Walmart-Confidence Interval and CLT

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

Business Problem

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)

1. Problem Statement and Analyzing basic metrics

The management team at Walmart Inc. seeks to analyze customer purchase behavior, particularly focusing on purchase amounts in relation to customer gender and various other factors

The objective is to facilitate informed decision-making within the business. Specifically, the team aims to investigate potential differences in spending habits between male and female customers, particularly on Black Friday. With a customer base consisting of 50 million males and 50 million females, the team aims to ascertain whether women exhibit higher spending on Black Friday compared to men

Basic Metrics

By analyzing these basic metrics, the management team at Walmart Inc. can gain valuable insights into customer spending habits and make data-driven decisions to optimize business outcomes

1. The dataset will be analysed to interpret the total purchase amount, average purchase amount, and purchase frequency for both male and female customers

2. Interpret the total spending and average spending on Black Friday for both genders

3. Analyse the spending metrics between male and female customers to identify any significant differences

4. Use statistical tests (e.g., t-test, chi-square test) to determine if the observed differences are statistically significant.

DATA DESCRIPTION: The data consists of the following attributes:

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)

StayInCurrentCityYears: Number of years stay in current city

Marital_Status: Marital Status

ProductCategory: Product Category (Masked)

Purchase: Purchase Amount

2. Basic EDA(Observations on Data)

In [1]:
```
#Import Libraries
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from scipy.stats import norm
import warnings
```

In [2]:
```
# Load Walmart data present in CSV file
data=pd.read_csv("walmart_data.csv")
```

Shape of the Data

In [3]:
```
# Shape of data to check the number of rows and columns
data.shape
```

Out[3]:
```
(550068, 10)
```

In [4]:
```
# To get the column names
data.columns
```

Out[4]:
```
Index(['User_ID', 'Product_ID', 'Gender', 'Age', 'Occupation', 'City_Category',
       'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category',
       'Purchase'],
      dtype='object')
```

Data types of all the attributes

In [5]:
```
#check the datatype of each variable
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 [6]:
```python
data.head()
```

Out[6]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Mari
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 [7]:
```python
# Convert all columns (except Purchase) to categorical type in the DataFrame

for _ in data.columns[:-1]:
 data[_] = data[_].astype('category')

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  category
 1   Product_ID                  550068 non-null  category
 2   Gender                      550068 non-null  category
 3   Age                         550068 non-null  category
 4   Occupation                  550068 non-null  category
 5   City_Category               550068 non-null  category
 6   Stay_In_Current_City_Years  550068 non-null  category
 7   Marital_Status              550068 non-null  category
 8   Product_Category            550068 non-null  category
 9   Purchase                    550068 non-null  int64   
dtypes: category(9), int64(1)
memory usage: 10.3 MB
```

In [8]:
```python
# number of missing values in each column
data.isnull().sum()
```

Out[8]:
```
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 [9]:
```
print(data.isnull().any())
```

```
User_ID                       False
Product_ID                    False
Gender                        False
Age                           False
Occupation                    False
City_Category                 False
Stay_In_Current_City_Years    False
Marital_Status                False
Product_Category              False
Purchase                      False
dtype: bool
```

Insights

There are no null values in the given dataset,it indicates that all the required data points are present and there are no missing values.

Statistical summary

In [10]:
```
data.describe()
```

Out[10]:

	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

Insights

Purchase amount might have outliers.

3. Non-Graphical Analysis - Data Preprocessing

Non-Graphical Analysis involves examining the characteristics and distributions of variables, identifying patterns, and extracting insights from the data

In [11]:
```
#number of unique values in our data
for i in data.columns:
  print(i,':',data[i].nunique())
warnings.simplefilter(action='ignore', category=FutureWarning)
warnings.filterwarnings("ignore")
```

```
User_ID : 5891
Product_ID : 3631
Gender : 2
Age : 7
Occupation : 21
City_Category : 3
Stay_In_Current_City_Years : 5
Marital_Status : 2
Product_Category : 20
Purchase : 18105
```

In [12]:
```
# Non-graphical analysis using value counts and unique attributes
non_graphical_analysis = {}
# Value counts for columns with missing values
columns_with_missing_values = data.columns[data.isnull().any()]
for col in columns_with_missing_values:
 non_graphical_analysis[col] = data[col].value_counts(dropna=False)
# Unique attributes for all columns
for col in data.columns:
 non_graphical_analysis[f'{col}_unique'] = data[col].unique()
# Print non-graphical analysis results
for key, value in non_graphical_analysis.items():
 print(f"{key}:\n{value}\n")
```

```
User_ID_unique:
[1000001, 1000002, 1000003, 1000004, 1000005, ..., 1004588, 1004871, 1004113, 1005
391, 1001529]
Length: 5891
Categories (5891, int64): [1000001, 1000002, 1000003, 1000004, ..., 1006037, 10060
38, 1006039, 1006040]

Product_ID_unique:
['P00069042', 'P00248942', 'P00087842', 'P00085442', 'P00285442', ..., 'P0037543
6', 'P00372445', 'P00370293', 'P00371644', 'P00370853']
Length: 3631
Categories (3631, object): ['P00000142', 'P00000242', 'P00000342', 'P00000442',
..., 'P0099642', 'P0099742', 'P0099842', 'P0099942']

Gender_unique:
['F', 'M']
Categories (2, object): ['F', 'M']

Age_unique:
['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25']
Categories (7, object): ['0-17', '18-25', '26-35', '36-45', '46-50', '51-55', '55
+']

Occupation_unique:
[10, 16, 15, 7, 20, ..., 18, 5, 14, 13, 6]
Length: 21
Categories (21, int64): [0, 1, 2, 3, ..., 17, 18, 19, 20]

City_Category_unique:
['A', 'C', 'B']
Categories (3, object): ['A', 'B', 'C']

Stay_In_Current_City_Years_unique:
['2', '4+', '3', '1', '0']
Categories (5, object): ['0', '1', '2', '3', '4+']

Marital_Status_unique:
[0, 1]
Categories (2, int64): [0, 1]

Product_Category_unique:
[3, 1, 12, 8, 5, ..., 10, 17, 9, 20, 19]
Length: 20
Categories (20, int64): [1, 2, 3, 4, ..., 17, 18, 19, 20]

Purchase_unique:
[ 8370 15200  1422 ...   135   123   613]
```

In [13]:
```
categorical_cols = ['Gender', 'Age', 'Occupation', 'City_Category', 'Stay_In_Currer
data[categorical_cols].melt().groupby(['variable', 'value'])[['value']].count()/ler
```

Out[13]:

variable	value	value
Age	0-17	0.027455
	18-25	0.181178
	26-35	0.399200
	36-45	0.199999
	46-50	0.083082
	51-55	0.069993
	55+	0.039093
City_Category	A	0.268549
	B	0.420263
	C	0.311189
Gender	F	0.246895
	M	0.753105
Marital_Status	0	0.590347
	1	0.409653
Occupation	0	0.126599
	1	0.086218
	2	0.048336
	3	0.032087
	4	0.131453
	5	0.022137
	6	0.037005
	7	0.107501
	8	0.002811
	9	0.011437
	10	0.023506
	11	0.021063
	12	0.056682
	13	0.014049
	14	0.049647
	15	0.022115
	16	0.046123
	17	0.072796
	18	0.012039
	19	0.015382
	20	0.061014

		value
variable	value	
Product_Category	1	0.255201
	2	0.043384
	3	0.036746
	4	0.021366
	5	0.274390
	6	0.037206
	7	0.006765
	8	0.207111
	9	0.000745
	10	0.009317
	11	0.044153
	12	0.007175
	13	0.010088
	14	0.002769
	15	0.011435
	16	0.017867
	17	0.001051
	18	0.005681
	19	0.002914
	20	0.004636
Stay_In_Current_City_Years	0	0.135252
	1	0.352358
	2	0.185137
	3	0.173224
	4+	0.154028

Insights

80% of the users are between the age 18-50 (40%: 26-35, 18%: 18-25, 20%: 36-45)

75% of the users are Male and 25% are Female

60% Single, 40%

35% Staying in the city from 1 year, 18% from 2 years, 17% from 3 years

Total of 20 product categories are there

There are 20 diffenent types of occupations in the city

In [14]:
```
# Map numerical values in 'Marital_Status' to categorical labels\
```

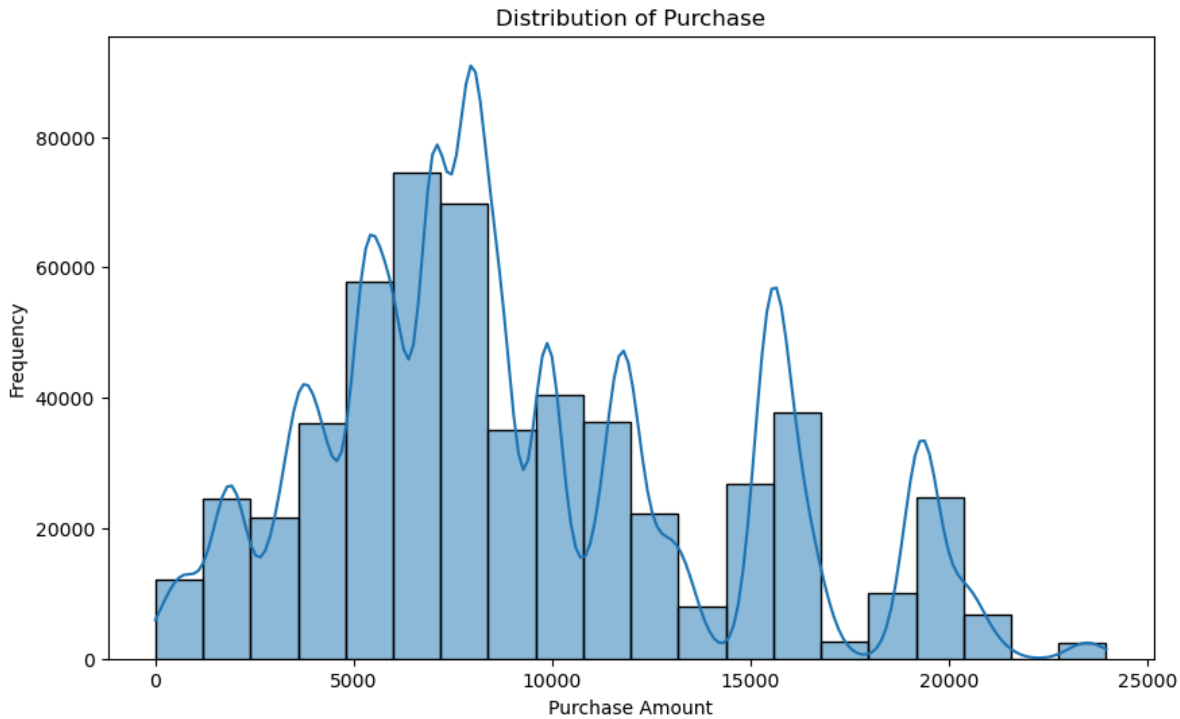
```
data['Marital_Status'] = data['Marital_Status'].apply(lambda x: 'Married' if x == 1
```

4. Visual Analysis - Univariate, Bivariate after pre processing of the data

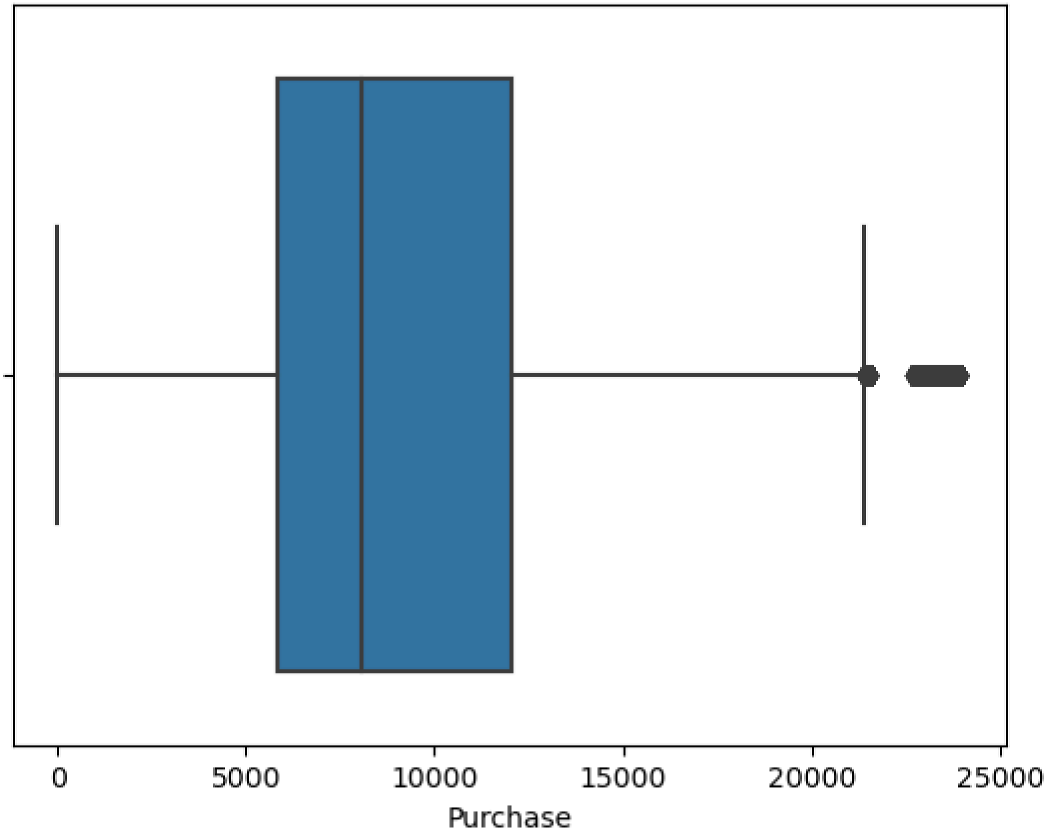
Univariate analysis involves examining the distribution and characteristics of a single variable in isolation.Following data pre-processing, univariateanalysis facilitates a visual understanding of the distinct properties and behaviors of individual variables.

Univariate Analysis - Distribution of Purchase : HistPlot

In [15]:
```
plt.figure(figsize=(10, 6))
sns.histplot(data['Purchase'], bins=20, kde=True)
plt.title('Distribution of Purchase')
plt.xlabel('Purchase Amount')
plt.ylabel('Frequency')
plt.show()
```



In [16]:
```
sns.boxplot(data=data, x='Purchase', orient='h')
plt.show()
```



Insights

There are outliers below 5th percentile and above 95 percentiles have extreme values, so we have to brought extreme values (outliers) within a specified range, which can be useful for data analysis and visualization, especially when extreme values might skew the interpretation of results.

In [17]:
```
# Calculate quartiles and IQR for the specified column
Q1 = np.percentile(data['Purchase'], 25)
Q3 = np.percentile(data['Purchase'], 75)
IQR = Q3 - Q1

# Upper and lower bounds for outliers
upper_bound = Q3 + (1.5 * IQR)
lower_bound = Q1 - (1.5 * IQR)

# Outliers in the specified column
upper_outliers_df = data[data['Purchase'] > upper_bound]
lower_outliers_df = data[data['Purchase'] < lower_bound]

# Count of outliers
upper_count = len(upper_outliers_df)
lower_count = len(lower_outliers_df)

total_count = upper_count + lower_count
```

In [18]:
```
print(f"Upper Outliers Count: {upper_count}")
print(f"Lower Outliers Count: {lower_count}")
print(f"Overall Outliers Count: {total_count}")
```

```
Upper Outliers Count: 2677
Lower Outliers Count: 0
Overall Outliers Count: 2677
```

In [19]:
```
# Extract rows where 'Purchase' values are greater than the upper bound to identify
```

```python
outliers_df = data[data['Purchase'] > upper_bound]
outliers_df
```

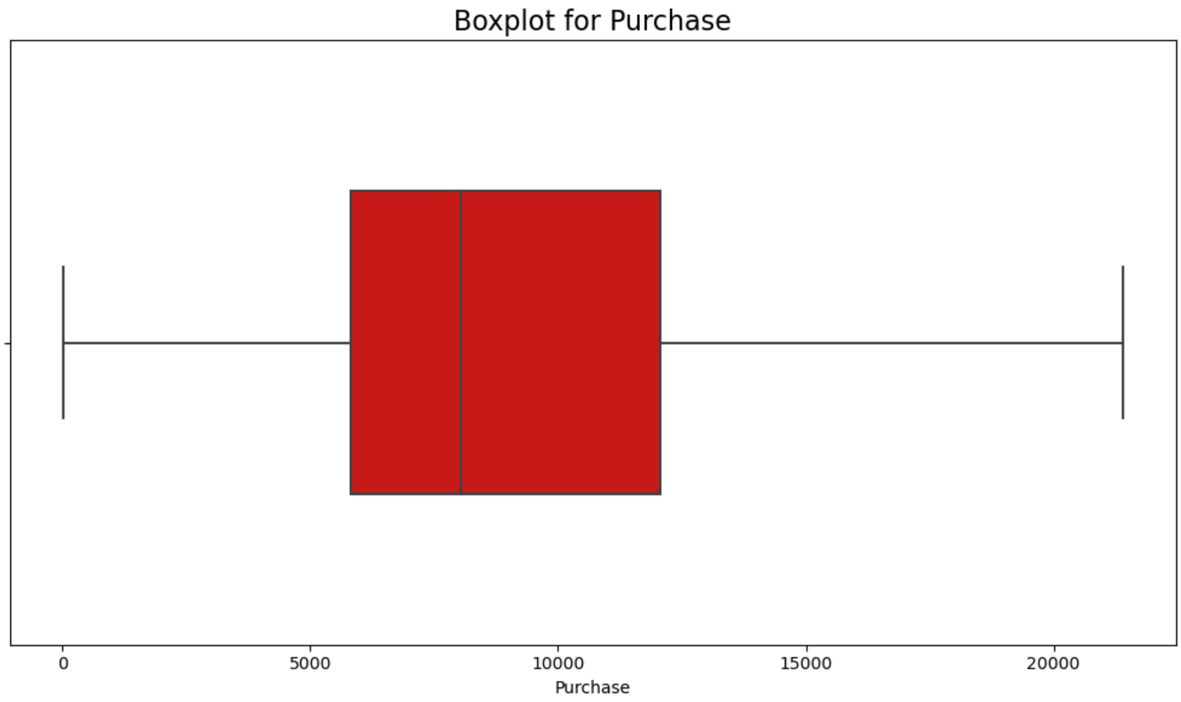
Out[19]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years
343	1000058	P00117642	M	26-35	2	B	3
375	1000062	P00119342	F	36-45	3	A	1
652	1000126	P00087042	M	18-25	9	B	1
736	1000139	P00159542	F	26-35	20	C	2
1041	1000175	P00052842	F	26-35	2	B	1
...	...	...	...	...	...	...	...
544488	1005815	P00116142	M	26-35	20	B	1
544704	1005847	P00085342	F	18-25	4	B	2
544743	1005852	P00202242	F	26-35	1	A	0
545663	1006002	P00116142	M	51-55	0	C	1
545787	1006018	P00052842	M	36-45	1	C	3

2677 rows × 10 columns

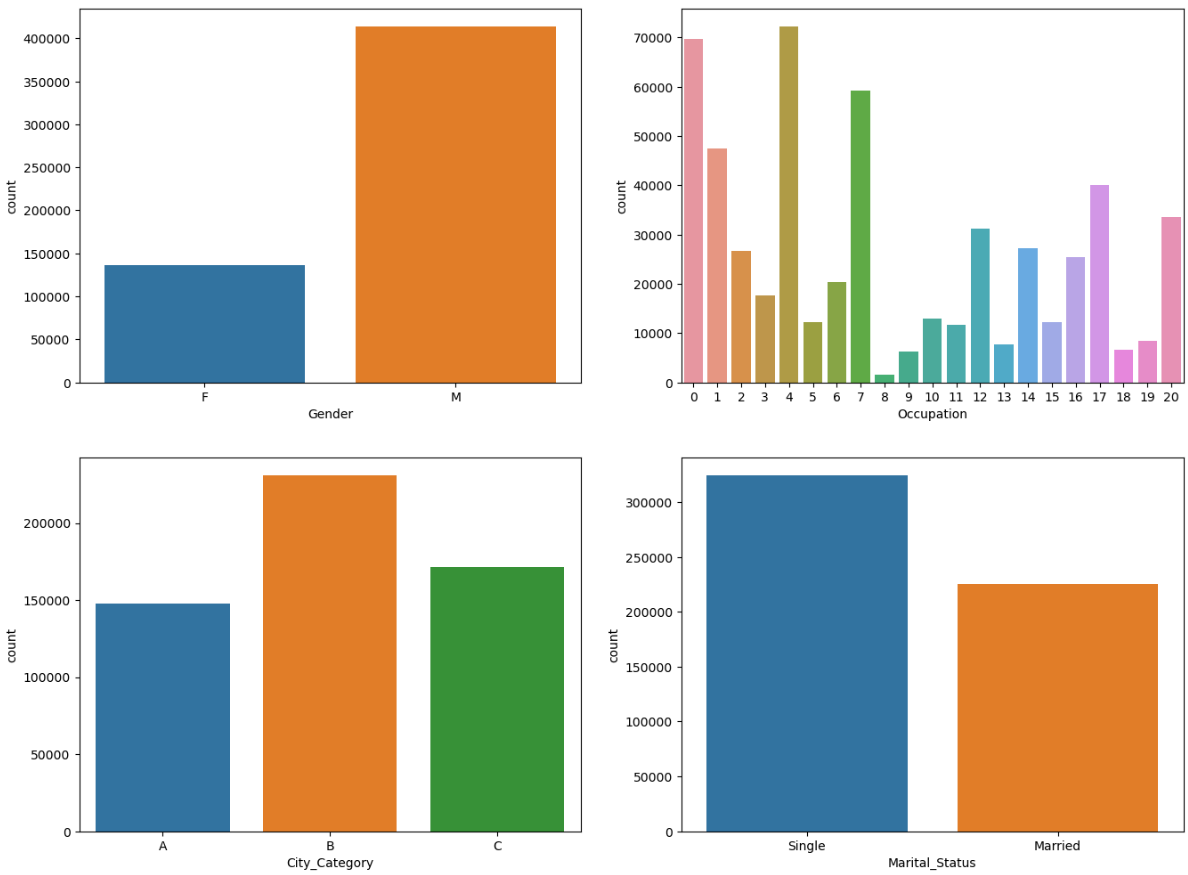
In [20]:
```python
clipped_data = np.clip(data['Purchase'], lower_bound, upper_bound)
```

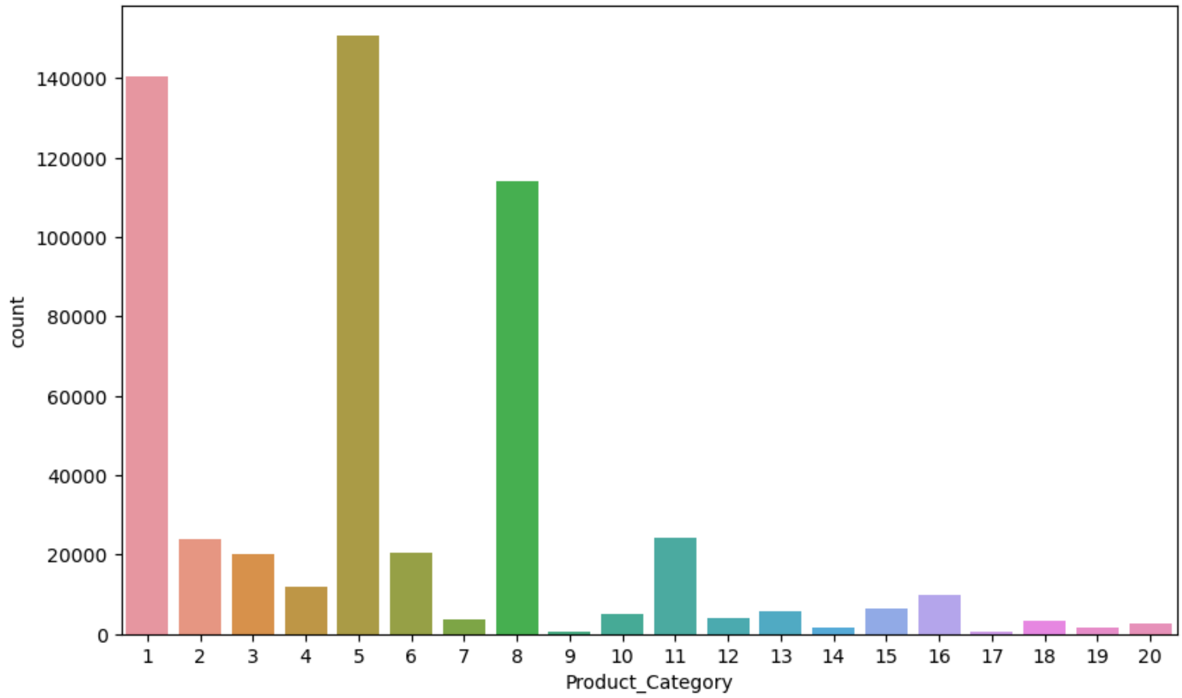
In [21]:
```python
plt.figure(figsize=(10, 6))

# Create a box plot for clipped data
sns.boxplot(x=clipped_data,color='#e60000', width=0.5, orient='h')
plt.title('Boxplot for Purchase', fontsize=16)
plt.tight_layout()
plt.show()
```



In [55]:
```python
category = ['Age', 'Occupation', 'City_Category', 'Stay_In_Current_City_Years', 'Ma
```

In [23]:
```python
fig, axs = plt.subplots(nrows=2, ncols=2, figsize=(16, 12))
sns.countplot(data=data, x='Gender', ax=axs[0,0])
sns.countplot(data=data, x='Occupation', ax=axs[0,1])
sns.countplot(data=data, x='City_Category', ax=axs[1,0])
sns.countplot(data=data, x='Marital_Status', ax=axs[1,1])
plt.show()

plt.figure(figsize=(10, 6))
sns.countplot(data=data, x='Product_Category')
plt.show()
```





Insights

Most of the users are Male

There are 20 different types of Occupation and Product_Category

More users belong to B City_Category

More users are Single as compare to Marrieds

Product_Category - 1, 5, 8, & 11 have highest purchasing frequency.

Bivariate Analysis

In [24]:
```
pivot = lambda index: data.pivot_table(index=data[index], columns='Gender', aggfunc
```

In [25]:
```
pivot('Age')
```

Out[25]:

Gender	F	M
Age		
0-17	5083	10019
18-25	24628	75032
26-35	50752	168835
36-45	27170	82843
46-50	13199	32502
51-55	9894	28607
55+	5083	16421

In [26]:
```
pivot('Occupation')
```

Out[26]:

Gender	F	M
Occupation		
0	18112	51526
1	17984	29442
2	8629	17959
3	7919	9731
4	17836	54472
5	2220	9957
6	8160	12195
7	10028	49105
8	361	1185
9	5843	448
10	4003	8927
11	1500	10086
12	3469	27710
13	1498	6230
14	6763	20546
15	2390	9775
16	4107	21264
17	3929	36114
18	230	6392
19	2017	6444
20	8811	24751

In [27]:

```
pivot('City_Category')
```

Out[27]:

Gender	F	M
City_Category		
A	35704	112016
B	57796	173377
C	42309	128866

In [28]:

```
pivot('Stay_In_Current_City_Years')
```

Out[28]:

Gender	F	M
Stay_In_Current_City_Years		
0	17063	57335
1	51298	142523
2	24332	77506
3	24520	70765
4+	18596	66130

In [29]:
```
pivot('Marital_Status')
```

Out[29]:

Gender	F	M
Marital_Status		
Single	78821	245910
Married	56988	168349

In [31]:
```
data.columns
```

Out[31]:
```
Index(['User_ID', 'Product_ID', 'Gender', 'Age', 'Occupation', 'City_Category',
       'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category',
       'Purchase'],
      dtype='object')
```

In [32]:
```
pivot('Product_Category')
```

Out[32]:

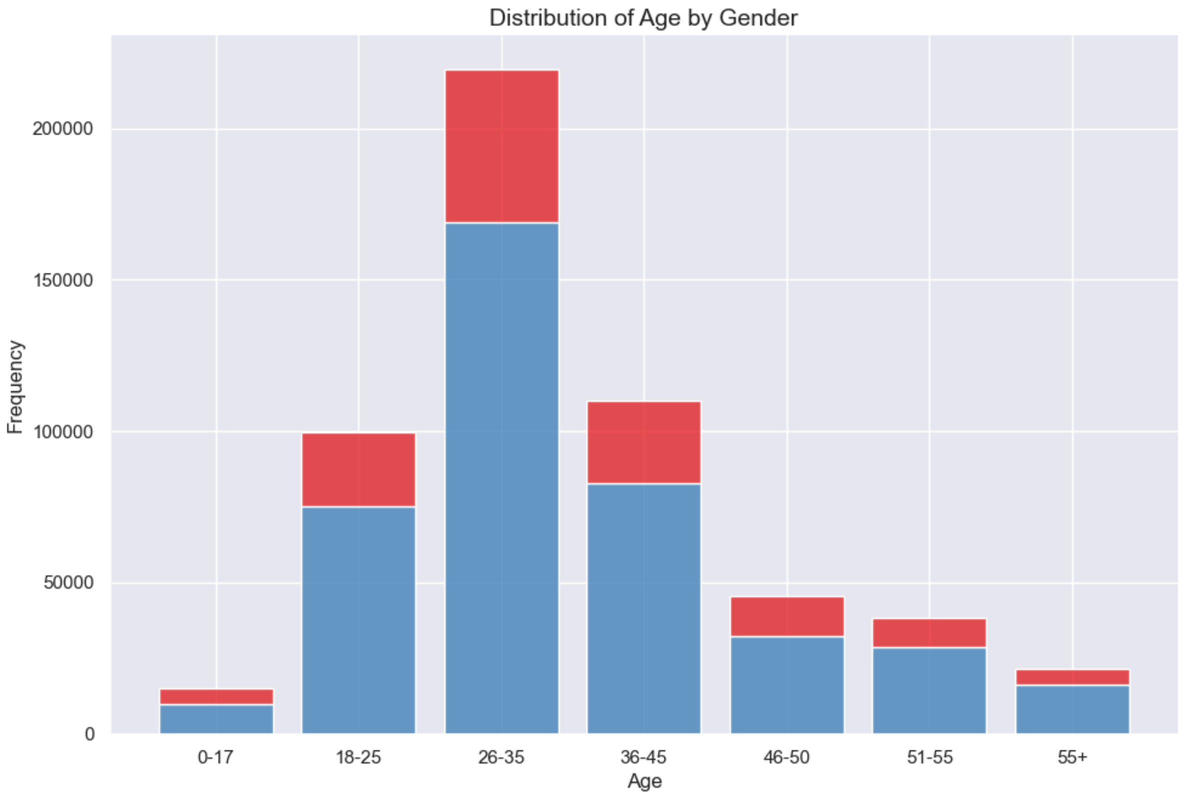
Gender	F	M
Product_Category		
1	24831	115547
2	5658	18206
3	6006	14207
4	3639	8114
5	41961	108972
6	4559	15907
7	943	2778
8	33558	80367
9	70	340
10	1162	3963
11	4739	19548
12	1532	2415
13	1462	4087
14	623	900
15	1046	5244
16	2402	7426
17	62	516
18	382	2743
19	451	1152
20	723	1827

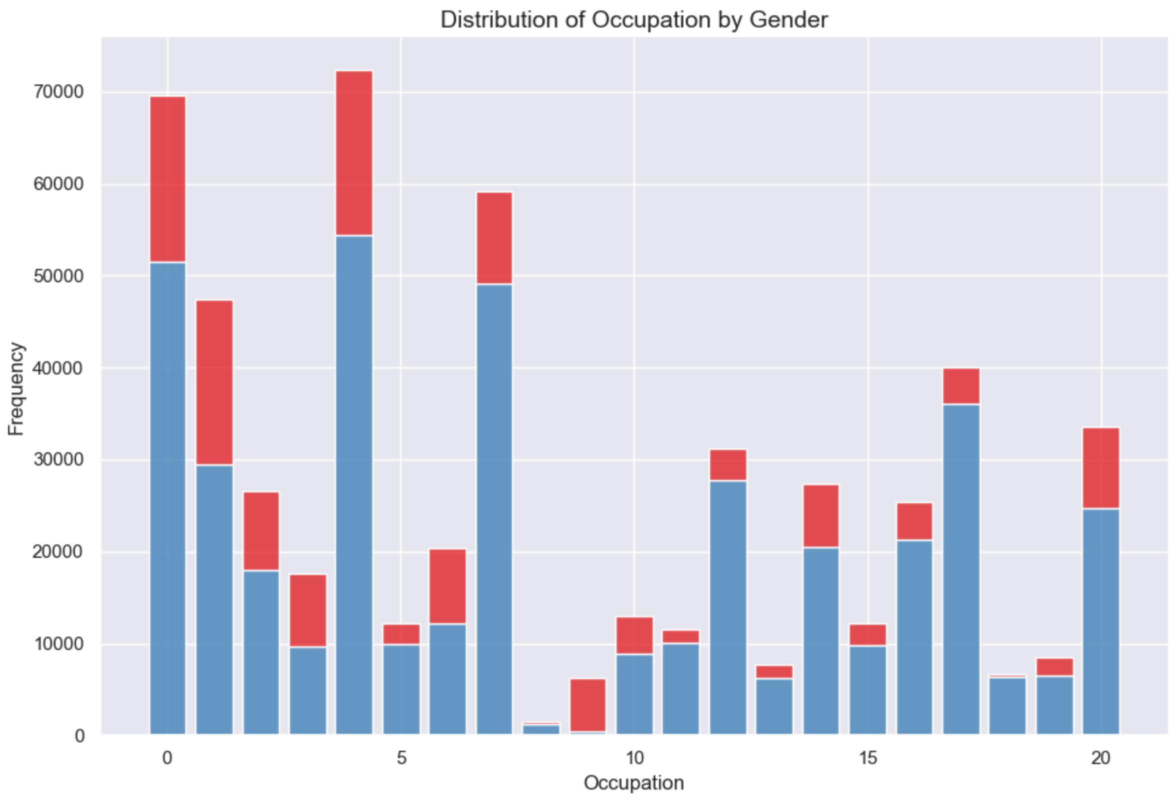
In [33]:

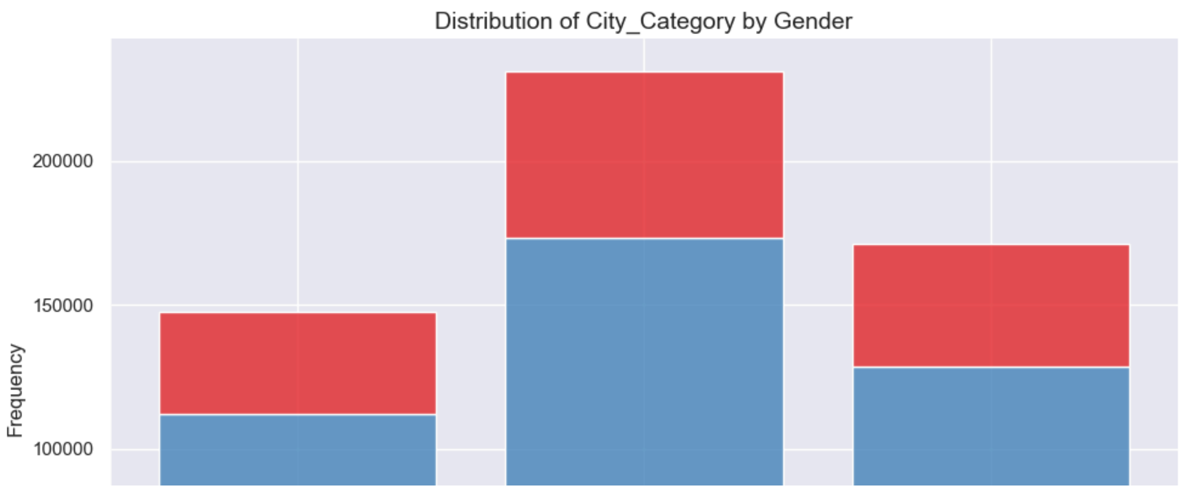
```
category = ['Age', 'Occupation', 'City_Category', 'Stay_In_Current_City_Years', 'Ma
```

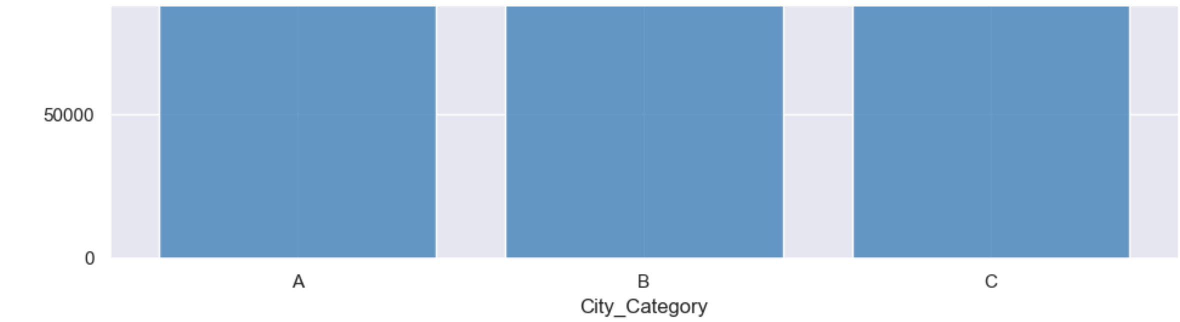
In [34]:

```
plt.figure(figsize=(10, 40))
sns.set(style='darkgrid')

# Plot each categorical column
for i, col in enumerate(category, 1):
    plt.subplot(6, 1, i)
    sns.histplot(data=data, x=col, hue='Gender', palette='Set1', legend=False, mult
    sns.despine()

    # Set labels and title
    plt.xlabel(f'{col}', fontsize=12)
    plt.ylabel('Frequency', fontsize=12)
    plt.title(f'Distribution of {col} by Gender', fontsize=14, fontfamily='sans-ser

    plt.tight_layout()

plt.show()
```

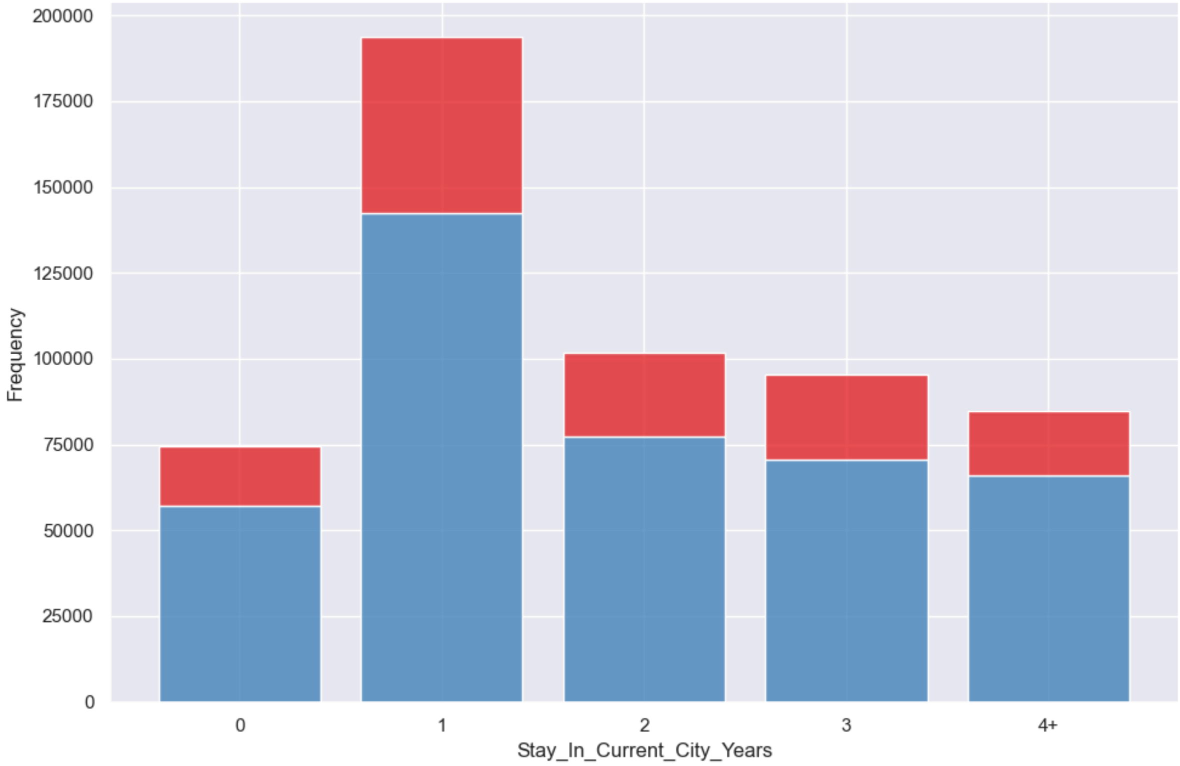

Distribution of Age by Gender
Frequency
0
50000
100000
150000
200000
0-17
18-25
26-35
36-45
46-50
51-55
55+
Age


Distribution of Occupation by Gender
Frequency
0
10000
20000
30000
40000
50000
60000
70000
0
5
10
15
20
Occupation

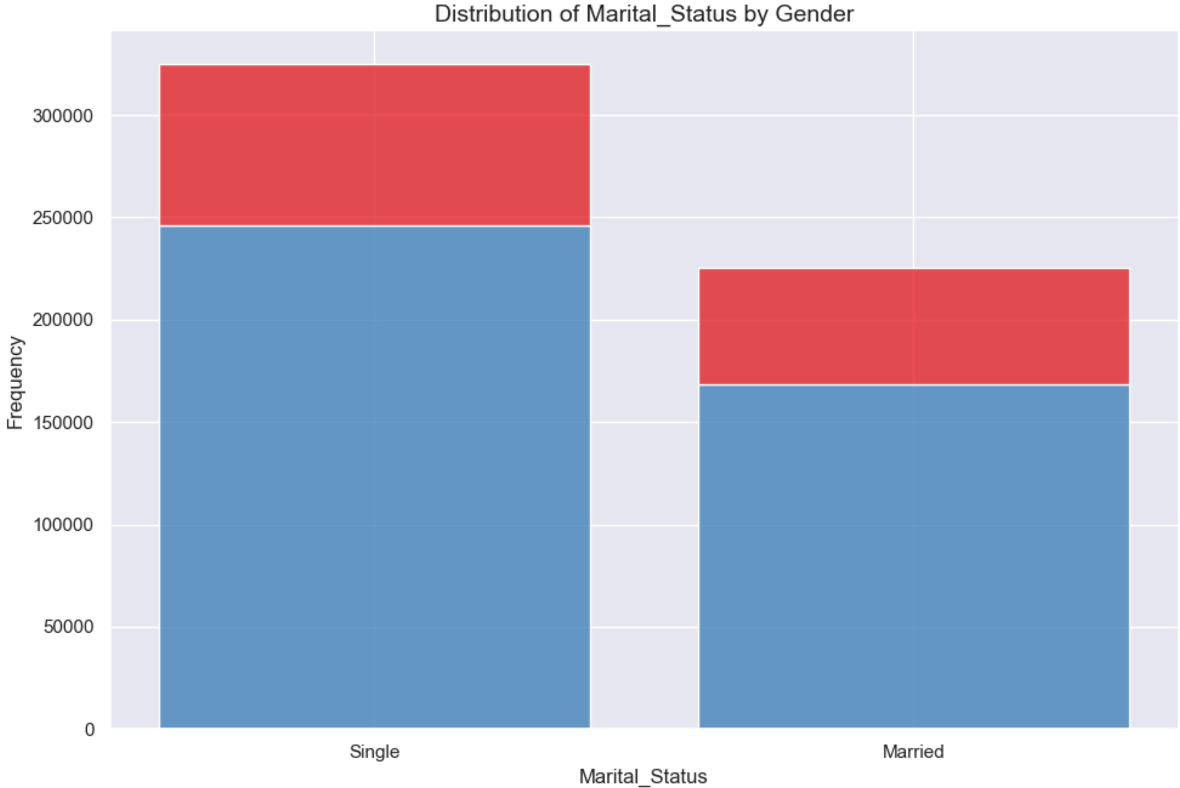

Distribution of City_Category by Gender
Frequency
100000
150000
200000



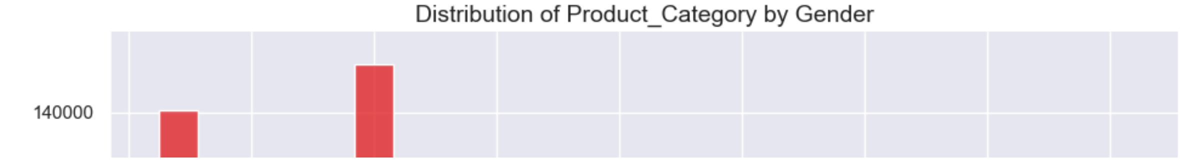
Distribution of Stay_In_Current_City_Years by Gender

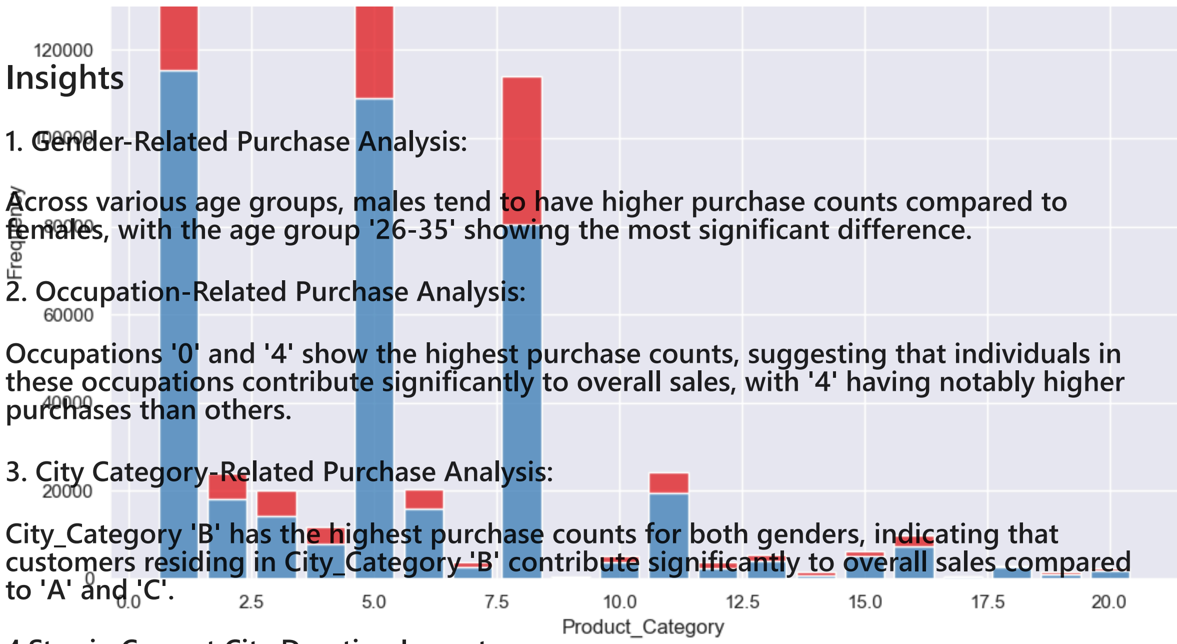


Distribution of Marital_Status by Gender



Distribution of Product_Category by Gender





Insights

1. Gender-Related Purchase Analysis:

Across various age groups, males tend to have higher purchase counts compared to females, with the age group '26-35' showing the most significant difference.

2. Occupation-Related Purchase Analysis:

Occupations '0' and '4' show the highest purchase counts, suggesting that individuals in these occupations contribute significantly to overall sales, with '4' having notably higher purchases than others.

3. City Category-Related Purchase Analysis:

City_Category 'B' has the highest purchase counts for both genders, indicating that customers residing in City_Category 'B' contribute significantly to overall sales compared to 'A' and 'C'.

4.Stay in Current City Duration Impact:

Customers who have stayed in their current city for 1 year exhibit the highest purchase counts, suggesting that individuals with a 1-year residence duration have a higher tendency to make purchases compared to other durations.

5. Marital Status-Related Purchase Analysis:

Individuals with a marital status of 'Single' have higher purchase counts compared to those who are 'Married', indicating that single individuals contribute more to overall sales.

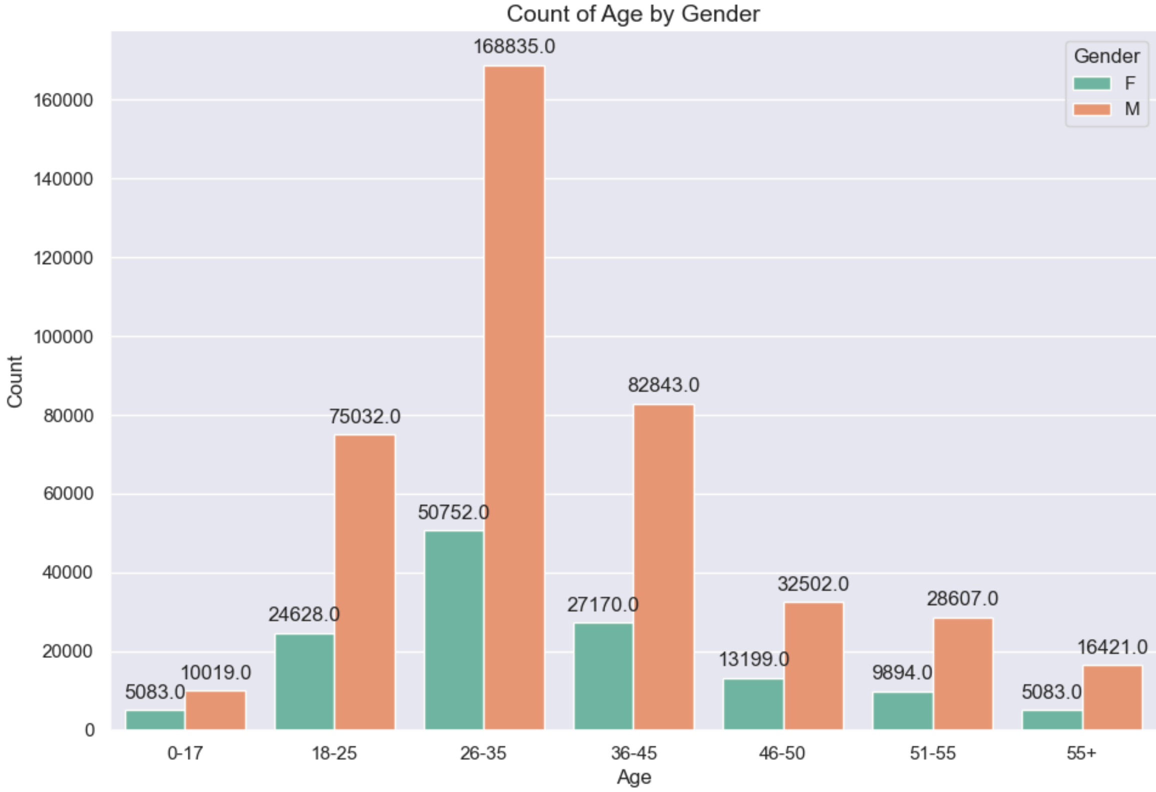
6.Product Category-Related Purchase Analysis:

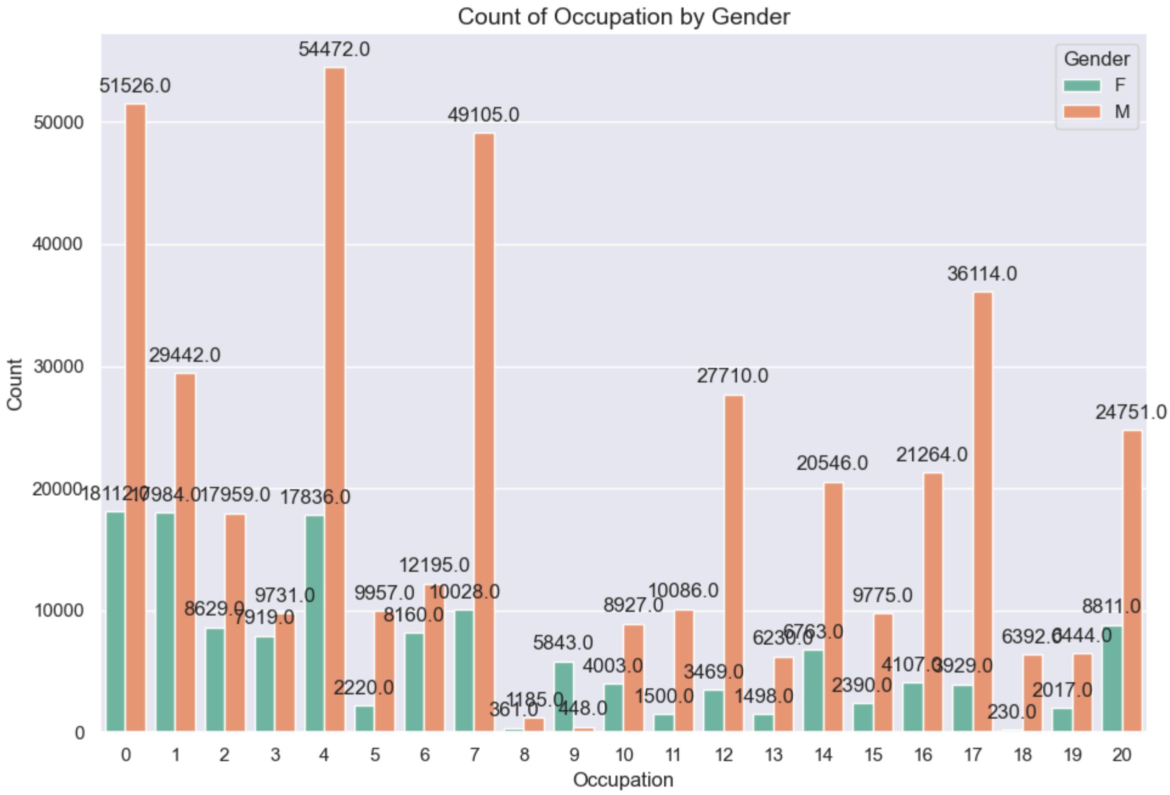
Product Category '1' has the highest purchase counts, indicating that it significantly contributes to overall sales. Product Categories '5' and '8' also show notable purchase counts.

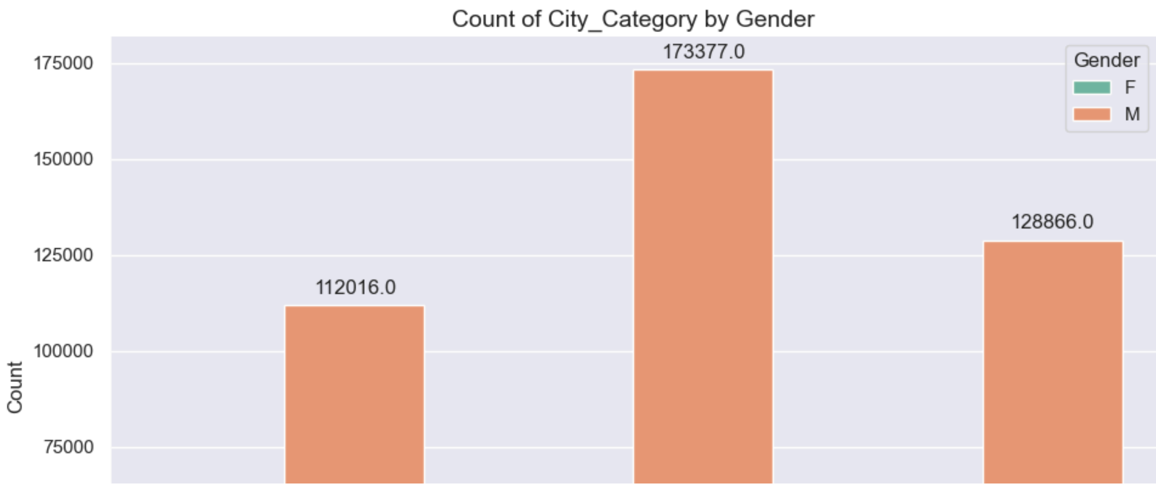
Multivariate Analysis

In [35]:
```
plt.figure(figsize=(10, 40))
sns.set(style='darkgrid')

# Plot each categorical column
for i, col in enumerate(category, 1):
    plt.subplot(6, 1, i)
    ax = sns.countplot(data=data, x=col, hue='Gender', palette='Set2')
    sns.despine()

    plt.title(f'Count of {col} by Gender', fontsize=14, fontfamily='sans-serif')
    plt.xlabel(col)
    plt.ylabel('Count')

    # Add bar counts as text labels
    for p in ax.patches:
        ax.annotate(f'{p.get_height()}',
                    (p.get_x() + p.get_width() / 2.,
                     p.get_height()),
                    ha='center',
                    va='center',
                    xytext=(0, 10),
                    textcoords='offset points')

    plt.tight_layout()
```

```
plt.show()
```

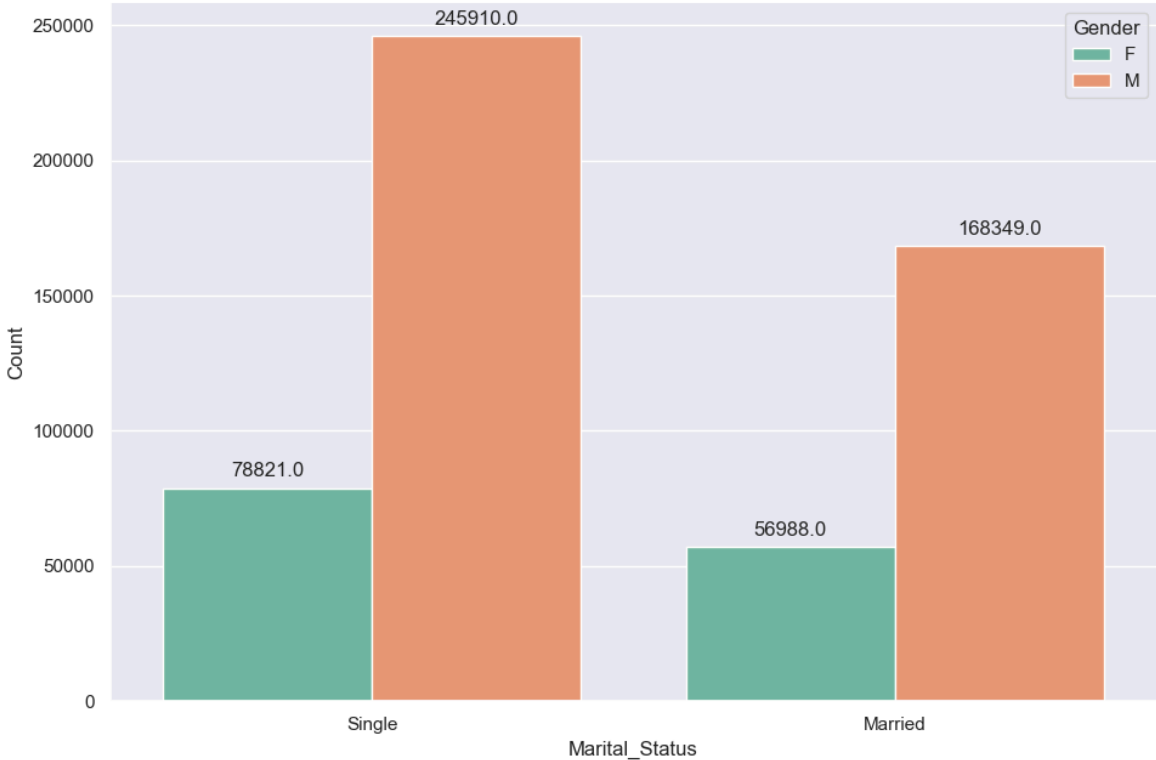

Count of Age by Gender
Count
Age
0-17
18-25
26-35
36-45
46-50
51-55
55+
Gender
F
M
5083.0
10019.0
24628.0
75032.0
50752.0
168835.0
27170.0
82843.0
13199.0
32502.0
9894.0
28607.0
5083.0
16421.0


Count of Occupation by Gender
Count
Occupation
Gender
F
M
51526.0
29442.0
54472.0
49105.0
36114.0
27710.0
24751.0
20546.0
21264.0
17959.0
17836.0
12195.0
10028.0
10086.0
9731.0
9957.0
8927.0
8629.0
7919.0
8160.0
9775.0
8811.0
5843.0
4003.0
3469.0
6230.0
6763.0
6392.0
6444.0
2220.0
1185.0
361.0
448.0
1500.0
1498.0
2390.0
4107.0
3929.0
230.0
2017.0

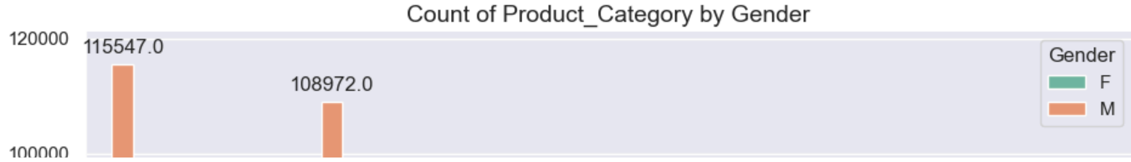

Count of City_Category by Gender
Count
Gender
F
M
112016.0
173377.0
128866.0

Count of Stay_In_Current_City_Years by Gender

Count of Marital_Status by Gender



Count of Product_Category by Gender



4. Balck friday Sales analysis on gender

In [36]:
```
avg_purchase = data.groupby('Gender')[['Purchase']].mean().reset_index().round(2)
avg_purchase
```

Out[36]:

	Gender	Purchase
0	F	8734.57
1	M	9437.53

In [37]:
```
df_male = data[data['Gender']=='M']
df_female = data[data['Gender']=='F']
```

In [38]:
```
print(f'Male customers - {len(df_male)}')
print(f'Female customers - {len(df_female)}')
```

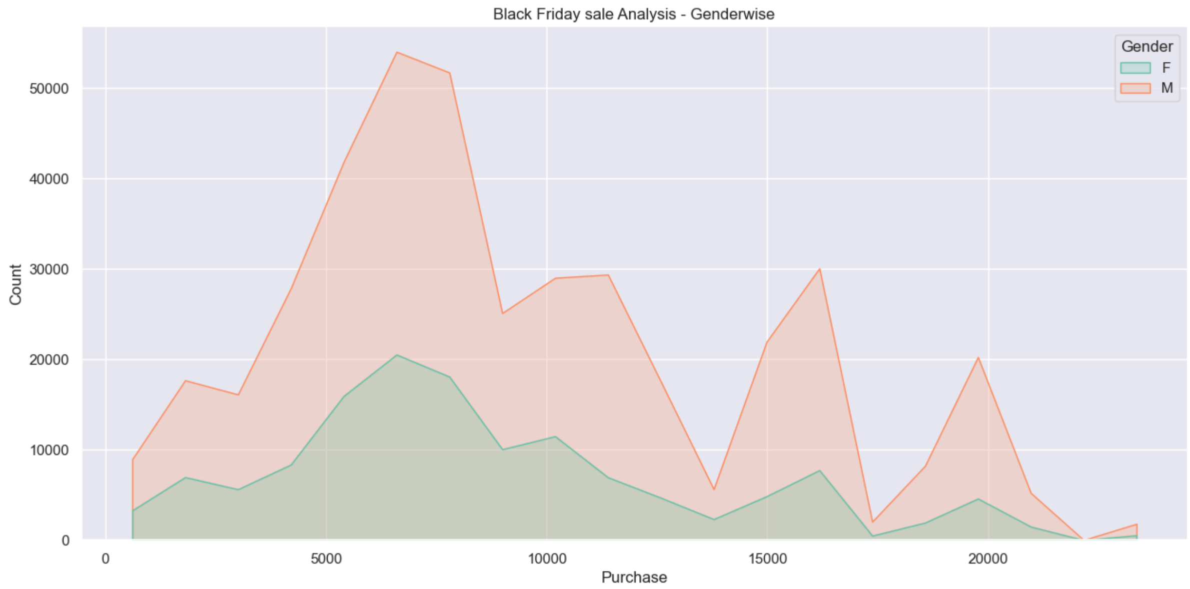
```
Male customers - 414259
Female customers - 135809
```

In [40]:
```
data.groupby('Gender')['Purchase'].describe().T
```

Out[40]:

Gender	F	M
count	135809.000000	414259.00000
mean	8734.565765	9437.52604
std	4767.233289	5092.18621
min	12.000000	12.00000
25%	5433.000000	5863.00000
50%	7914.000000	8098.00000
75%	11400.000000	12454.00000
max	23959.000000	23961.00000

In [41]:
```
plt.figure(figsize=(15,7))
sns.set(style='darkgrid')
sns.histplot(data=data, x = "Purchase", bins=20, hue = "Gender",element='poly',pale
sns.despine()
plt.title('Black Friday sale Analysis - Genderwise')
plt.show()
```



Insights

Men spent more money than women during the Black Friday sale.

The total number of male customers (4225) exceeds the total number of female customers (1666).

The average amount spent by male customers (9437) is higher than the average amount spent by female customers (8734).

With a larger male customer base, it is likely that men will make more purchases compared to females.

The higher sales among male customers could be attributed to a product range better suited to their preferences, leading to increased sales of products targeted towards men.

In [42]:
```
# Calculates the 95% confidence interval and width for a specified category within

def data_ci(data, variable, category, confidence_level=0.95):

    category_data = data[data[variable] == category]['Purchase']
    category_mean = category_data.mean()
    category_std = category_data.std()

    # standard error of the mean
    category_sem = category_std / np.sqrt(len(category_data))

    # margin of error
    category_moe = category_sem * norm.ppf((1 + confidence_level) / 2)

    # confidence interval
    category_ci = (category_mean - category_moe, category_mean + category_moe)

    # width
    category_width = category_ci[1] - category_ci[0]

    print(f'{category} 95% confidence interval: {category_ci}')
    print(f'{category} Width: {category_width}')
```

In [43]:
```
# Calculates the 95% confidence interval and width for a specified category within

def sample_ci(data, variable, category, sample_size):

    category_data = data[data[variable] == category]['Purchase']
```

```
    sample_data = category_data.sample(n=sample_size, random_state=42)
    mean_val = sample_data.mean()
    std_dev = sample_data.std()

    # standard error of the mean
    sem = std_dev / np.sqrt(sample_size)

    # margin of error
    moe = sem * norm.ppf((1 + 0.95) / 2)  # 1.96 corresponds to the Z-score for a 9

    # confidence interval
    ci = (mean_val - moe, mean_val + moe)

    category_width = ci[1] - ci[0]

    print(f"\nSample Size: {sample_size}")
    print(f'{category} 95% confidence interval: {ci}')
    print(f'{category} Width: {category_width}')
```

5. Confidence intervals for the Average amount spent per gender

95% confidence interval of Entire Dataset

In [44]:
```
data_ci(data, 'Gender', 'M')
```

```
M 95% confidence interval: (9422.01944736257, 9453.032633581959)
M Width: 31.013186219388444
```

In [45]:
```
data_ci(data, 'Gender', 'F')
```

```
F 95% confidence interval: (8709.21154714068, 8759.919983170272)
F Width: 50.70843602959212
```

95% confidence interval of 300 samples

In [46]:
```
sample_ci(data, 'Gender', 'M', 300)
```

```
Sample Size: 300
M 95% confidence interval: (9283.731565877591, 10491.715100789075)
M Width: 1207.9835349114837
```

In [47]:
```
sample_ci(data, 'Gender', 'F', 300)
```

```
Sample Size: 300
F 95% confidence interval: (8308.865304074718, 9426.034695925284)
F Width: 1117.1693918505662
```

95% confidence interval of 3000 samples

In [49]:
```
sample_ci(data, 'Gender', 'M', 3000)
```

```
Sample Size: 3000
M 95% confidence interval: (9460.10182838994, 9831.170171610062)
M Width: 371.0683432201222
```

In [50]:
```
sample_ci(data, 'Gender', 'F', 3000)
```

```
Sample Size: 3000
F 95% confidence interval: (8630.481387808419, 8982.545945524913)
F Width: 352.06455771649416
```

95% confidence interval of 30000 samples

In [51]:
```
sample_ci(data, 'Gender', 'M', 30000)
```

```
Sample Size: 30000
M 95% confidence interval: (9428.950211018666, 9544.881322314668)
M Width: 115.9311112960022
```

In [52]:
```
sample_ci(data, 'Gender', 'F', 30000)
```

```
Sample Size: 30000
F 95% confidence interval: (8602.340431075772, 8709.62250225756)
F Width: 107.28207118178761
```

Insights:

The confidence interval computed using the entire dataset is wider for males compared to females, indicating higher variability in the amount spent by males.

The width of the confidence interval is inversely affected by the sample size; as the sample size increases, the interval becomes narrower, providing more precise estimates.

The confidence intervals for different sample sizes overlap, suggesting that observed differences may not be statistically significant.

Larger sample sizes result in more normally shaped distributions of means due to the Central Limit Theorem.

Confidence intervals for the average amount spent per Marital_Status

95% confidence interval of Entire Dataset

In [54]:
```
data_ci(data, 'Marital_Status', 'Married')
```

```
Married 95% confidence interval: (9240.460427057078, 9281.888721107669)
Married Width: 41.42829405059092
```

In [55]:
```
data_ci(data, 'Marital_Status', 'Single')
```

```
Single 95% confidence interval: (9248.61641818668, 9283.198819656332)
Single Width: 34.58240146965181
```

95% confidence interval of 300 samples

In [57]:
```
sample_ci(data, 'Marital_Status', 'Married', 300)
```

```
Sample Size: 300
Married 95% confidence interval: (8887.305881933493, 10041.72745139984)
Married Width: 1154.4215694663471
```

In [58]:
```
sample_ci(data, 'Marital_Status', 'Single', 300)
```

```
Sample Size: 300
Single 95% confidence interval: (9051.928693931213, 10213.504639402121)
Single Width: 1161.5759454709078
```

95% confidence interval of 3000 samples

In [59]:
```python
sample_ci(data, 'Marital_Status', 'Married', 3000)
```

```
Sample Size: 3000
Married 95% confidence interval: (9118.562018709765, 9482.974647956902)
Married Width: 364.4126292471374
```

In [60]:
```python
sample_ci(data, 'Marital_Status', 'Single', 3000)
```

```
Sample Size: 3000
Single 95% confidence interval: (9246.175079645862, 9612.375587020804)
Single Width: 366.2005073749424
```

95% confidence interval of 30000 samples

In [61]:
```python
sample_ci(data, 'Marital_Status', 'Married', 30000)
```

```
Sample Size: 30000
Married 95% confidence interval: (9198.15616601518, 9312.029900651485)
Married Width: 113.87373463630502
```

In [62]:
```python
sample_ci(data, 'Marital_Status', 'Single', 30000)
```

```
Sample Size: 30000
Single 95% confidence interval: (9229.816006946752, 9343.573126386582)
Single Width: 113.7571194398297
```

Insights:

The confidence interval for the 'Married' group is wider than that for the 'Single' group, indicating higher variability in the amount spent for married individuals.

The width of the confidence interval decreases as the sample size increases, showcasing the impact of larger sample sizes on precision.

Yes, the confidence intervals for 'Married' and 'Single' groups overlap, suggesting that observed differences may not be statistically significant across sample sizes.

As the sample size increases, the width of the confidence interval decreases, leading to a more precise estimate of the mean and resulting in a more normal distribution of sample means.

Confidence intervals for the average amount spent per City_Category

In [63]:
```python
data_ci(data, 'City_Category', 'A')
```

```
A 95% confidence interval: (8886.991825864907, 8936.88660630406)
A Width: 49.89478043915369
```

In [64]:
```python
data_ci(data, 'City_Category', 'B')
```

```
B 95% confidence interval: (9131.099848963764, 9171.501276600207)
B Width: 40.40142763644326
```

In [65]:
```python
data_ci(data, 'City_Category', 'C')
```

```
C 95% confidence interval: (9695.337107885243, 9744.504878386117)
C Width: 49.1677705008733
```

In [ ]:
```python
95% confidence interval of 300 samples
```

In [66]:
```python
sample_ci(data, 'City_Category', 'A', 300)
```

```
Sample Size: 300
A 95% confidence interval: (8098.995845827299, 9266.9641541727)
A Width: 1167.968308345401
```

In [67]:
```python
sample_ci(data, 'City_Category', 'B', 300)
```

```
Sample Size: 300
B 95% confidence interval: (8571.45829896875, 9684.755034364583)
B Width: 1113.2967353958338
```

In [68]:
```python
sample_ci(data, 'City_Category', 'C', 300)
```

```
Sample Size: 300
C 95% confidence interval: (8630.994793994194, 9728.831872672474)
C Width: 1097.8370786782798
```

95% confidence interval of 3000 samples

In [69]:
```python
sample_ci(data, 'City_Category', 'A', 3000)
```

```
Sample Size: 3000
A 95% confidence interval: (8812.739396324683, 9167.82993700865)
A Width: 355.09054068396654
```

In [70]:
```python
sample_ci(data, 'City_Category', 'B', 3000)
```

```
Sample Size: 3000
B 95% confidence interval: (8791.70616073309, 9141.478505933577)
B Width: 349.7723452004866
```

In [71]:
```python
sample_ci(data, 'City_Category', 'C', 3000)
```

```
Sample Size: 3000
C 95% confidence interval: (9442.853994951975, 9813.490671714693)
C Width: 370.6366767627187
```

95% confidence interval of 30000 samples

In [72]:
```python
sample_ci(data, 'City_Category', 'A', 30000)
```

```
Sample Size: 30000
A 95% confidence interval: (8836.46007218682, 8947.056727813182)
A Width: 110.59665562636292
```

In [73]:
```python
sample_ci(data, 'City_Category', 'B', 30000)
```

```
Sample Size: 30000
B 95% confidence interval: (9079.173984592268, 9191.2066820744)
B Width: 112.03269748213279
```

In [74]:
```python
sample_ci(data, 'City_Category', 'C', 30000)
```

```
Sample Size: 30000
C 95% confidence interval: (9656.973563549582, 9774.566303117084)
C Width: 117.59273956750258
```

Insights:

The confidence interval for City Category C is wider than others, indicating higher variability in the entire dataset for City Category C.

Generally, as sample size increases, the width of confidence intervals decreases. This is evident in the decreasing width for all city categories (A, B, C) with increasing sample size.

Yes, the confidence intervals for different sample sizes overlap, suggesting no significant differences in means between sample sizes.

Larger sample sizes result in narrower confidence intervals, indicating a more precise estimate of the mean and a more normal distribution due to the Central Limit Theorem.

6 .Business Recommendations:

Targeted Marketing for Age Group '26-35':

Focus marketing efforts on individuals in the age group '26-35', as they demonstrate the highest purchase counts. Tailor promotions and advertisements to resonate with this demographic.

Occupation-Based Product Offerings:

Since Occupation '4' has the highest representation and notable purchases, consider customizing product offerings or promotions to cater specifically to individuals in this occupation.

Strategic City_Category 'B' Promotions:

Allocate promotional resources strategically, with a focus on City_Category 'B' where the highest purchases are observed. Tailor promotions to resonate with the preferences of customers in this category.

Targeted Campaigns for Singles:

Launch targeted marketing campaigns for individuals with a marital status of 'Single', as they contribute significantly more to overall sales. Understand and appeal to the preferences of this demographic.

Encourage Long-Term Residency:

Develop strategies to encourage customers to stay in their current city for more than 1 year. Consider loyalty programs or special incentives for long-term residents to enhance their purchasing tendency.

Product Category Optimization:

Optimize the inventory and promotion of products in categories '1' and '5', as they exhibit higher purchase amounts. Strategically manage these categories to maximize overall sales revenue.

Gender-Targeted Marketing Strategies:

Implement gender-targeted marketing strategies, especially focusing on males across various age groups. Leverage insights from the age-based gender analysis to tailor promotions effectively.

Occupation-Driven Promotions:

Design promotions or incentives based on the top occupations, such as '0' and '4', to further boost sales from these occupational groups.

City_Category 'B' Specific Initiatives:

Consider implementing specific initiatives, offers, or events in City_Category 'B' to capitalize on the higher purchasing behavior observed in this category.

Data-Driven Product Development:

Analyze the product preferences of male customers to inform product development. Ensure that the product range aligns with the preferences of the larger male customer base, leading to increased sales.

```
In [ ]:
```