1. Objective

The objective of this project is to conduct a comprehensive analysis of customer purchase behavior, with a specific focus on purchase amounts, in relation to customer gender during the Black Friday sales event at Walmart Inc. This study aims to provide valuable insights that can assist the management team at Walmart Inc. in making data-driven decisions.

1.1 About Data

The company collected the transactional data of customers who purchased products from the Walmart Stores during Black Friday.It has information of about 0.5 Million transactions during Black Friday throughout various years. 📃 Features of the dataset:

1.2 Feature Description

User_ID User ID of the Customer

- **User_ID** -- User ID of the Customer
- **Product ID** -- Product ID of the Purchased Product
- **Gender** -- Gender of the Customer (Male/Female)
- **Age** -- Age of the Customer (in bins)
- **Occupation** -- Occupation of the Customer (Masked)
- **City_Category** -- Category of the City (A,B,C)
- **StayInCurrentCityYears** -- Number of years stay in current city
- **Marital_Status** -- Marital Status (0 - Unmarried / 1 - Married)
- **ProductCategory** -- Product Category (Masked)
- **Purchase** -- Purchase Amount

2. Exploratory Data Analysis

```
#importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import t
import warnings
warnings.filterwarnings('ignore')
import copy
```

```
df = pd.read_csv('Walmart_Dataset.csv')
df.head()
```

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

```
df.tail()
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Pu
48909	1001496	P00039742	M	26-35	17	A	2	0	5.0	
48910	1001496	P00258842	M	26-35	17	A	2	0	5.0	
48911	1001496	P00086442	M	26-35	17	A	2	0	8.0	
48912	1001496	P00183042	M	26-35	17	A	2	0	15.0	1
48913	1001496	P00233342	M	26-35	17	A	2	0	NaN	

```
df.shape
```

```
(293522, 10)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 293522 entries, 0 to 293521
Data columns (total 10 columns):
 #   Column                      Non-Null Count   Dtype  
---  ------                      --------------   -----  
 0   User_ID                     293522 non-null  int64  
 1   Product_ID                  293522 non-null  object 
 2   Gender                      293521 non-null  object 
 3   Age                         293521 non-null  object 
 4   Occupation                  293521 non-null  float64
 5   City_Category               293521 non-null  object 
 6   Stay_In_Current_City_Years  293521 non-null  object 
 7   Marital_Status              293521 non-null  float64
 8   Product_Category            293521 non-null  float64
 9   Purchase                    293521 non-null  float64
dtypes: float64(4), int64(1), object(5)
memory usage: 22.4+ MB
```

Insights

1. From the above analysis, it is clear that , data has total 10 features with lots of mixed alpha numeric data.
2. Apart from Purchase column, all the other data types are categorical type. We will change datatypes of all such columns to category

```
##Changing the datatype of columns

for i in df.columns[:-1]:
  df[i] = df[i].astype('category')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 195673 entries, 0 to 195672
Data columns (total 10 columns):
 #   Column                      Non-Null Count   Dtype   
---  ------                      --------------   -----   
 0   User_ID                     195673 non-null  category
 1   Product_ID                  195673 non-null  category
 2   Gender                      195673 non-null  category
 3   Age                         195673 non-null  category
 4   Occupation                  195673 non-null  category
 5   City_Category               195673 non-null  category
 6   Stay_In_Current_City_Years  195673 non-null  category
 7   Marital_Status              195672 non-null  category
 8   Product_Category            195672 non-null  category
 9   Purchase                    195672 non-null  float64 
dtypes: category(9), float64(1)
memory usage: 3.9 MB
```

Statistical Summary of object type columns

```
df.describe(include = 'category')
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category
count	440259	440259	440259	440259	440259.0	440259	440259	440259.0	440259
unique	5891	3594	2	7	21.0	3	5	2.0	18
top	1001680	P00265242	M	26-35	4.0	B	1	0.0	5
freq	881	1481	331739	175573	57946.0	185291	154810	259897.0	121764

** Insights**

1. **User_ID** :- Among 293522 transactions there are 5891 unique user_idd, indicating same customers buying multiple products.
2. **Product_ID** :- Among 293522 transactions there are 3527 unique products,with the product having the code P00265242 being the highest seller , with a maximum of 966 units sold.
3. **Gender** :- Out of 293522 transactions, 221170 (nearly 75%) were done by male gender indicating a significant disparity in purchase behavior between males and females during the Black Friday event.
4. **Age** :- We have 7 unique age groups in the dataset. 26 - 35 Age group has maximum of 116775 transactions. We will analyse this feature in detail in future.
5. **Stay_In_Current_City_Years** :- Customers with 1 year of stay in current city accounted to maximum of 103361 transactions among all the other customers with (0,2,3,4+) years of stay in current city.
6. **Marital_Status** :- 59% of the total transactions were done by Unmarried Customers and 41% by Married Customers.

Statistical Summary of numerical Data Type Columns

```
df.describe()
```

	Purchase
count	293521.000000
mean	9319.461759
std	4971.543985
min	185.000000
25%	5866.000000
50%	8059.000000
75%	12060.000000
max	23961.000000

Insights

The purchase amounts vary widely, with the minimum recorded purchase being $12andthemaximumreaching$23961 . The median purchase amount of $8047isnotablylowerthanthemeanpurchaseamountof$9264 , indicating a right-skewed distribution where a few high-value purchases pull up the mean.

Duplicate Detection

```
df.duplicated().value_counts()
```

```
False    48914
Name: count, dtype: int64
```

Insights

There are no duplicate entries in the dataset

Sanity Checks

```
#Checking the unique values for the columns

for i in df.columns:
  print('Unique values in ',i,' column are :- ')
  print(df[i].unique())
  print('-'*70)
```

```
Unique values in  User_ID  column are :-
[1000001, 1000002, 1000003, 1000004, 1000005, ..., 1004588, 1004871, 1004113, 1005391, 1001529]
Length: 5891
Categories (5891, int64): [1000001, 1000002, 1000003, 1000004, ..., 1006037, 1006038, 1006039, 1006040]
-----------------------------------------------------------------------
Unique values in  Product_ID  column are :-
['P00069042', 'P00248942', 'P00087842', 'P00085442', 'P00285442', ..., 'P00144142', 'P00169842', 'P00262842', 'P00065542', 'P000']
Length: 3527
Categories (3527, object): ['P000', 'P00000142', 'P00000242', 'P00000342', ..., 'P0099642',
                            'P0099742', 'P0099842', 'P0099942']
-----------------------------------------------------------------------
Unique values in  Gender  column are :-
['F', 'M', NaN]
Categories (2, object): ['F', 'M']
-----------------------------------------------------------------------
Unique values in  Age  column are :-
['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25', NaN]
Categories (7, object): ['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55+']
-----------------------------------------------------------------------
Unique values in  Occupation  column are :-
[10.0, 16.0, 15.0, 7.0, 20.0, ..., 5.0, 14.0, 13.0, 6.0, NaN]
Length: 22
Categories (21, float64): [0.0, 1.0, 2.0, 3.0, ..., 17.0, 18.0, 19.0, 20.0]
-----------------------------------------------------------------------
Unique values in  City_Category  column are :-
['A', 'C', 'B', NaN]
Categories (3, object): ['A', 'B', 'C']
-----------------------------------------------------------------------
Unique values in  Stay_In_Current_City_Years  column are :-
['2', '4+', '3', '1', '0', NaN]
Categories (5, object): ['0', '1', '2', '3', '4+']
-----------------------------------------------------------------------
Unique values in  Marital_Status  column are :-
[0.0, 1.0, NaN]
Categories (2, float64): [0.0, 1.0]
-----------------------------------------------------------------------
Unique values in  Product_Category  column are :-
[3.0, 1.0, 12.0, 8.0, 5.0, ..., 18.0, 10.0, 17.0, 9.0, NaN]
Length: 19
Categories (18, float64): [1.0, 2.0, 3.0, 4.0, ..., 15.0, 16.0, 17.0, 18.0]
-----------------------------------------------------------------------
Unique values in  Purchase  column are :-
[ 8370. 15200.  1422. ... 21363. 11214.    nan]
-----------------------------------------------------------------------
```

Insights

1. The dataset does not contain any abnormal values.
2. We will convert the 0,1 in Marital Status column as married and unmarried

```
#replacing the values in marital_status column
df['Marital_Status'] = df['Marital_Status'].replace({0:'Unmarried',1:'Married'})
df['Marital_Status'].unique()
```

```
['Unmarried', 'Married', NaN]
Categories (2, object): ['Unmarried', 'Married']
```

Missing Value Analysis

```
df.isnull().sum()
```

```
User_ID                       0
Product_ID                    0
Gender                        0
Age                           0
Occupation                    0
City_Category                 0
Stay_In_Current_City_Years    0
Marital_Status                1
Product_Category              1
Purchase                      1
dtype: int64
```

Dropping Rows having missing values

```
df = df.dropna()
df.isnull().sum()
```

```
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
```

```
df
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category	Pu
0	1000001	P00069042	F	0-17	10	A	2	Unmarried	3.0	
1	1000001	P00248942	F	0-17	10	A	2	Unmarried	1.0	1
2	1000001	P00087842	F	0-17	10	A	2	Unmarried	12.0	
3	1000001	P00085442	F	0-17	10	A	2	Unmarried	12.0	
4	1000002	P00285442	M	55+	16	C	4+	Unmarried	8.0	
...	...	...	...	...	...	...	...	...	...	
73373	1005306	P00140042	F	26-35	17	B	4+	Unmarried	1.0	1
73374	1005306	P00317942	F	26-35	17	B	4+	Unmarried	8.0	
73375	1005306	P00045042	F	26-35	17	B	4+	Unmarried	6.0	
73376	1005306	P00234642	F	26-35	17	B	4+	Unmarried	1.0	
73377	1005306	P00146042	F	26-35	17	B	4+	Unmarried	1.0	

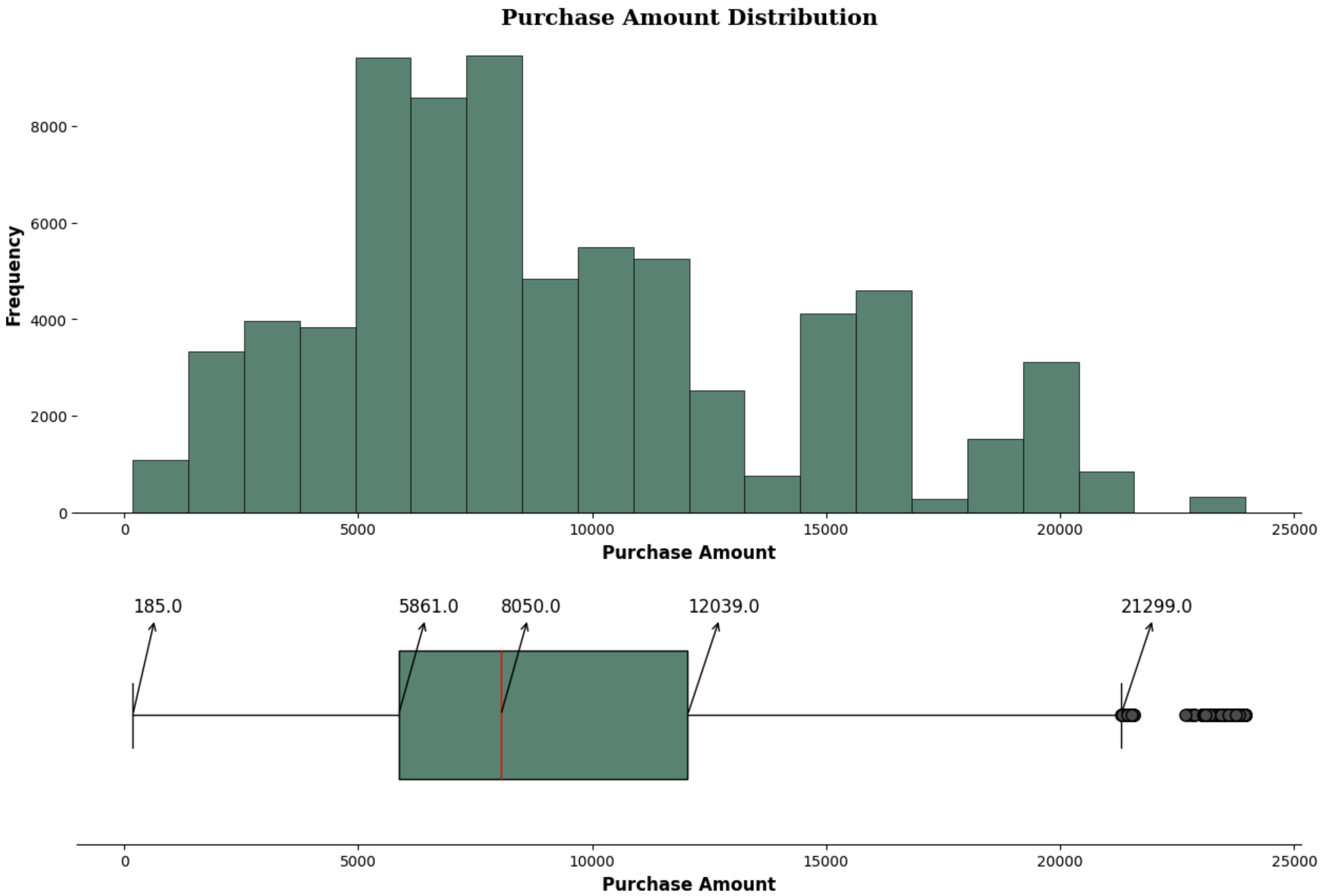
73378 rows × 10 columns

3. Univariate Analysis

3.1 Numerical Variables

3.1.1 Purchase Amount Distribution

```
#setting the plot style
fig = plt.figure(figsize = (15,10))
gs = fig.add_gridspec(2,1,height_ratios=[0.65, 0.35])
 #creating purchase amount histogram

ax0 = fig.add_subplot(gs[0,0])
ax0.hist(df['Purchase'],color= '#5C8374',linewidth=0.5,edgecolor='black',bins = 20)
ax0.set_xlabel('Purchase Amount',fontsize = 12,fontweight = 'bold')
ax0.set_ylabel('Frequency',fontsize = 12,fontweight = 'bold')
#removing the axis lines
for s in ['top','left','right']:
 ax0.spines[s].set_visible(False)

#setting title for visual
ax0.set_title('Purchase Amount Distribution',{'font':'serif', 'size':15,'weight':'bold'})

 #creating box plot for purchase amount

ax1 = fig.add_subplot(gs[1,0])
boxplot = ax1.boxplot(x = df['Purchase'],vert = False,patch_artist = True,widths = 0.5)
# Customize box and whisker colors
boxplot['boxes'][0].set(facecolor='#5C8374')
# Customize median line
boxplot['medians'][0].set(color='red')
# Customize outlier markers
for flier in boxplot['fliers']:
 flier.set(marker='o', markersize=8, markerfacecolor= "#4b4b4c")

#removing the axis lines
for s in ['top','left','right']:
 ax1.spines[s].set_visible(False)
#adding 5 point summary annotations
info = [i.get_xdata() for i in boxplot['whiskers']] #getting the upperlimit,Q1,Q3 and lowerlimit
median = df['Purchase'].quantile(0.5) #getting Q2
for i,j in info: #using i,j here because of the output type of info list comprehension

 ax1.annotate(text = f"{i:.1f}", xy = (i,1), xytext = (i,1.4),fontsize = 12,
 arrowprops= dict(arrowstyle="<-", lw=1, connectionstyle="arc,rad=0"))

 ax1.annotate(text = f"{j:.1f}", xy = (j,1), xytext = (j,1.4),fontsize = 12,
 arrowprops= dict(arrowstyle="<-", lw=1, connectionstyle="arc,rad=0"))
#adding the median separately because it was included in info list
ax1.annotate(text = f"{median:.1f}",xy = (median,1),xytext = (median + 1,1.4),fontsize = 12,
 arrowprops= dict(arrowstyle="<-", lw=1, connectionstyle="arc,rad=0"))
#removing y-axis ticks
ax1.set_yticks([])
#adding axis label
ax1.set_xlabel('Purchase Amount',fontweight = 'bold',fontsize = 12)
plt.show()
```



Calculating the Number of Outliers

As seen above, Purchase amount over 21299 is considered as outlier. We will count the number of outliers as below

```
len(df.loc[df['Purchase'] > 21299,'Purchase'])
```

242

Insights

Outliers

There are total of 242 outliers which is roughly 0.49% of the total data present in purchase amount. We will not remove them as it indicates a broad range of spending behaviors during the sale, highlighting the importance of tailoring marketing strategies to both regular and high-value customers to maximize revenue.

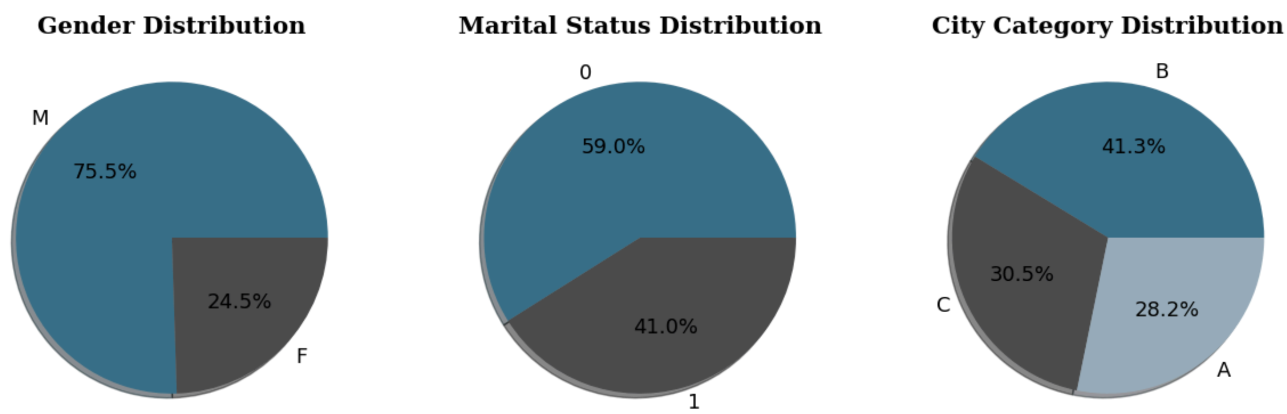
Distribution

Data suggests that the majority of customers spent between 5,861 USD and 12,039 USD , with the median purchase amount being 8,050 USD . The lower limit of 185 USD while the upper limit of 21,299 USD reveal significant variability in customer spending.

3.2 Categorical Variables

3.2.1 Gender, Marital Status and City Category Distribution

```
#setting the plot style
fig = plt.figure(figsize = (15,12))
gs = fig.add_gridspec(1,3)
 # creating pie chart for gender disribution
ax0 = fig.add_subplot(gs[0,0])
color_map = ["#3A7089", "#4b4b4c"]
ax0.pie(df['Gender'].value_counts().values,labels = df['Gender'].value_counts().index,autopct = '%.1f%%',
 shadow = True,colors = color_map,textprops={'fontsize': 13, 'color': 'black'})
#setting title for visual
ax0.set_title('Gender Distribution',{'font':'serif', 'size':15,'weight':'bold'})
 # creating pie chart for marital status
ax1 = fig.add_subplot(gs[0,1])
color_map = ["#3A7089", "#4b4b4c"]
ax1.pie(df['Marital_Status'].value_counts().values,labels = df['Marital_Status'].value_counts().index,autopct = '%.1f%%',
 shadow = True,colors = color_map,textprops={'fontsize': 13, 'color': 'black'})

#setting title for visual
ax1.set_title('Marital Status Distribution',{'font':'serif', 'size':15,'weight':'bold'})
 # creating pie chart for city category
ax1 = fig.add_subplot(gs[0,2])
color_map = ["#3A7089", "#4b4b4c",'#99AEBB']
ax1.pie(df['City_Category'].value_counts().values,labels = df['City_Category'].value_counts().index,autopct = '%.1f%%',
 shadow = True,colors = color_map,textprops={'fontsize': 13, 'color': 'black'})
#setting title for visual
ax1.set_title('City Category Distribution',{'font':'serif', 'size':15,'weight':'bold'})
plt.show()
```



Insights

1. Gender Distribution## -

Data indicates a significant disparity in purchase behavior between males and females during the Black Friday event.

2. Marital Status## -

Given that unmarried customers account for a higher percentage of transactions, it may be worthwhile to consider specific marketing campaigns or promotions that appeal to this group.

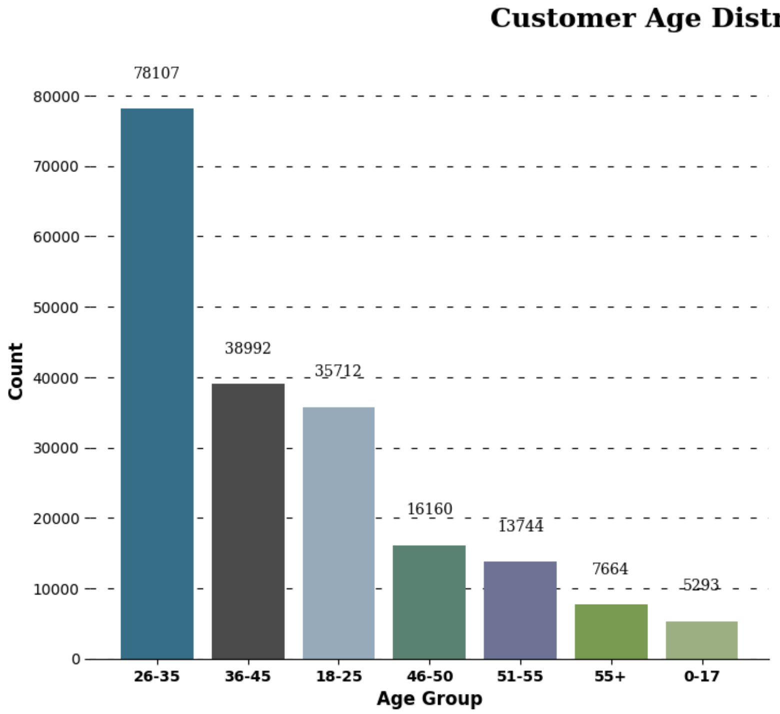
3. City Category## -

City B saw the most number of transactions followed by City C and City A respectively.

3.2.2 Customer Age Distribution

```
#setting the plot style
fig = plt.figure(figsize = (15,7))
gs = fig.add_gridspec(1,2,width_ratios=[0.6, 0.4])
 # creating bar chart for age disribution

ax0 = fig.add_subplot(gs[0,0])
temp = df['Age'].value_counts()
color_map = ["#3A7089", "#4b4b4c",'#99AEBB','#5C8374','#6F7597','#7A9D54','#9EB384']
ax0.bar(x=temp.index,height = temp.values,color = color_map,zorder = 2)
```

```
#adding the value_counts
for i in temp.index:
 ax0.text(i,temp[i]+5000,temp[i],{'font':'serif','size' : 10},ha = 'center',va = 'center')
#adding grid lines
ax0.grid(color = 'black',linestyle = '--', axis = 'y', zorder = 0, dashes = (5,10))
#removing the axis lines
for s in ['top','left','right']:
 ax0.spines[s].set_visible(False)

#adding axis label
ax0.set_ylabel('Count',fontweight = 'bold',fontsize = 12)
ax0.set_xlabel('Age Group',fontweight = 'bold',fontsize = 12)
ax0.set_xticklabels(temp.index,fontweight = 'bold')

#creating a info table for age

ax1 = fig.add_subplot(gs[0,1])
age_info = age_info = [['26-35','40%'],['36-45','20%'],['18-25','18%'],['46-50','8%'],['51-55','7%'],['55+','4%'],
 ['0-17','3%']]
color_2d = [["#3A7089",'#FFFFFF'],["#4b4b4c",'#FFFFFF'],['#99AEBB','#FFFFFF'],['#5C8374','#FFFFFF'],['#6F7597','#FFFFFF'],
 ['#7A9D54','#FFFFFF'],['#9EB384','#FFFFFF']]
table = ax1.table(cellText = age_info, cellColours=color_2d, cellLoc='center',colLabels =['Age Group','Percent Dist.'],
 colLoc = 'center',bbox =[0, 0, 1, 1])
table.set_fontsize(15)
#removing axis
ax1.axis('off')
#setting title for visual
fig.suptitle('Customer Age Distribution',font = 'serif', size = 18, weight = 'bold')
plt.show()
```



Age Group	Percent Dist.
26-35	40%
36-45	20%
18-25	18%
46-50	8%
51-55	7%
55+	4%
0-17	3%

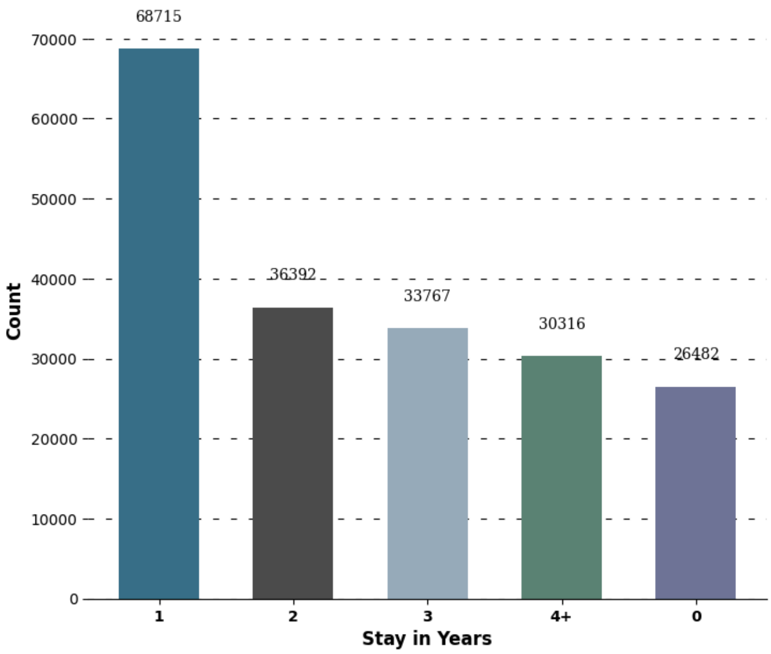
Insights

- The age group of 26-35 represents the largest share of Walmart's Black Friday sales, accounting for 40% of the sales. This suggests that the young and middle-aged adults are the most active and interested in shopping for deals and discounts .
- The 36-45 and 18-25 age groups are the second and third largest segments, respectively, with 20% and 18% of the sales. This indicates that Walmart has a diverse customer base that covers different life stages and preferences.
- The 46-50, 51-55, 55+, and 0-17 age groups are the smallest customer segments , with less than 10% of the total sales each. This implies that Walmart may need to improve its marketing strategies and product offerings to attract more customers from these age groups, especially the seniors and the children.

3.2.3 Customer Stay In current City Distribution

```
#setting the plot style
fig = plt.figure(figsize = (15,7))
gs = fig.add_gridspec(1,2,width_ratios=[0.6, 0.4])
 # creating bar chart for Customer Stay In current City

ax1 = fig.add_subplot(gs[0,0])
temp = df['Stay_In_Current_City_Years'].value_counts()
color_map = ["#3A7089", "#4b4b4c",'#99AEBB','#5C8374','#6F7597']
ax1.bar(x=temp.index,height = temp.values,color = color_map,zorder = 2,width = 0.6)
#adding the value_counts
for i in temp.index:
 ax1.text(i,temp[i]+4000,temp[i],{'font':'serif','size' : 10},ha = 'center',va = 'center')
#adding grid lines
ax1.grid(color = 'black',linestyle = '--', axis = 'y', zorder = 0, dashes = (5,10))
#removing the axis lines
for s in ['top','left','right']:
 ax1.spines[s].set_visible(False)

#adding axis label
ax1.set_ylabel('Count',fontweight = 'bold',fontsize = 12)
ax1.set_xlabel('Stay in Years',fontweight = 'bold',fontsize = 12)
ax1.set_xticklabels(temp.index,fontweight = 'bold')

#creating a info table for Customer Stay In current City

ax2 = fig.add_subplot(gs[0,1])
stay_info = [['1','35%'],['2','19%'],['3','17%'],['4+','15%'],['0','14%']]
color_2d = [["#3A7089",'#FFFFFF'],["#4b4b4c",'#FFFFFF'],['#99AEBB','#FFFFFF'],['#5C8374','#FFFFFF'],['#6F7597','#FFFFFF']]
table = ax2.table(cellText = stay_info, cellColours=color_2d, cellLoc='center',colLabels =['Stay in Years','Percent Dist.'],
 colLoc = 'center',bbox =[0, 0, 1, 1])
table.set_fontsize(15)
#removing axis
ax2.axis('off')
#setting title for visual
fig.suptitle('Customer Current City Stay Distribution',font = 'serif', size = 18, weight = 'bold')
plt.show()
```

Customer Current City Stay Distribution



Stay in Years	Percent Dist.
1	35%
2	19%
3	17%
4+	15%
0	14%

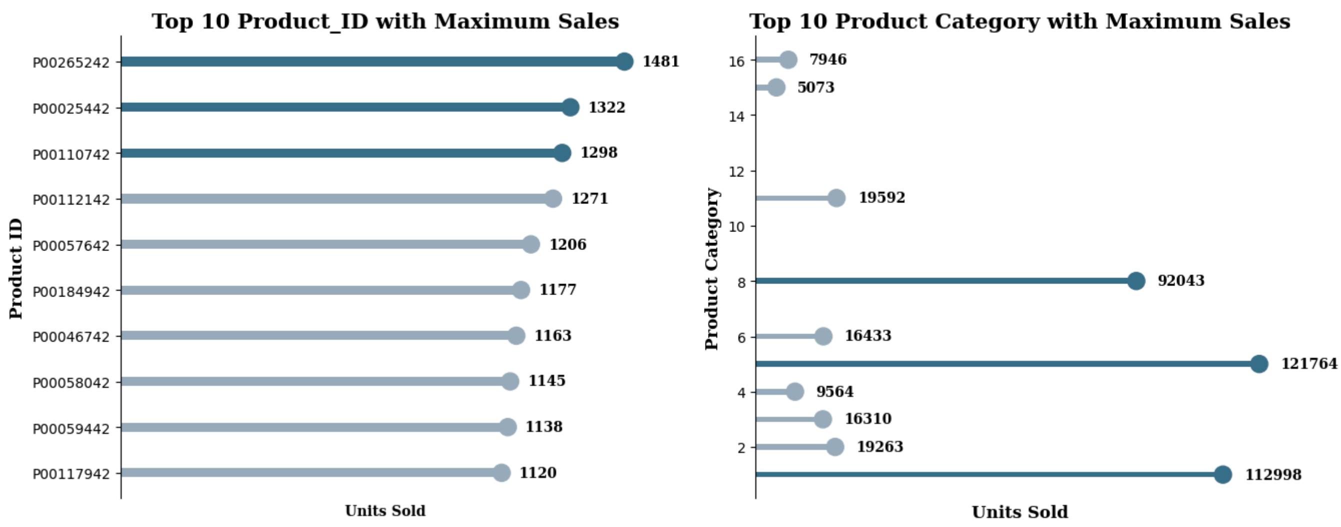
Insights

- The data suggests that the customers are either new to the city or move frequently, and may have different preferences and needs than long-term residents.
- The majority of the customers (49%) have stayed in the current city for one year or less . This suggests that Walmart has a strong appeal to newcomers who may be looking for affordable and convenient shopping options.
- 4+ years category (14%) customers indicates that Walmart has a loyal customer base who have been living in the same city for a long time.
- The percentage of customers decreases as the stay in the current city increases which suggests that Walmart may benefit from targeting long-term residents for loyalty programs and promotions .

3.2.4 Top 10 Products and Categories: Sales Snapshot

- Top 10 Products and Product Categories which has sold most during Black Friday Sales

```
#setting the plot style
fig = plt.figure(figsize = (15,6))
gs = fig.add_gridspec(1,2)
 #Top 10 Product_ID Sales
ax = fig.add_subplot(gs[0,0])
temp = df['Product_ID'].value_counts()[0:10]
# reversing the list
temp = temp.iloc[-1:-11:-1]
color_map = ['#99AEBB' for i in range(7)] + ["#3A7089" for i in range(3)]
#creating the plot
ax.barh(y = temp.index,width = temp.values,height = 0.2,color = color_map)
ax.scatter(y = temp.index, x = temp.values, s = 150 , color = color_map )
#removing x-axis
ax.set_xticks([])
#adding label to each bar
for y,x in zip(temp.index,temp.values):
 ax.text( x + 50 , y , x,{'font':'serif', 'size':10,'weight':'bold'},va='center')
#removing the axis lines
for s in ['top','bottom','right']:
 ax.spines[s].set_visible(False)

#adding axis labels
ax.set_xlabel('Units Sold',{'font':'serif', 'size':10,'weight':'bold'})
ax.set_ylabel('Product ID',{'font':'serif', 'size':12,'weight':'bold'})
#creating the title
ax.set_title('Top 10 Product_ID with Maximum Sales',
 {'font':'serif', 'size':15,'weight':'bold'})
 #Top 10 Product Category Sales
ax = fig.add_subplot(gs[0,1])
df['Product_Category'] = df['Product_Category'].astype('int')
temp = df['Product_Category'].value_counts()[0:10]
# reversing the list
temp = temp.iloc[-1:-11:-1]
#creating the plot
ax.barh(y = temp.index,width = temp.values,height = 0.2,color = color_map)
ax.scatter(y = temp.index, x = temp.values, s = 150 , color = color_map )
#removing x-axis
ax.set_xticks([])
#adding label to each bar
for y,x in zip(temp.index,temp.values):
 ax.text( x + 5000 , y , x,{'font':'serif', 'size':10,'weight':'bold'},va='center')
#removing the axis lines
for s in ['top','bottom','right']:
 ax.spines[s].set_visible(False)

#adding axis labels
ax.set_xlabel('Units Sold',{'font':'serif', 'size':12,'weight':'bold'})
ax.set_ylabel('Product Category',{'font':'serif', 'size':12,'weight':'bold'})
#creating the title
ax.set_title('Top 10 Product Category with Maximum Sales',
 {'font':'serif', 'size':15,'weight':'bold'})
plt.show()
```



Insights

1. Top 10 Products Sold - The top-selling products during Walmart's Black Friday sales are characterized by a relatively small variation in sales numbers, suggesting that Walmart offers a variety of products that many different customers like to buy.
2. Top 10 Product Categories - Categories 5,1 and 8 have significantly outperformed other categories with combined Sales of nearly 75% of the total sales suggesting a strong preference for these products among customers.

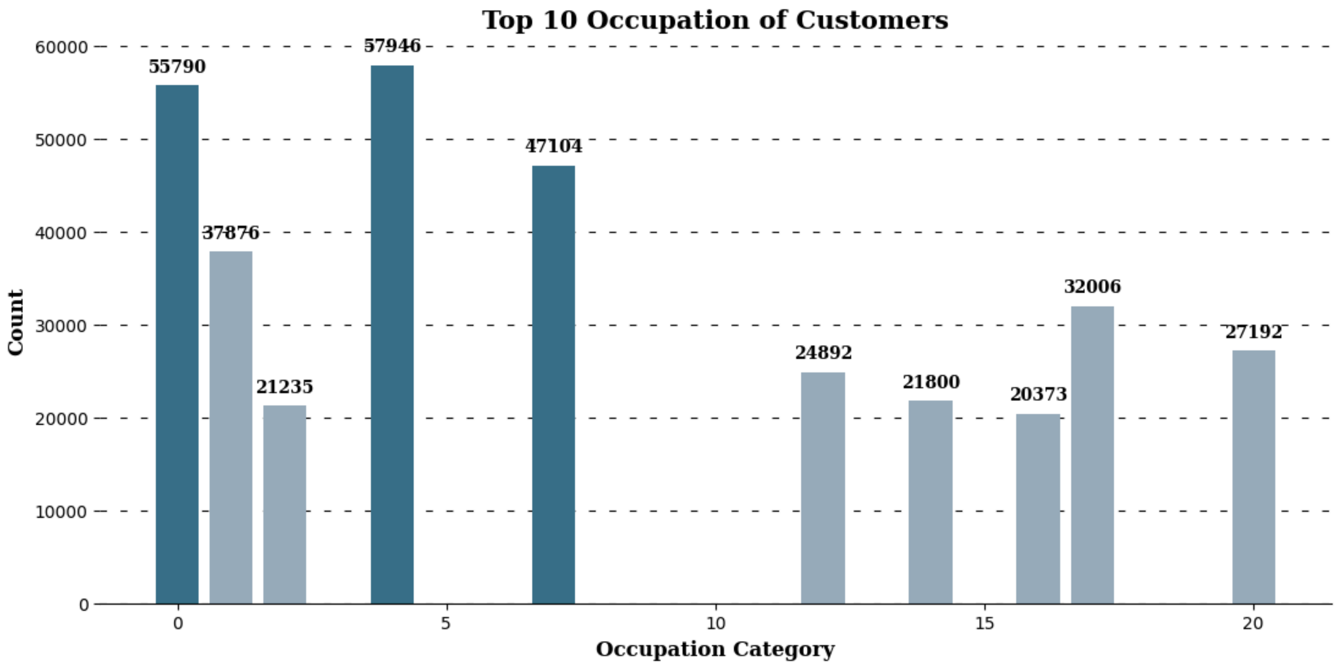
Start coding or generate with AI.

```
0         10.0
1         10.0
2         10.0
3         10.0
4         16.0
          ...
440254    20.0
440255    20.0
440256    20.0
440257    20.0
440258    20.0
Name: Occupation, Length: 440259, dtype: category
Categories (21, float64): [0.0, 1.0, 2.0, 3.0, ..., 17.0, 18.0, 19.0, 20.0]
```

3.2.5 Top 10 Customer Occupation

- Top 10 Occupation of Customer in Black Friday Sales

```
#df['Occupation'] = df['Occupation'].astype('int')
temp = df['Occupation'].value_counts()[0:10]
#setting the plot style
fig,ax = plt.subplots(figsize = (13,6))
color_map = ["#3A7089" for i in range(3)] + ['#99AEBB' for i in range(7)]
#creating the plot
ax.bar(temp.index,temp.values,color = color_map,zorder = 2)
#adding valuecounts
for x,y in zip(temp.index,temp.values):
 ax.text(x, y + 2000, y,{'font':'serif', 'size':10,'weight':'bold'},va='center',ha = 'center')

#setting grid style
ax.grid(color = 'black',linestyle = '--',axis = 'y',zorder = 0,dashes = (5,10))
#customizing the axis labels
#ax.set_xticklabels(temp.index,fontweight = 'bold',fontfamily='serif')
ax.set_xlabel('Occupation Category',{'font':'serif', 'size':12,'weight':'bold'})
ax.set_ylabel('Count',{'font':'serif', 'size':12,'weight':'bold'})
#removing the axis lines
for s in ['top','left','right']:
 ax.spines[s].set_visible(False)

#adding title to the visual
ax.set_title('Top 10 Occupation of Customers',
 {'font':'serif', 'size':15,'weight':'bold'})
plt.show()
```



Insights

Customers with Occupation category 4,0 and 7 contributed significantly i.e. almost 37% of the total purchases suggesting that these occupations have a high demand for Walmart products or services, or that they have more disposable income to spend on Black Friday.

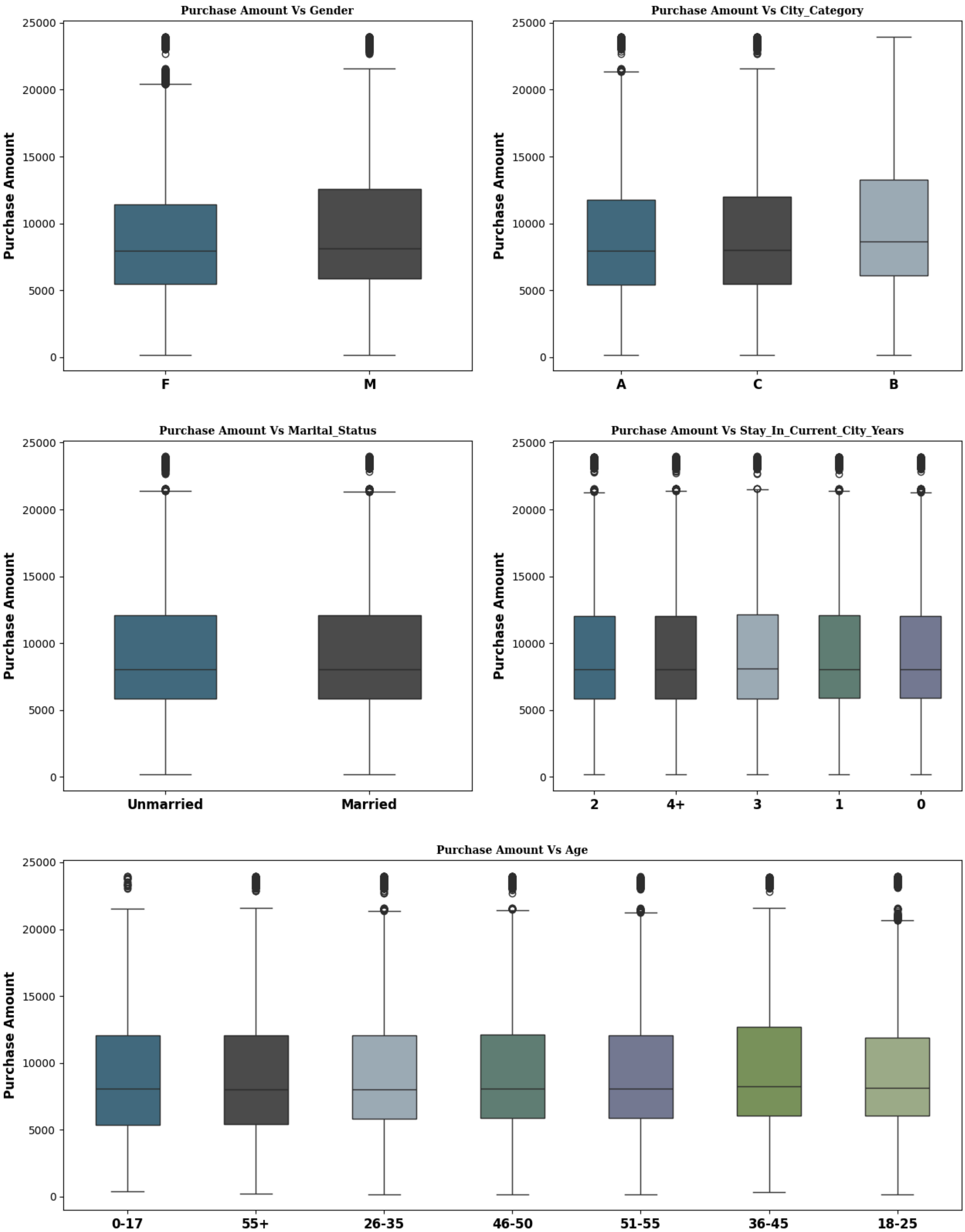
4.Bivariate Analysis

4.1 📊 Exploring Purchase Patterns

- Boxplots of Purchase Amount Across various Variables

```
#setting the plot style
fig = plt.figure(figsize = (15,20))
gs = fig.add_gridspec(3,2)
for i,j,k in [(0,0,'Gender'),(0,1,'City_Category'),(1,0,'Marital_Status'),(1,1,'Stay_In_Current_City_Years'),(2,1,'Age')]:

 #plot position
 if i <= 1:
  ax0 = fig.add_subplot(gs[i,j])
 else:
  ax0 = fig.add_subplot(gs[i,:])
```

```
    #plot
    color_map = ["#3A7089", "#4b4b4c",'#99AEBB','#5C8374','#6F7597','#7A9D54','#9EB384']
    sns.boxplot(data = df, x = k, y = 'Purchase' ,ax = ax0,width = 0.5, palette =color_map)
    #plot title
    ax0.set_title(f'Purchase Amount Vs {k}',{'font':'serif', 'size':10,'weight':'bold'})

    #customizing axis
    ax0.set_xticklabels(df[k].unique(),fontweight = 'bold',fontsize = 12)
    ax0.set_ylabel('Purchase Amount',fontweight = 'bold',fontsize = 12)
    ax0.set_xlabel('')

plt.show()
```


Purchase Amount Vs Gender
Purchase Amount
25000
20000
15000
10000
5000
0
F
M
Purchase Amount Vs City_Category
Purchase Amount
A
C
B
Purchase Amount Vs Marital_Status
Purchase Amount
Unmarried
Married
Purchase Amount Vs Stay_In_Current_City_Years
Purchase Amount
2
4+
3
1
0
Purchase Amount Vs Age
Purchase Amount
0-17
55+
26-35
46-50
51-55
36-45
18-25

Insights

Out of all the variables analysed above, it's noteworthy that the purchase amount remains relatively stable regardless of the variable under consideration. As indicated in the data, the median purchase amount consistently hovers around 8,000 USD , regardless of the specific variable being examined.

5. Gender VS Purchase Amount

5.1 Data Visualization

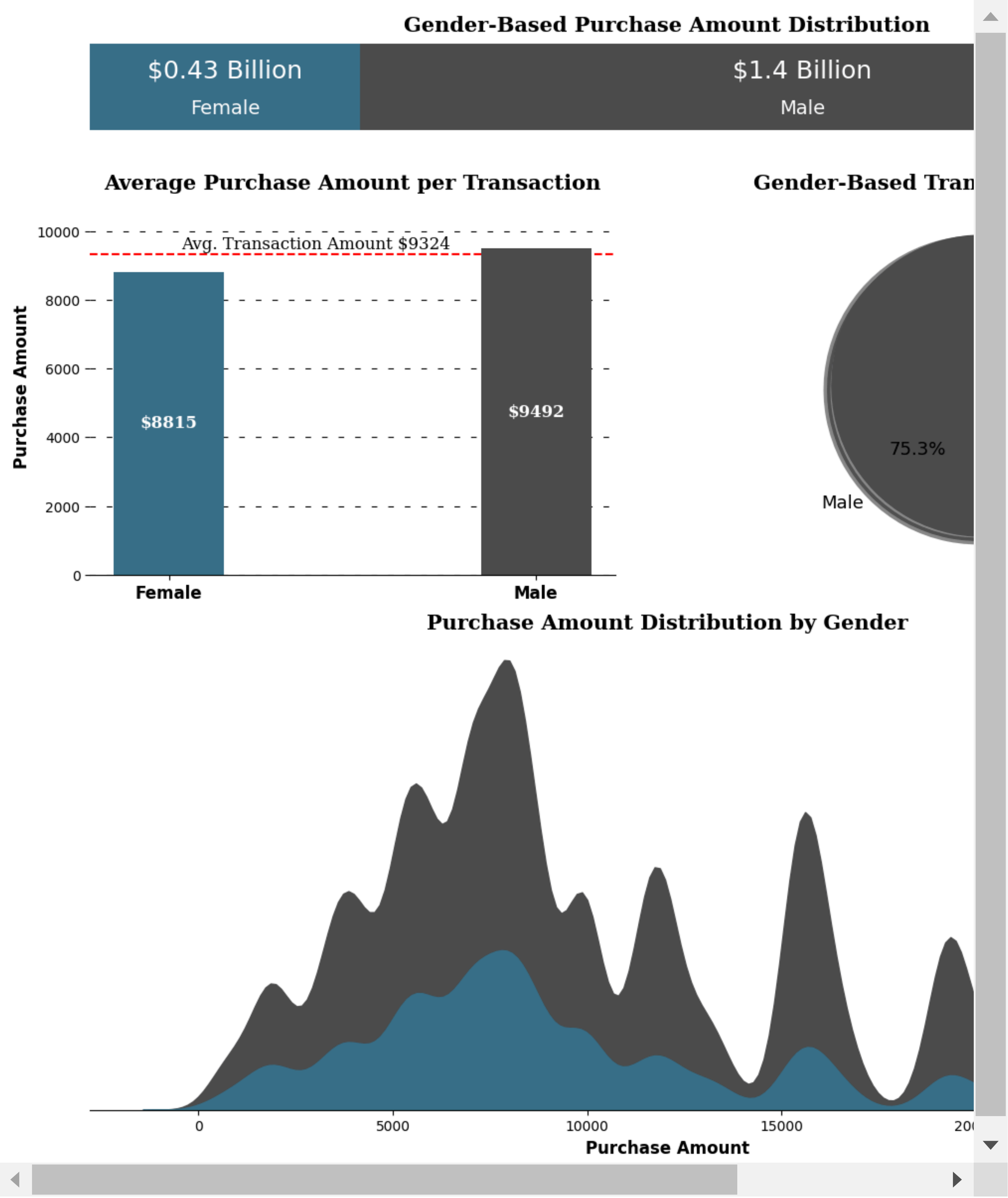
```
#creating a df for purchase amount vs gender
temp = df.groupby('Gender')['Purchase'].agg(['sum','count']).reset_index()
#calculating the amount in billions
temp['sum_in_billions'] = round(temp['sum'] / 10**9,2)
#calculationg percentage distribution of purchase amount
temp['%sum'] = round(temp['sum']/temp['sum'].sum(),3)
#calculationg per purchase amount
temp['per_purchase'] = round(temp['sum']/temp['count'])
#renaming the gender
temp['Gender'] = temp['Gender'].replace({'F':'Female','M':'Male'})
temp
```

	Gender	sum	count	sum_in_billions	%sum	per_purchase
0	Female	4.267188e+08	48411	0.43	0.234	8815.0
1	Male	1.397793e+09	147261	1.40	0.766	9492.0

Next steps: Generate code with temp View recommended plots

```
#setting the plot style
fig = plt.figure(figsize = (15,14))
gs = fig.add_gridspec(3,2,height_ratios =[0.10,0.4,0.5])
 #Distribution of Purchase Amount
ax = fig.add_subplot(gs[0,:])
#plotting the visual
ax.barh(temp.loc[0,'Gender'],width = temp.loc[0,'%sum'],color = "#3A7089",label = 'Female')
ax.barh(temp.loc[0,'Gender'],width = temp.loc[1,'%sum'],left =temp.loc[0,'%sum'], color = "#4b4b4c",label = 'Male' )
#inserting the text
txt = [0.0] #for left parameter in ax.text()
for i in temp.index:
 #for amount
 ax.text(temp.loc[i,'%sum']/2 + txt[0],0.15,f"${temp.loc[i,'sum_in_billions']} Billion",
 va = 'center', ha='center',fontsize=18, color='white')

 #for gender
 ax.text(temp.loc[i,'%sum']/2 + txt[0],- 0.20 ,f"{temp.loc[i,'Gender']}",
 va = 'center', ha='center',fontsize=14, color='white')

 txt += temp.loc[i,'%sum']

#removing the axis lines
for s in ['top','left','right','bottom']:
 ax.spines[s].set_visible(False)

#customizing ticks
ax.set_xticks([])
ax.set_yticks([])
ax.set_xlim(0,1)
#plot title
ax.set_title('Gender-Based Purchase Amount Distribution',{'font':'serif', 'size':15,'weight':'bold'})
 #Distribution of Purchase Amount per Transaction

ax1 = fig.add_subplot(gs[1,0])

color_map = ["#3A7089", "#4b4b4c"]
#plotting the visual
ax1.bar(temp['Gender'],temp['per_purchase'],color = color_map,zorder = 2,width = 0.3)
#adding average transaction line
avg = round(df['Purchase'].mean())
ax1.axhline(y = avg, color ='red', zorder = 0,linestyle = '--')
#adding text for the line
ax1.text(0.4,avg + 300, f"Avg. Transaction Amount ${avg:.0f}",
 {'font':'serif','size' : 12},ha = 'center',va = 'center')
#adjusting the ylimits
ax1.set_ylim(0,11000)
#adding the value_counts
for i in temp.index:
 ax1.text(temp.loc[i,'Gender'],temp.loc[i,'per_purchase']/2,f"${temp.loc[i,'per_purchase']:.0f}",
 {'font':'serif','size' : 12,'color':'white','weight':'bold' },ha = 'center',va = 'center')

#adding grid lines
ax1.grid(color = 'black',linestyle = '--', axis = 'y', zorder = 0, dashes = (5,10))
#removing the axis lines
for s in ['top','left','right']:
 ax1.spines[s].set_visible(False)

#adding axis label
ax1.set_ylabel('Purchase Amount',fontweight = 'bold',fontsize = 12)
ax1.set_xticklabels(temp['Gender'],fontweight = 'bold',fontsize = 12)
#setting title for visual
ax1.set_title('Average Purchase Amount per Transaction',{'font':'serif', 'size':15,'weight':'bold'})
 # creating pie chart for gender disribution
ax2 = fig.add_subplot(gs[1,1])
color_map = ["#3A7089", "#4b4b4c"]
ax2.pie(temp['count'],labels = temp['Gender'],autopct = '%.1f%%',
 shadow = True,colors = color_map,wedgeprops = {'linewidth': 5},textprops={'fontsize': 13, 'color': 'black'})
#setting title for visual
ax2.set_title('Gender-Based Transaction Distribution',{'font':'serif', 'size':15,'weight':'bold'})
 # creating kdeplot for purchase amount distribution
ax3 = fig.add_subplot(gs[2,:])
#plotting the kdeplot
sns.kdeplot(data = df, x = 'Purchase', hue = 'Gender', palette = color_map,fill = True, alpha = 1,ax = ax3)
#removing the axis lines
for s in ['top','left','right']:
 ax3.spines[s].set_visible(False)

# adjusting axis labels
ax3.set_yticks([])
ax3.set_ylabel('')
ax3.set_xlabel('Purchase Amount',fontweight = 'bold',fontsize = 12)
#setting title for visual
```

```
ax3.set_title('Purchase Amount Distribution by Gender',{'font':'serif', 'size':15,'weight':'bold'})
plt.show()
```



Insights

1. Total Sales and Transactions Comparison

The total purchase amount and number of transactions by male customers was more than three times the amount and transactions by female customers indicating that they had a more significant impact on the Black Friday sales.

2. Average Transaction Value

The average purchase amount per transaction was slightly higher for male customers than female customers ($9492 vs 8815$) .

3. Distribution of Purchase Amount

As seen above, the purchase amount for both the genders is not normally distributed .

5.2 Confidence Interval Construction: Estimating Average Purchase Amount per Transaction

1. Step 1 - Building CLT Curve

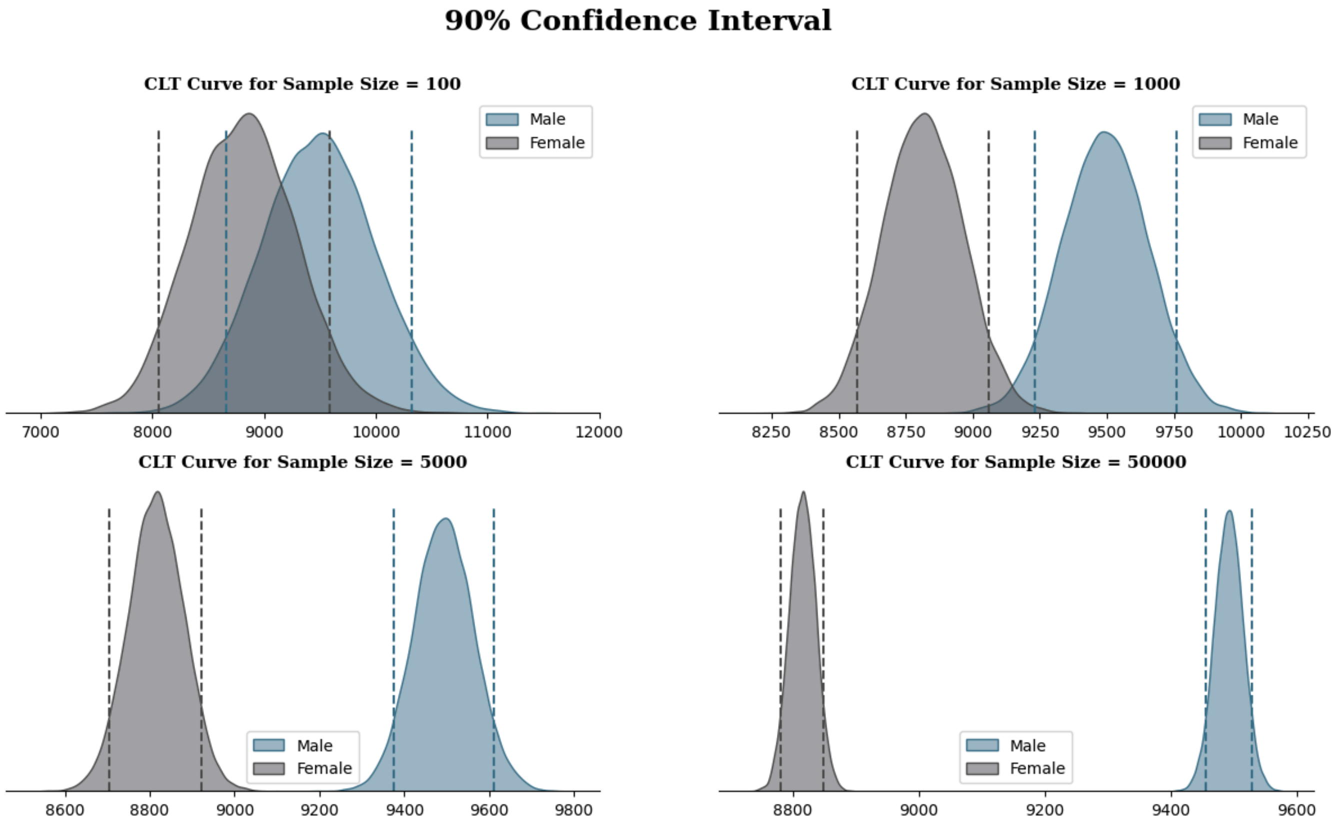
As seen above, the purchase amount distribution is not Normal. So we need to use Central Limit Theorem . It states the distribution of sample means will approximate a normal distribution, regardless of the underlying population distribution

2. Step 2 - Building Confidence Interval

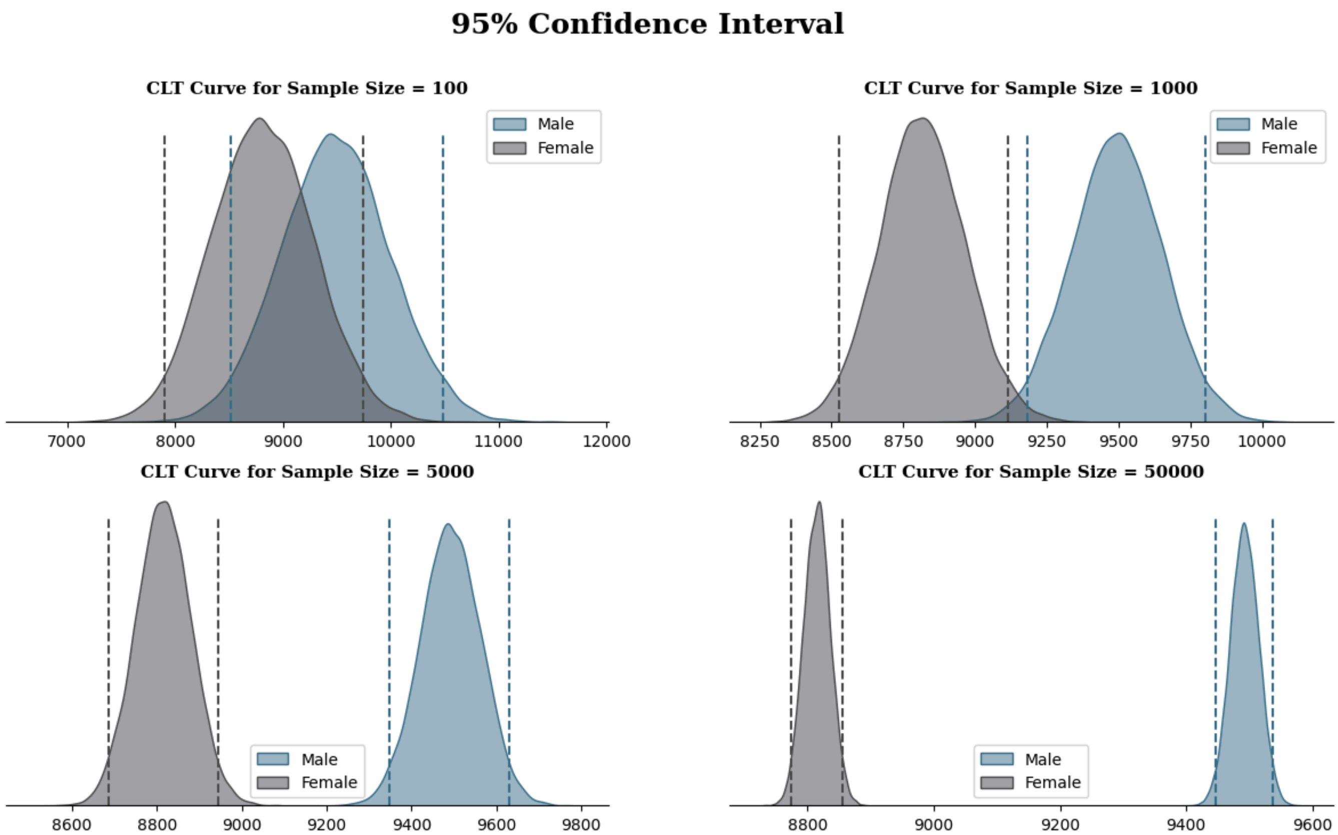
After building CLT curve, we will create a confidence interval predicting population mean at 99%,95% and 90% Confidence level . Note - We will use different sample sizes of [100,1000,5000,50000]

```
#creating a function to calculate confidence interval
def confidence_interval(data,ci):
 #converting the list to series
 l_ci = (100-ci)/2
 u_ci = (100+ci)/2

 #calculating lower limit and upper limit of confidence interval
 interval = np.percentile(data,[l_ci,u_ci]).round(0)

 return interval
```

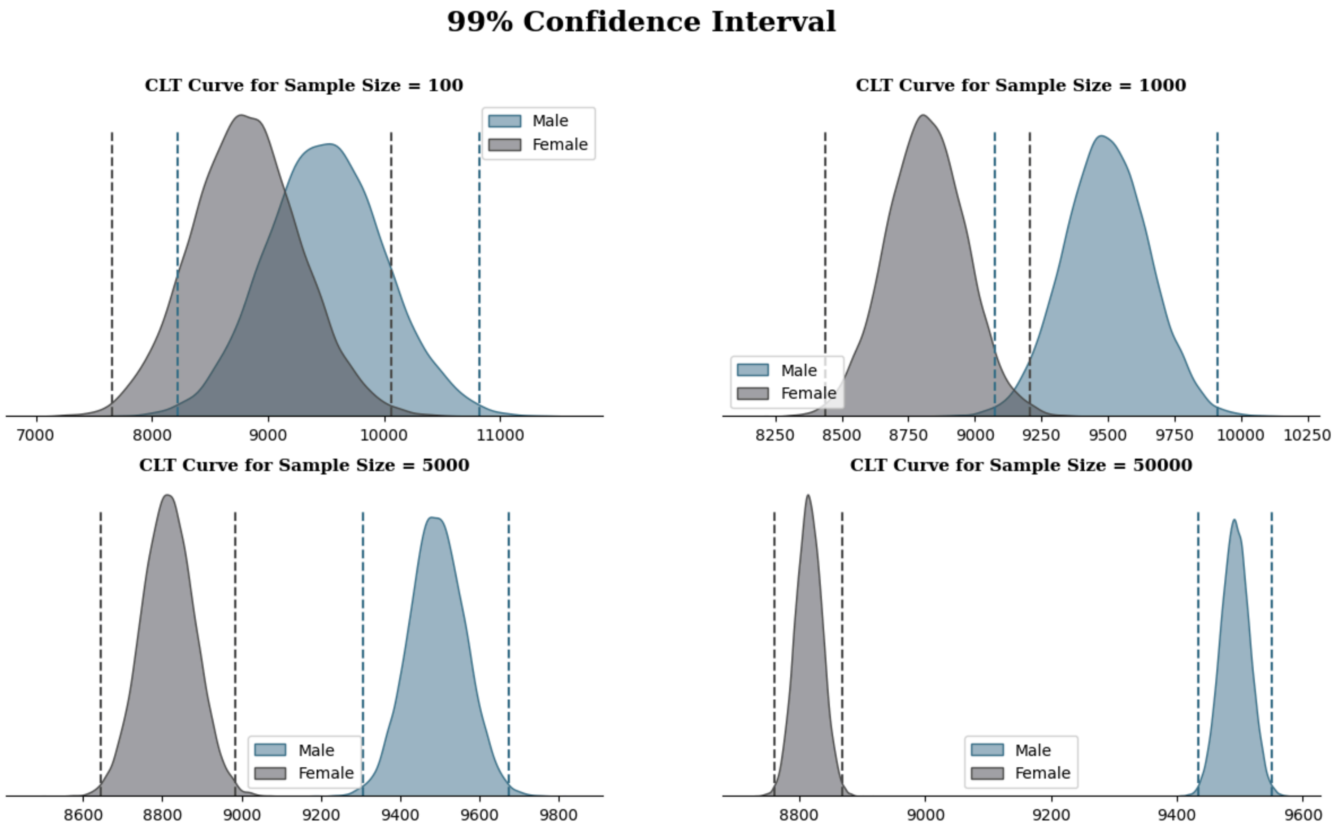
```
#defining a function for plotting the visual for given confidence interval
def plot(ci):
  #setting the plot style
  fig = plt.figure(figsize = (15,8))
  gs = fig.add_gridspec(2,2)
  #creating separate data frames for each gender
  df_male = df.loc[df['Gender'] == 'M','Purchase']
  df_female = df.loc[df['Gender'] == 'F','Purchase']
  #sample sizes and corresponding plot positions
  sample_sizes = [(100,0,0),(1000,0,1),(5000,1,0),(50000,1,1)]
  #number of samples to be taken from purchase amount
  bootstrap_samples = 20000
  male_samples = {}
  female_samples = {}

  for i,x,y in sample_sizes:
    male_means = [] #list for collecting the means of male sample
    female_means = [] #list for collecting the means of female sample
    for j in range(bootstrap_samples):
      #creating random 5000 samples of i sample size
      male_bootstrapped_samples = np.random.choice(df_male,size = i)
      female_bootstrapped_samples = np.random.choice(df_female,size = i)
      #calculating mean of those samples
      male_sample_mean = np.mean(male_bootstrapped_samples)
      female_sample_mean = np.mean(female_bootstrapped_samples)

      #appending the mean to the list
      male_means.append(male_sample_mean)
      female_means.append(female_sample_mean)

    #storing the above sample generated
    male_samples[f'{ci}%_{i}'] = male_means
    female_samples[f'{ci}%_{i}'] = female_means
    #creating a temporary dataframe for creating kdeplot
    temp_df = pd.DataFrame(data = {'male_means':male_means,'female_means':female_means})
    #plotting kdeplots
    #plot position
    ax = fig.add_subplot(gs[x,y])

    #plots for male and female
    sns.kdeplot(data = temp_df,x = 'male_means',color ="#3A7089" ,fill = True, alpha = 0.5,ax = ax,label = 'Male')
    sns.kdeplot(data = temp_df,x = 'female_means',color ="#4b4b4c" ,fill = True, alpha = 0.5,ax = ax,label = 'Female')
    #calculating confidence intervals for given confidence level(ci)
    m_range = confidence_interval(male_means,ci)
    f_range = confidence_interval(female_means,ci)
    #plotting confidence interval on the distribution
    for k in m_range:
      ax.axvline(x = k,ymax = 0.9, color ="#3A7089",linestyle = '--')
    for k in f_range:
      ax.axvline(x = k,ymax = 0.9, color ="#4b4b4c",linestyle = '--')
    #removing the axis lines
    for s in ['top','left','right']:
      ax.spines[s].set_visible(False)
    #adjusting axis labels
    ax.set_yticks([])
    ax.set_ylabel('')
    ax.set_xlabel('')
    #setting title for visual
    ax.set_title(f'CLT Curve for Sample Size = {i}',{'font':'serif', 'size':11,'weight':'bold'})
    plt.legend()

  #setting title for visual
  fig.suptitle(f'{ci}% Confidence Interval',font = 'serif', size = 18, weight = 'bold')
  plt.show()

  return male_samples,female_samples


m_samp_90,f_samp_90 = plot(90)
```




```
m_samp_95,f_samp_95 = plot(95)
```



```
m_samp_99,f_samp_99 = plot(99)
```



Are confidence intervals of average male and female spending overlapping?

```
fig = plt.figure(figsize = (20,10))
gs = fig.add_gridspec(3,1)
for i,j,k,l in [(m_samp_90,f_samp_90,90,0),(m_samp_95,f_samp_95,95,1),(m_samp_99,f_samp_99,99,2)]:
  #list for collecting ci for given cl
  m_ci = ['Male']
  f_ci = ['Female']

  #finding ci for each sample size (males)
  for m in i:
    m_range = confidence_interval(i[m],k)
    m_ci.append(f"CI = ${m_range[0]:.0f} - ${m_range[1]:.0f}, Range = {(m_range[1] - m_range[0]):.0f}")

  #finding ci for each sample size (females)
  for f in j:
    f_range = confidence_interval(j[f],k)
    f_ci.append(f"CI = ${f_range[0]:.0f} - ${f_range[1]:.0f}, Range = {(f_range[1] - f_range[0]):.0f}")

  #plotting the summary
  ax = fig.add_subplot(gs[l])

  #contents of the table
  ci_info = [m_ci,f_ci]

  #plotting the table
  table = ax.table(cellText = ci_info, cellLoc='center',
  colLabels =['Gender','Sample Size = 100','Sample Size = 1000','Sample Size = 5000','Sample Size = 50000'],
  colLoc = 'center',colWidths = [0.05,0.2375,0.2375,0.2375,0.2375],bbox =[0, 0, 1, 1])
  table.set_fontsize(13)
  #removing axis
  ax.axis('off')

  #setting title
  ax.set_title(f"{k}% Confidence Interval Summary",{'font':'serif', 'size':14,'weight':'bold'})
```

90% Confidence Interval Summary

Gender	Sample Size = 100	Sample Size = 1000	Sample Size = 5000	Sample Size = 50000
Male	CI = 8662 – 10326, Range = 1664	CI = 9231 – 9760, Range = 529	CI = 9375 – 9612, Range = 237	CI = 9455 – 9529, Range = 74
Female	CI = 8055 – 9590, Range = 1535	CI = 8570 – 9061, Range = 491	CI = 8705 – 8923, Range = 218	CI = 8780 – 8849, Range = 69

95% Confidence Interval Summary

Gender	Sample Size = 100	Sample Size = 1000	Sample Size = 5000	Sample Size = 50000
Male	CI = 8513 – 10489, Range = 1976	CI = 9183 – 9803, Range = 620	CI = 9349 – 9630, Range = 281	CI = 9447 – 9537, Range = 90
Female	CI = 7906 – 9741, Range = 1835	CI = 8526 – 9113, Range = 587	CI = 8685 – 8944, Range = 259	CI = 8774 – 8856, Range = 82

99% Confidence Interval Summary

Gender	Sample Size = 100	Sample Size = 1000	Sample Size = 5000	Sample Size = 50000
Male	CI = 8218 – 10819, Range = 2601	CI = 9077 – 9911, Range = 834	CI = 9305 – 9674, Range = 369	CI = 9434 – 9551, Range = 117
Female	CI = 7657 – 10062, Range = 2405	CI = 8438 – 9207, Range = 769	CI = 8645 – 8985, Range = 340	CI = 8760 – 8869, Range = 109

Insights

1. Sample Size

The analysis highlights the importance of sample size in estimating population parameters. It suggests that as the sample size increases, the confidence intervals become narrower and more precise . In business, this implies that larger sample sizes can provide more reliable insights and estimates.

2. Confidence Intervals

From the above analysis, we can see that except for the Sample Size of 100, the confidence interval do not overlap as the sample size increases. This means that there is a statistically significant difference between the average spending per transaction for men and women within the given samples.

3. Population Average

We are 95% confident that the true population average for males falls between $9,447and$9,537 , and for females , it falls between $8,774and$ 8,856 .

4. Women spend less

Men tend to spend more money per transaction on average than women , as the upper bounds of the confidence intervals for men are consistently higher than those for women across different sample sizes.

5. How can Walmart leverage this conclusion to make changes or improvements?

5.1. Segmentation Opportunities

Walmart can create targeted marketing campaigns, loyalty programs, or product bundles to cater to the distinct spending behaviors of male and female customers. This approach may help maximize revenue from each customer segment.

5.2. Pricing Strategies

Based on the above data of average spending per transaction by gender, they might adjust pricing or discount strategies to incentivize higher spending among male customers while ensuring competitive pricing for female-oriented products.

Note

Moving forward in our analysis, we will use 95% Confidence Level only.

6. Marital Status VS Purchase Amount

6.1 Data Visualization

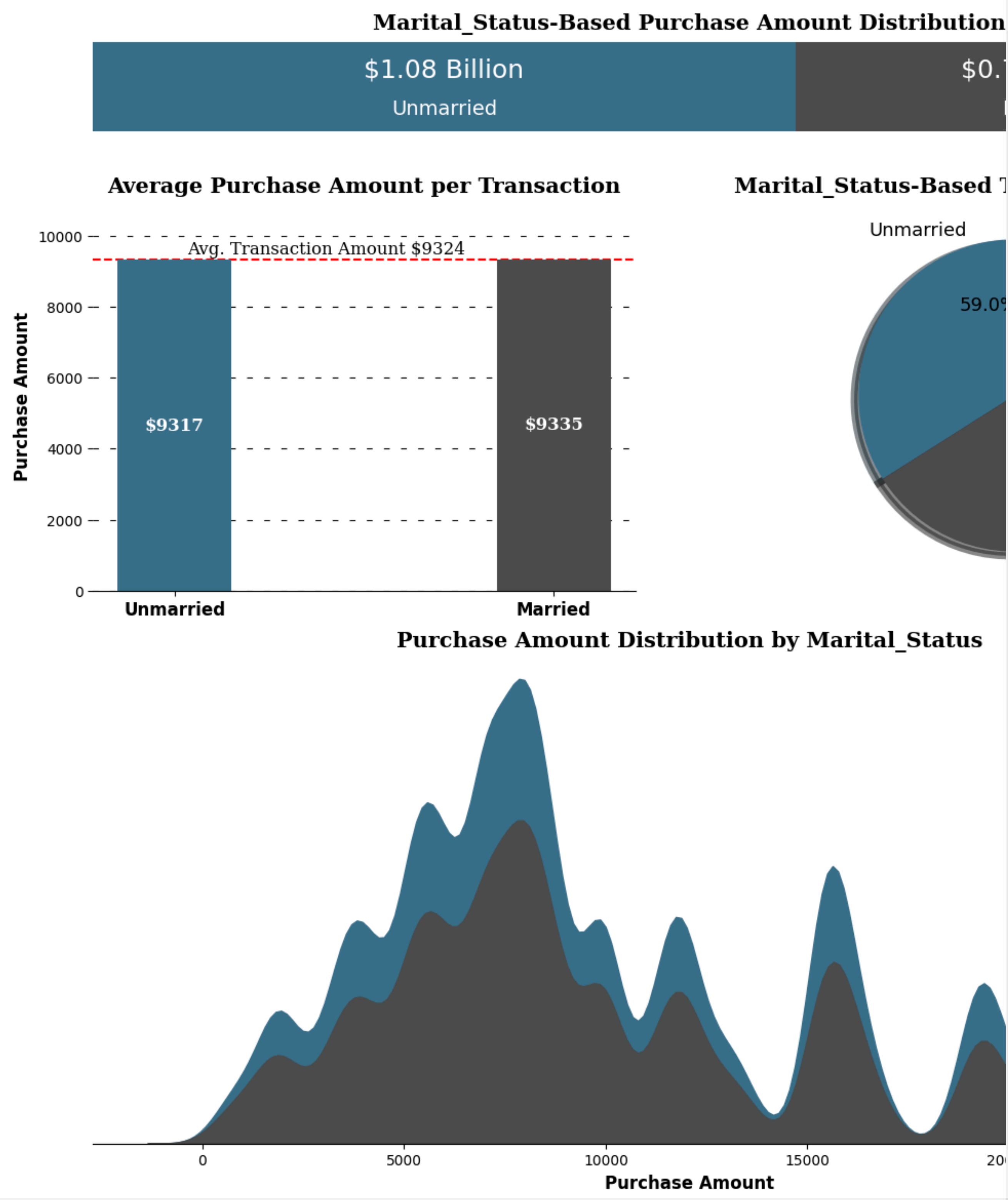
```
#creating a df for purchase amount vs marital status
temp = df.groupby('Marital_Status')['Purchase'].agg(['sum','count']).reset_index()
#calculating the amount in billions
temp['sum_in_billions'] = round(temp['sum'] / 10**9,2)
#calculationg percentage distribution of purchase amount
temp['%sum'] = round(temp['sum']/temp['sum'].sum(),3)
#calculationg per purchase amount
temp['per_purchase'] = round(temp['sum']/temp['count'])
temp
```

	Marital_Status	sum	count	sum_in_billions	%sum	per_purchase
0	Unmarried	1.075380e+09	115419	1.08	0.589	9317.0
1	Married	7.491315e+08	80253	0.75	0.411	9335.0

Next steps: Generate code with `temp` View recommended plots

```
#setting the plot style
fig = plt.figure(figsize = (15,14))
gs = fig.add_gridspec(3,2,height_ratios =[0.10,0.4,0.5])
 #Distribution of Purchase Amount
ax = fig.add_subplot(gs[0,:])
#plotting the visual
ax.barh(temp.loc[0,'Marital_Status'],width = temp.loc[0,'%sum'],color = "#3A7089",label = 'Unmarried')
ax.barh(temp.loc[0,'Marital_Status'],width = temp.loc[1,'%sum'],left =temp.loc[0,'%sum'], color = "#4b4b4c",label = 'Married')
#inserting the text
txt = [0.0] #for left parameter in ax.text()
for i in temp.index:
  #for amount
  ax.text(temp.loc[i,'%sum']/2 + txt[0],0.15,f"${temp.loc[i,'sum_in_billions']} Billion",
  va = 'center', ha='center',fontsize=18, color='white')

 #for marital status
  ax.text(temp.loc[i,'%sum']/2 + txt[0],- 0.20 ,f"{temp.loc[i,'Marital_Status']}",
  va = 'center', ha='center',fontsize=14, color='white')

  txt += temp.loc[i,'%sum']

#removing the axis lines
for s in ['top','left','right','bottom']:
  ax.spines[s].set_visible(False)

#customizing ticks
ax.set_xticks([])
ax.set_yticks([])
ax.set_xlim(0,1)
#plot title
ax.set_title('Marital_Status-Based Purchase Amount Distribution',{'font':'serif', 'size':15,'weight':'bold'})
 #Distribution of Purchase Amount per Transaction

ax1 = fig.add_subplot(gs[1,0])
color_map = ["#3A7089", "#4b4b4c"]
#plotting the visual
ax1.bar(temp['Marital_Status'],temp['per_purchase'],color = color_map,zorder = 2,width = 0.3)
#adding average transaction line
avg = round(df['Purchase'].mean())
ax1.axhline(y = avg, color ='red', zorder = 0,linestyle = '--')
#adding text for the line
ax1.text(0.4,avg + 300, f"Avg. Transaction Amount ${avg:.0f}",
 {'font':'serif','size' : 12},ha = 'center',va = 'center')
#adjusting the ylimits
ax1.set_ylim(0,11000)
#adding the value_counts
for i in temp.index:
  ax1.text(temp.loc[i,'Marital_Status'],temp.loc[i,'per_purchase']/2,f"${temp.loc[i,'per_purchase']:.0f}",
 {'font':'serif','size' : 12,'color':'white','weight':'bold' },ha = 'center',va = 'center')

#adding grid lines
ax1.grid(color = 'black',linestyle = '--', axis = 'y', zorder = 0, dashes = (5,10))
#removing the axis lines
for s in ['top','left','right']:
  ax1.spines[s].set_visible(False)

  #adding axis label
ax1.set_ylabel('Purchase Amount',fontweight = 'bold',fontsize = 12)
ax1.set_xticklabels(temp['Marital_Status'],fontweight = 'bold',fontsize = 12)
#setting title for visual
ax1.set_title('Average Purchase Amount per Transaction',{'font':'serif', 'size':15,'weight':'bold'})
 # creating pie chart for Marital_Status disribution
ax2 = fig.add_subplot(gs[1,1])
color_map = ["#3A7089", "#4b4b4c"]
ax2.pie(temp['count'],labels = temp['Marital_Status'],autopct = '%.1f%%',
 shadow = True,colors = color_map,wedgeprops = {'linewidth': 5},textprops={'fontsize': 13, 'color': 'black'})
#setting title for visual
ax2.set_title('Marital_Status-Based Transaction Distribution',{'font':'serif', 'size':15,'weight':'bold'})
 # creating kdeplot for purchase amount distribution
ax3 = fig.add_subplot(gs[2,:])
color_map = [ "#4b4b4c","#3A7089"]
#plotting the kdeplot
sns.kdeplot(data = df, x = 'Purchase', hue = 'Marital_Status', palette = color_map,fill = True, alpha = 1,
 ax = ax3,hue_order = ['Married','Unmarried'])
#removing the axis lines
for s in ['top','left','right']:
  ax3.spines[s].set_visible(False)

# adjusting axis labels
ax3.set_yticks([])
ax3.set_ylabel('')
ax3.set_xlabel('Purchase Amount',fontweight = 'bold',fontsize = 12)
```

```
#setting title for visual
ax3.set_title('Purchase Amount Distribution by Marital_Status',{'font':'serif', 'size':15,'weight':'bold'})
plt.show()
```



Insights

1. Total Sales and Transactions Comparison

The total purchase amount and number of transactions by Unmarried customers was more than 20% the amount and transactions by married customers indicating that they had a more significant impact on the Black Friday sales.

2. Average Transaction Value

The average purchase amount per transaction was almost similar for married and unmarried customers $(9335 vs 9317)$.

3. Distribution of Purchase Amount

As seen above, the purchase amount for both married and unmarried customers is not normally distributed .

6.2 Confidence Interval Construction: Estimating Average Purchase Amount per Transaction

1. Step 1 - Building CLT Curve

As seen above, the purchase amount distribution is not Normal. So we need to use Central Limit Theorem . It states the distribution of sample means will approximate a normal distribution, regardless of the underlying population distribution

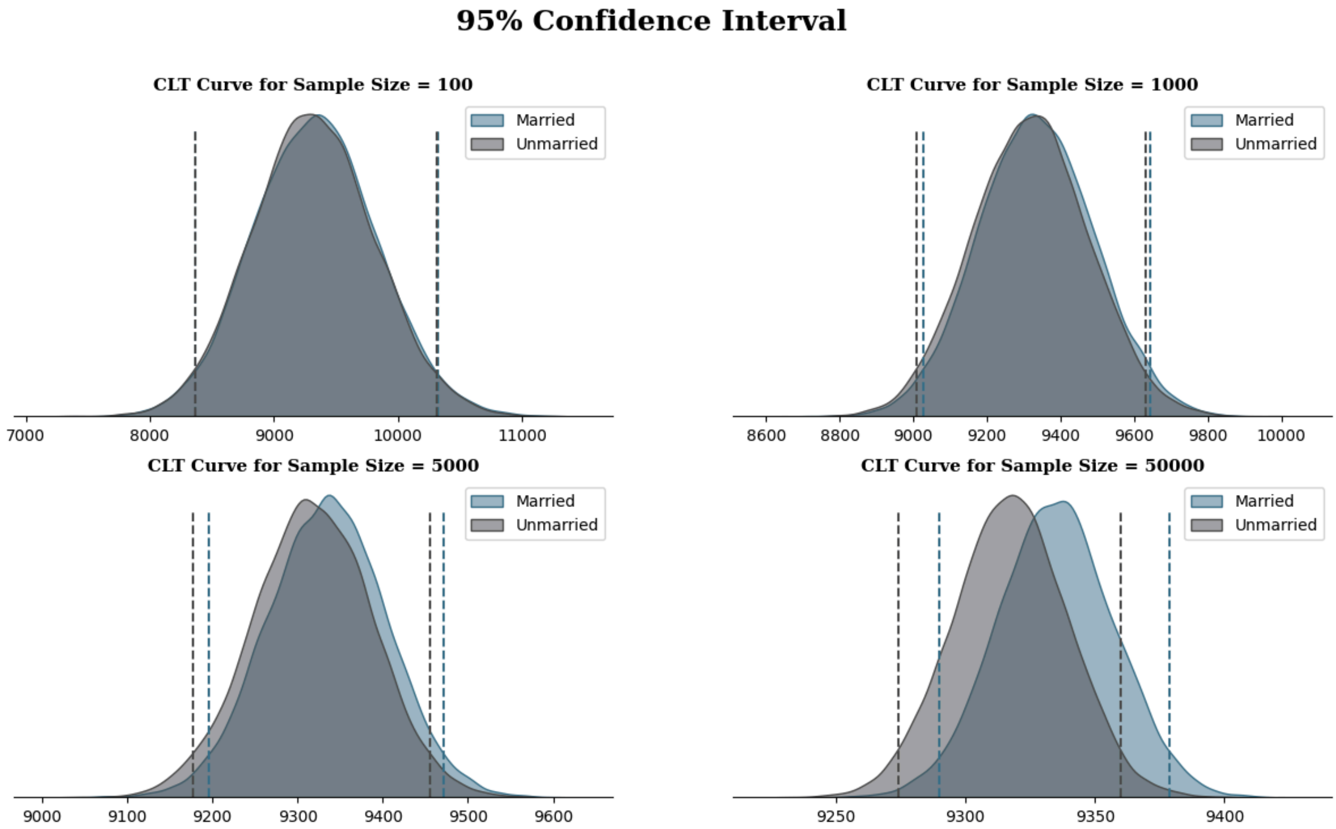
2. Step 2 - Building Confidence Interval

After building CLT curve, we will create a confidence interval predicting population mean at 95% Confidence level .

Note

We will use different sample sizes of [100,1000,5000,50000]

```
#defining a function for plotting the visual for given confidence interval
def plot(ci):
  #setting the plot style
  fig = plt.figure(figsize = (15,8))
  gs = fig.add_gridspec(2,2)
  #creating separate data frames
  df_married = df.loc[df['Marital_Status'] == 'Married','Purchase']
  df_unmarried = df.loc[df['Marital_Status'] == 'Unmarried','Purchase']
  #sample sizes and corresponding plot positions
  sample_sizes = [(100,0,0),(1000,0,1),(5000,1,0),(50000,1,1)]
  #number of samples to be taken from purchase amount
  bootstrap_samples = 20000
  married_samples = {}
  unmarried_samples = {}

  for i,x,y in sample_sizes:
    married_means = [] #list for collecting the means of married sample
    unmarried_means = [] #list for collecting the means of unmarried sample
    for j in range(bootstrap_samples):
      #creating random 5000 samples of i sample size
      married_bootstrapped_samples = np.random.choice(df_married,size = i)
      unmarried_bootstrapped_samples = np.random.choice(df_unmarried,size = i)
      #calculating mean of those samples
      married_sample_mean = np.mean(married_bootstrapped_samples)
      unmarried_sample_mean = np.mean(unmarried_bootstrapped_samples)
      #appending the mean to the list
      married_means.append(married_sample_mean)
      unmarried_means.append(unmarried_sample_mean)

    #storing the above sample generated
    married_samples[f'{ci}%_{i}'] = married_means
    unmarried_samples[f'{ci}%_{i}'] = unmarried_means
    #creating a temporary dataframe for creating kdeplot
    temp_df = pd.DataFrame(data = {'married_means':married_means,'unmarried_means':unmarried_means})
    #plotting kdeplots
    #plot position
    ax = fig.add_subplot(gs[x,y])
    #plots for married and unmarried
    sns.kdeplot(data = temp_df,x = 'married_means',color ="#3A7089" ,fill = True, alpha = 0.5,ax = ax,label = 'Married')
    sns.kdeplot(data = temp_df,x = 'unmarried_means',color ="#4b4b4c" ,fill = True, alpha = 0.5,ax = ax,label = 'Unmarried')
    #calculating confidence intervals for given confidence level(ci)
    m_range = confidence_interval(married_means,ci)
    u_range = confidence_interval(unmarried_means,ci)
    #plotting confidence interval on the distribution
    for k in m_range:
      ax.axvline(x = k,ymax = 0.9, color ="#3A7089",linestyle = '--')
    for k in u_range:
      ax.axvline(x = k,ymax = 0.9, color ="#4b4b4c",linestyle = '--')
    #removing the axis lines
    for s in ['top','left','right']:
      ax.spines[s].set_visible(False)
    # adjusting axis labels
    ax.set_yticks([])
    ax.set_ylabel('')
    ax.set_xlabel('')
    #setting title for visual
    ax.set_title(f'CLT Curve for Sample Size = {i}',{'font':'serif', 'size':11,'weight':'bold'})
    plt.legend()

  #setting title for visual
  fig.suptitle(f'{ci}% Confidence Interval',font = 'serif', size = 18, weight = 'bold')
  plt.show()

  return married_samples,unmarried_samples


m_samp_95,u_samp_95 = plot(95)
```



Are confidence intervals of average married and unmarried customer spending overlapping?

```
#setting the plot style
fig,ax = plt.subplots(figsize = (20,3))
#list for collecting ci for given cl
m_ci = ['Married']
u_ci = ['Unmarried']
#finding ci for each sample size (married)
for m in m_samp_95:
  m_range = confidence_interval(m_samp_95[m],95)
  m_ci.append(f"CI = ${m_range[0]:.0f} - ${m_range[1]:.0f}, Range = {(m_range[1] - m_range[0]):.0f}")
#finding ci for each sample size (unmarried)
for u in u_samp_95:
  u_range = confidence_interval(u_samp_95[u],95)
  u_ci.append(f"CI = ${u_range[0]:.0f} - ${u_range[1]:.0f}, Range = {(u_range[1] - u_range[0]):.0f}")
 #plotting the summary
#contents of the table
ci_info = [m_ci,u_ci]
#plotting the table
table = ax.table(cellText = ci_info, cellLoc='center',
 colLabels =['Marital_Status','Sample Size = 100','Sample Size = 1000','Sample Size = 5000','Sample Size = 50000'],
 colLoc = 'center',colWidths = [0.1,0.225,0.225,0.225,0.225],bbox =[0, 0, 1, 1])
table.set_fontsize(13)
#removing axis
ax.axis('off')
#setting title
ax.set_title(f"95% Confidence Interval Summary",{'font':'serif', 'size':14,'weight':'bold'})
plt.show()
```

95% Confidence Interval Summary

Marital_Status	Sample Size = 100	Sample Size = 1000	Sample Size = 5000	Sample Size = 50000
Married	CI = 8370 – 10326, Range = 1956	CI = 9026 – 9643, Range = 617	CI = 9196 – 9471, Range = 275	CI = 9290 – 9379, Range = 89
Unmarried	CI = 8369 – 10312, Range = 1943	CI = 9010 – 9630, Range = 620	CI = 9177 – 9455, Range = 278	CI = 9274 – 9360, Range = 86

Insights

1. Sample Size

The analysis highlights the importance of sample size in estimating population parameters. It suggests that as the sample size increases, the confidence intervals become narrower and more precise . In business, this implies that larger sample sizes can provide more reliable insights and estimates.

2. Confidence Intervals

From the above analysis, we can see that the confidence interval overlap for all the sample sizes. This means that there is no statistically significant difference between the average spending per transaction for married and unmarried customers within the given samples.

3. Population Average

We are 95% confident that the true population average for married customers falls between $9,290 and$9,379 , and for unmarried customers , it falls between $9,274 and$9,360 .

4. Both the customers spend equal

The overlapping confidence intervals of average spending for married and unmarried customers indicate that both married and unmarried customers spend a similar amount per transaction . This implies a resemblance in spending behavior between the two groups.

5. How can Walmart leverage this conclusion to make changes or improvements?

5.1. Marketing Resources

Walmart may not need to allocate marketing resources specifically targeting one group over the other. Instead, they can focus on broader marketing strategies that appeal to both groups.

7. Customer Age VS Purchase Amount

7.1 Data Visualization

```
#creating a df for purchase amount vs age group
temp = df.groupby('Age')['Purchase'].agg(['sum','count']).reset_index()
#calculating the amount in billions
temp['sum_in_billions'] = round(temp['sum'] / 10**9,2)
#calculationg percentage distribution of purchase amount
temp['%sum'] = round(temp['sum']/temp['sum'].sum(),3)
#calculationg per purchase amount
temp['per_purchase'] = round(temp['sum']/temp['count'])
temp
```

	Age	sum	count	sum_in_billions	%sum	per_purchase
0	0-17	48182771.0	5293	0.05	0.026	9103.0
1	18-25	328672004.0	35712	0.33	0.180	9203.0
2	26-35	726365910.0	78107	0.73	0.398	9300.0
3	36-45	366625025.0	38992	0.37	0.201	9403.0

Next steps: Generate code with temp View recommended plots

```
#setting the plot style
fig = plt.figure(figsize = (20,14))
gs = fig.add_gridspec(3,1,height_ratios =[0.10,0.4,0.5])
 #Distribution of Purchase Amount
ax = fig.add_subplot(gs[0])
color_map = ["#3A7089", "#4b4b4c",'#99AEBB','#5C8374','#6F7597','#7A9D54','#9EB384']
#plotting the visual
left = 0
for i in temp.index:
  ax.barh(temp.loc[0,'Age'],width = temp.loc[i,'%sum'],left = left,color = color_map[i],label = temp.loc[i,'Age'])
  left += temp.loc[i,'%sum']
#inserting the text
```