying ANOVA Test

In [125…

```
l_stat, p_val = st.levene(city_A_purchase_data, city_B_purchase_data, city_C_purchase_data)

print(f"l_stat: {l_stat:4f}, p_val: {p_val:4f}")


alpha = 0.05
if p_val > alpha:
    print(f"There is no significant difference variances of avg spending between city categor
else:
    print(f"There is a significant difference variances of avg spending between city categori
```

```
l_stat: 16.735004, p_val: 0.000000
There is a significant difference variances of avg spending between city categories at 95% con
fidence level
```

Observation:

- There is a significant difference in variances across city categories at 95% confidence level
- Hence, ANOVA test can not be applied in this scenario

Observations:

- Kruskal Wallis: There is a significant difference between avg spending between city groups of customers

Next Steps:

- Apply ttest for all combinations to identify similar and significantly different groups
- Merge the subsequent groups that are not significantly different
- Compare the confidence intervals of the final groups and check for overlaps

Calculating the ttest results and confidence intervals of avg purchase amount for all combinations of age groups

In [126…

```
city_category_names = ['C', 'A', 'B']#list(city_category_purchase_data_dict.keys())
city_category_ttest_results_data = pd.DataFrame()
```

```
alpha= 0.05; width = 1 - alpha

for i in range(len(city_category_names)):
    for j in range(i + 1, len(city_category_names)):

        result = dict()
        result['left_city_category'], result['right_city_category'] = city_category_names[i],
        result.update(
            get_ttest_result(
                city_category_purchase_data_dict[city_category_names[i]],
                city_category_purchase_data_dict[city_category_names[j]],
                alpha
            )
        )
        left_confidence_interval = get_confidence_interval(
            city_category_purchase_data_dict[city_category_names[i]], sample_pct= 1, width= 1
            )
        right_confidence_interval = get_confidence_interval(
            city_category_purchase_data_dict[city_category_names[j]], sample_pct= 1, width= 1
            )

        result.update(
            {
                'left_interval': f'[{left_confidence_interval[0]:2f}, {left_confidence_interv
                'right_interval': f'[{right_confidence_interval[0]:2f}, {right_confidence_int
                'overlap_status': check_overlap(left_confidence_interval, right_confidence_in
            }
        )
        result_data = pd.DataFrame(
            data= result, index= [0]
        )

        city_category_ttest_results_data = pd.concat([city_category_ttest_results_data, resul

city_category_ttest_results_data
```

Out[126…

	left_city_category	right_city_category	two_tailed_p_val	two_tailed_result	one_tailed_p_val	one_taile
0	C	A	0.00000	different	0.00000	
1	C	B	0.00001	different	0.00001	
2	A	B	0.21021	same	0.10510	

Observations:

- The avg purchase amount of city C is significantly greater that other groups
- The avg purchase amount of city A and B are same

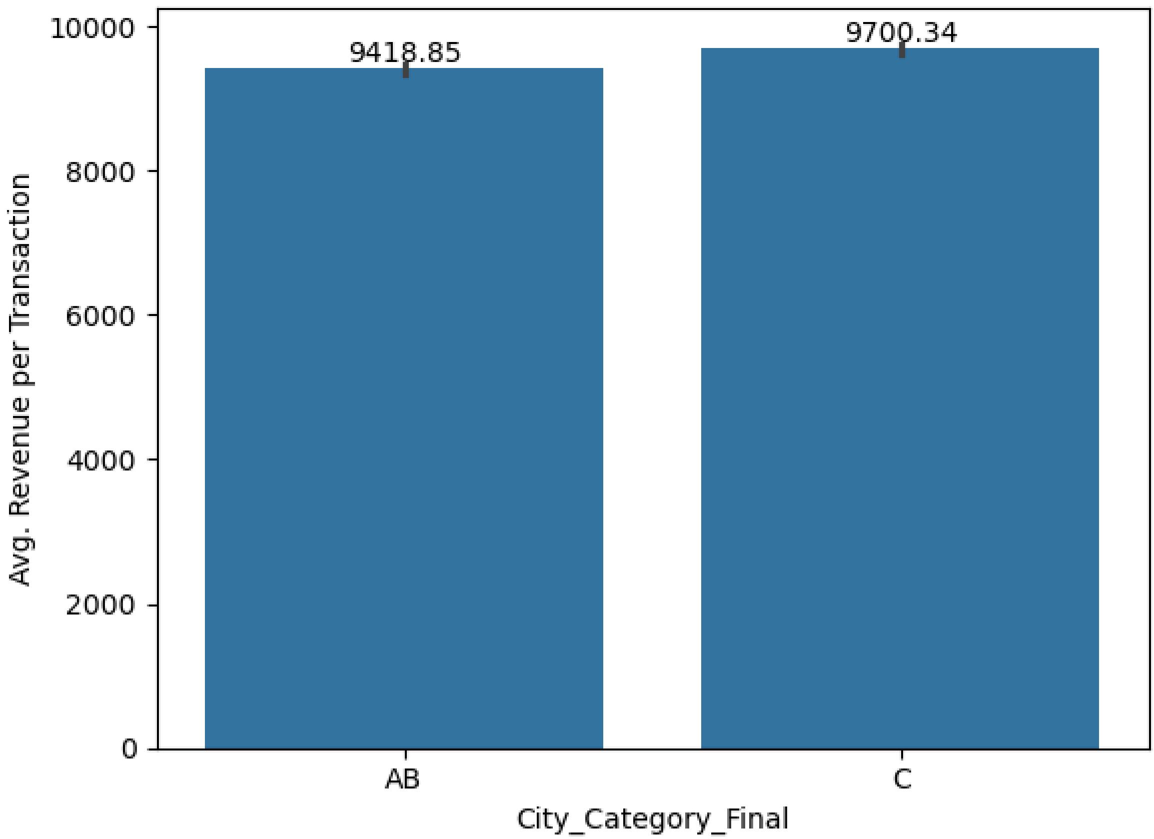
In [127…

```
city_category_final_mapping = {
    'A': 'AB',
    'B': 'AB',
    'C': 'C',
}

user_agg_data['City_Category_Final'] = user_agg_data['City_Category'].map(city_category_final_
```

In [128…

```
ax = sns.barplot(data= user_agg_data, x= 'City_Category_Final', y= 'Avg. Revenue per Transact
```

```
ax.bar_label(ax.containers[0])
plt.show()
```



Validating the overlap of confidence intervals for age <18 and 18+ avg purchase amount at different widths and sample sizes

In [129…

```
city_category_final_AB_purchase_data = user_agg_data[user_agg_data['City_Category_Final'] ==
city_category_final_C_purchase_data = user_agg_data[user_agg_data['City_Category_Final'] == '
```

In [130…

```
params = {
    'width': [0.90, 0.95, 0.99],
    'sample_pct': [0.10, 0.50, 0.90]
}

confidence_intervals_data = pd.DataFrame()

for w in params['width']:
    for pct in params['sample_pct']:
        city_category_final_AB_confidence_interval = get_confidence_interval(city_category_fi
        city_category_final_C_confidence_interval = get_confidence_interval(city_category_fin

        current_confidence_intervals = pd.DataFrame(
            {
                'width': w, 'sample_pct': pct,
                'city_AB_interval': f'[{city_category_final_AB_confidence_interval[0]:2f}, {c
                'city_AB_interval_range': city_category_final_AB_confidence_interval[1] - cit
                'city_C_interval': f'[{city_category_final_C_confidence_interval[0]:2f}, {cit
                'city_C_interval_range': city_category_final_C_confidence_interval[1] - city_
                'overlap_status': check_overlap(city_category_final_C_confidence_interval, ci
            },
            index= [0]
        )

        confidence_intervals_data = (
            pd.concat([confidence_intervals_data, current_confidence_intervals], ignore_index
        )

confidence_intervals_data
```

Out[130…

	width	sample_pct	city_AB_interval	city_AB_interval_range	city_C_interval	city_C_interval_range	ov
0	0.90	0.1	[9174.169841, 9448.138046]	273.968205	[9514.982222, 9819.570509]	304.588286	
1	0.90	0.5	[9363.216917, 9492.459860]	129.242943	[9597.152451, 9729.420313]	132.267862	
2	0.90	0.9	[9349.667854, 9445.597751]	95.929897	[9619.252526, 9718.841940]	99.589413	
3	0.95	0.1	[9214.321667, 9555.030345]	340.708678	[9384.749193, 9750.359754]	365.610561	
4	0.95	0.5	[9351.962420, 9511.324195]	159.361775	[9561.544348, 9729.132875]	167.588528	
5	0.95	0.9	[9339.071374, 9459.354236]	120.282861	[9598.127453, 9723.691477]	125.564024	
6	0.99	0.1	[9255.903852, 9804.028602]	548.124749	[9236.542475, 9763.822874]	527.280399	
7	0.99	0.5	[9257.958858, 9485.992784]	228.033926	[9600.561610, 9834.714026]	234.152416	
8	0.99	0.9	[9317.156850, 9485.094515]	167.937665	[9585.817625, 9761.478076]	175.660451	

Observations:

- There is no overlap at most of the combinations of width and sample sizes between confidence intervals of city category AB vs city C customers, except for 10% sample pct at 95% and 99% confidence intervals
- Hence, it can be concluded that there **is a significant difference** between avg spend amount for city category AB vs city C customers

Actionable Recommendations

- More than 70% of customers are male and 75% of revenue on black friday is contributed by male customers, the average speding amount per transaction is 8% more for male customers which is significantly different from that of female customers. The following actions are recommended based on gender:
  - Targeted marketing towards male customers while justifying the customer acquisition cost, to boost sales and revenue on black friday
  - Recommendation of bundled and relevant products while fine tuning the discounts so that the total value sums up within the average purchase amount confidence interval for the respective genders
- There are 3.7% of customers with age less than 18 and contributing to 2.6% of revenue on black friday, the average spending is 6% lower compared to the other age groups with significance. The following actions are recommende based on age group:
  - Decreasing the marketing spends on <18 customers to improve the profitabilty for this customer segment with respect to the low average order value and revenue contribution
  - Including more products relevant to the <18 age group to generate more revenue from the customers that are making purchases

- There are 53% of customers in City C with only 31% of revenue contribution, the average no. of transactions made are 60% lower compared to other cities while the average order value is 6% more for City C with significance. The following actions are recommended based on city category:
    - Inclusion of more products relevant to city C to improve the volume of transactions
    - Bundling of relevant products and while optimizing the pricing so the total combo value falls within the average purchase interval for City C

Future Work:

- Similar analysis of average spending for stay in current city, occupation and product category
- Root cause analysis for why the revenue contribution is disproportionate to the percentage of customer from City C and why there are very few transactions per customer with high average spending compared to other city categories
- Analysis to find segments of Gender, Age and City with deterministic average purchase amount to optimize pricing strategies within those segments to improve revenue
- Analysis of product categoried to find relevant product combinations for each segment of Gender, Age, Marital Status and Age to improve revenue

In [131…

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!export PATH=/Library/TeX/texbin:$PATH
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operable program or batch file.
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