In [1]:
```
# Importing the necessary libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import norm
```

In [2]:
```
# converting data into dataf

walmart = pd.read_csv("walmart_data.csv")
```

In [3]:
```
# making an copy of the dataset

df = walmart.copy()
```

In [4]:
```
# Top 5 rows of the dataframe

df.head()
```

Out[4]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years
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 [5]:
```
# No of rows & columns

df.shape
```

Out[5]: (550068, 10)

In [6]:
```
# Data info

df.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 [7]:
```
# Checking of null values

df.isna().sum()
```

Out[7]:
```
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 [8]:
```
# Duplicate values check

df.duplicated().sum()
```

Out[8]: 0

In [9]:
```
# Uniques values of each columns

df.nunique()
```

Out[9]:
```
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
dtype: int64
```

In [10]:
```
# Convert all columns (except Purchase) to categorical type in the DataFrame

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

df.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 [11]:
```
df.describe()
```

Out[11]:

	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

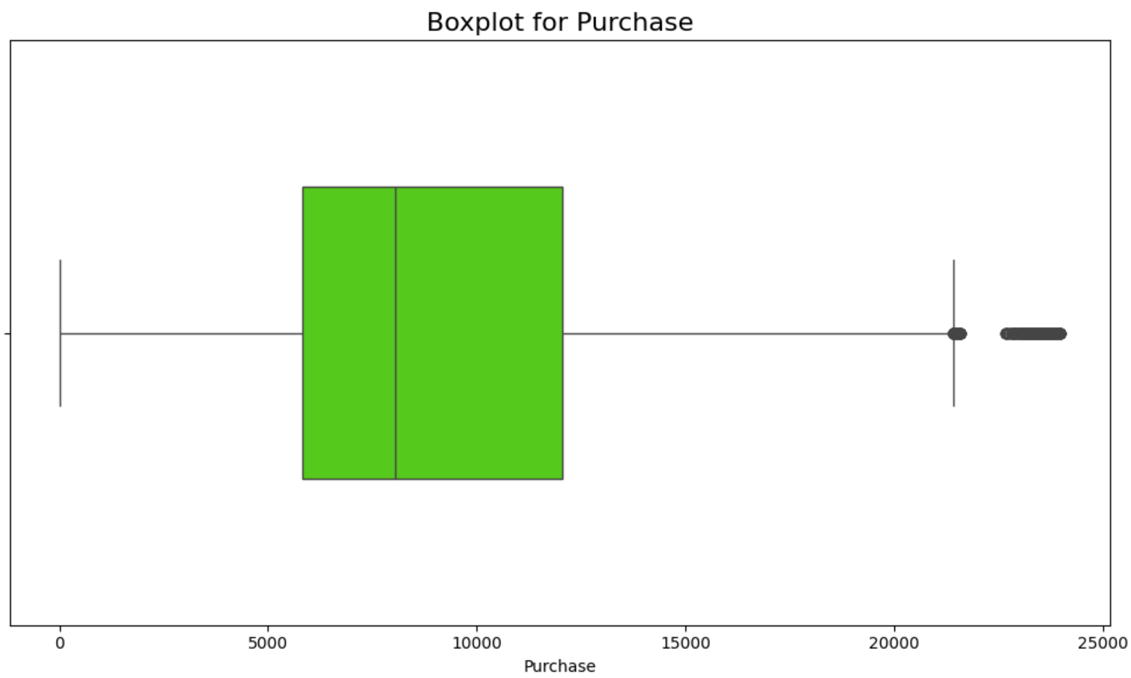
In [12]:
```
df.describe( include = 'category').T
```

Out[12]:

	count	unique	top	freq
User_ID	550068	5891	1001680	1026
Product_ID	550068	3631	P00265242	1880
Gender	550068	2	M	414259
Age	550068	7	26-35	219587
Occupation	550068	21	4	72308
City_Category	550068	3	B	231173
Stay_In_Current_City_Years	550068	5	1	193821
Marital_Status	550068	2	0	324731
Product_Category	550068	20	5	150933

Outlier detection

In [13]:
```
plt.figure(figsize=(10, 6))

# Create a box plot for 'Purchase'
sns.boxplot(x='Purchase', data=df, color='#4ce600', width=0.5)
plt.title('Boxplot for Purchase', fontsize=16)
plt.tight_layout()
plt.show()
```



In [14]:
```
# Calculate quartiles and IQR for the specified column
Q1 = np.percentile(df['Purchase'], 25)
Q3 = np.percentile(df['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 = df[df['Purchase'] > upper_bound]
lower_outliers_df = df[df['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 [15]:
```
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 [16]:
```
# Extract rows where 'Purchase' values are greater than the upper bound to '

outliers_df = df[df['Purchase'] > upper_bound]
outliers_df
```

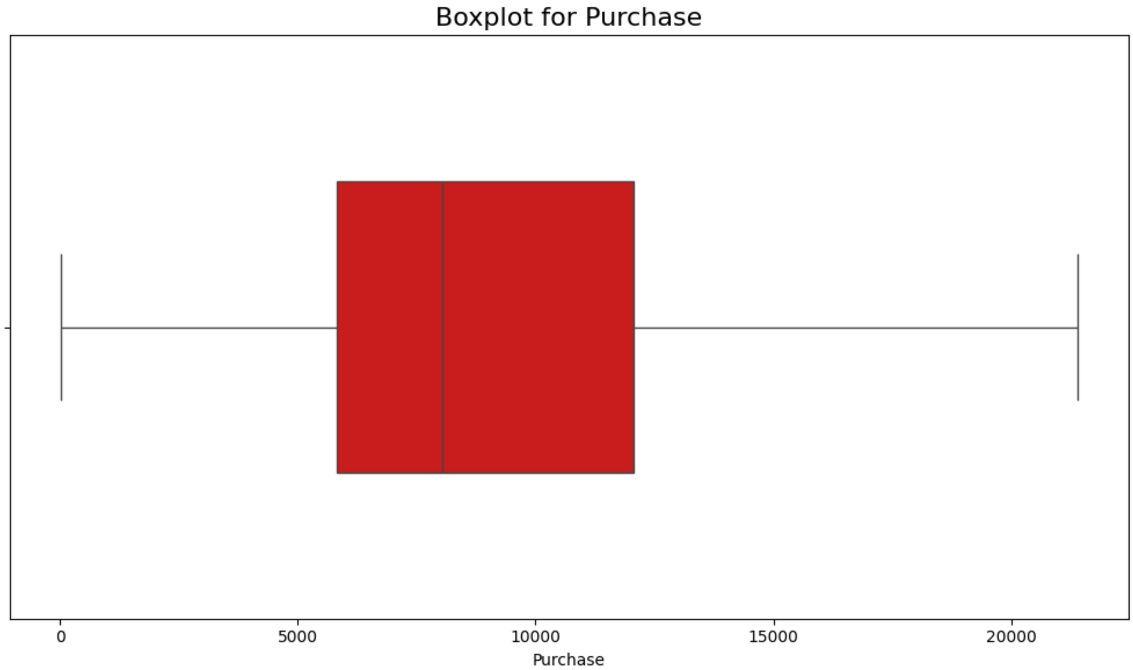
Out[16]:

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

2677 rows × 10 columns

In [17]:
```
clipped_data = np.clip(df['Purchase'], lower_bound, upper_bound)
```

In [18]:
```
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 [19]:
```
# Map numerical values in 'Marital_Status' to categorical labels\

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

In [20]:
```
df.head(3)
```

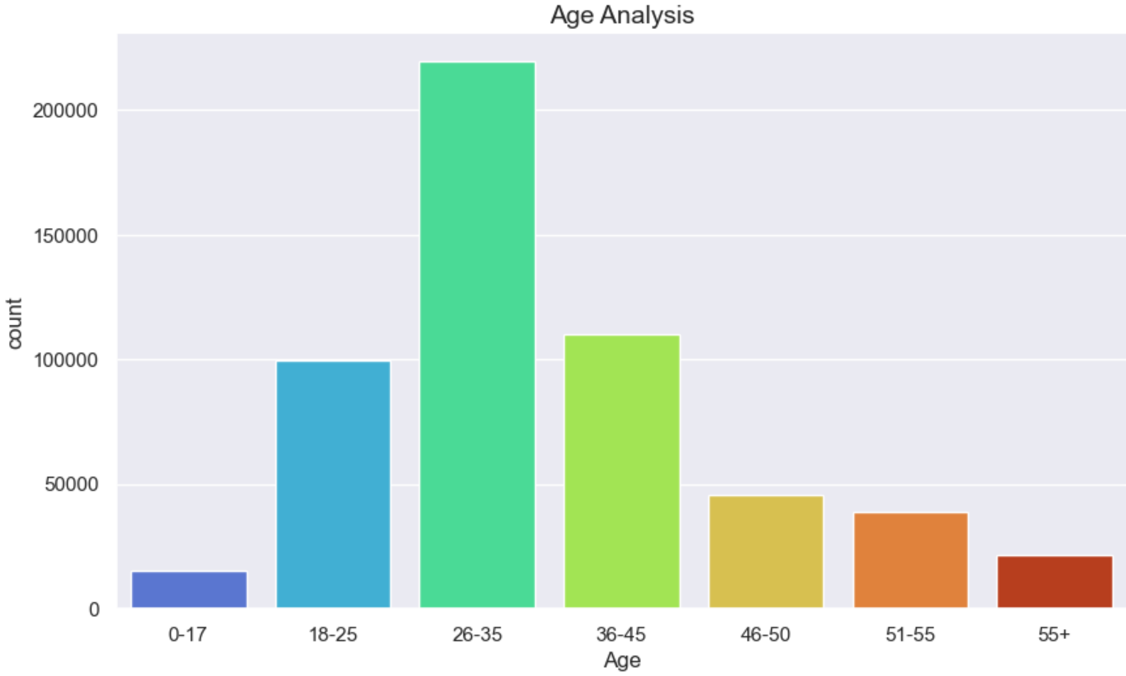
Out[20]:

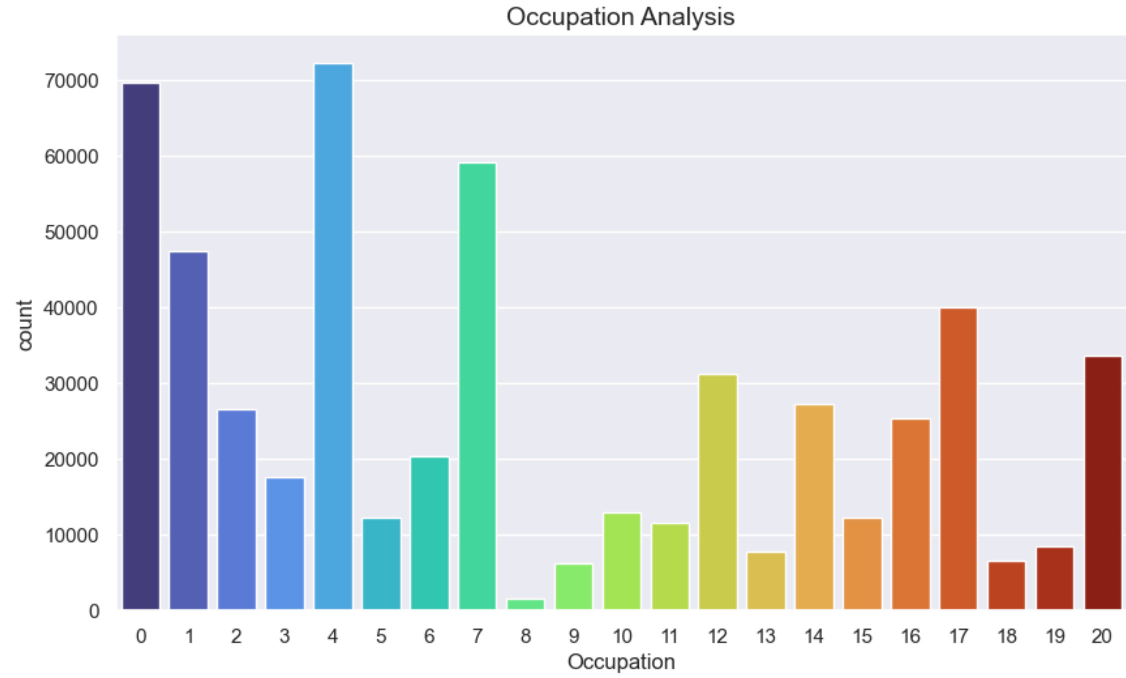
	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years
0	1000001	P00069042	F	0-17	10	A	2
1	1000001	P00248942	F	0-17	10	A	2
2	1000001	P00087842	F	0-17	10	A	2

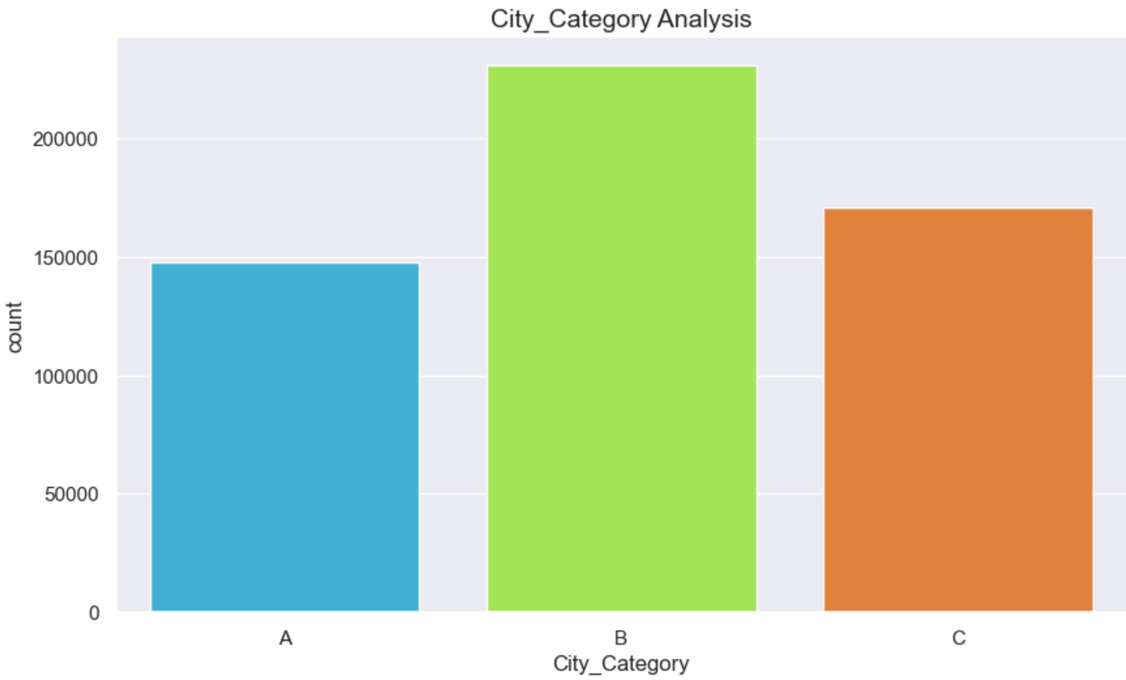
Univariate Analysis

In [21]:
```
category = ['Age', 'Occupation', 'City_Category', 'Stay_In_Current_City_Year
```

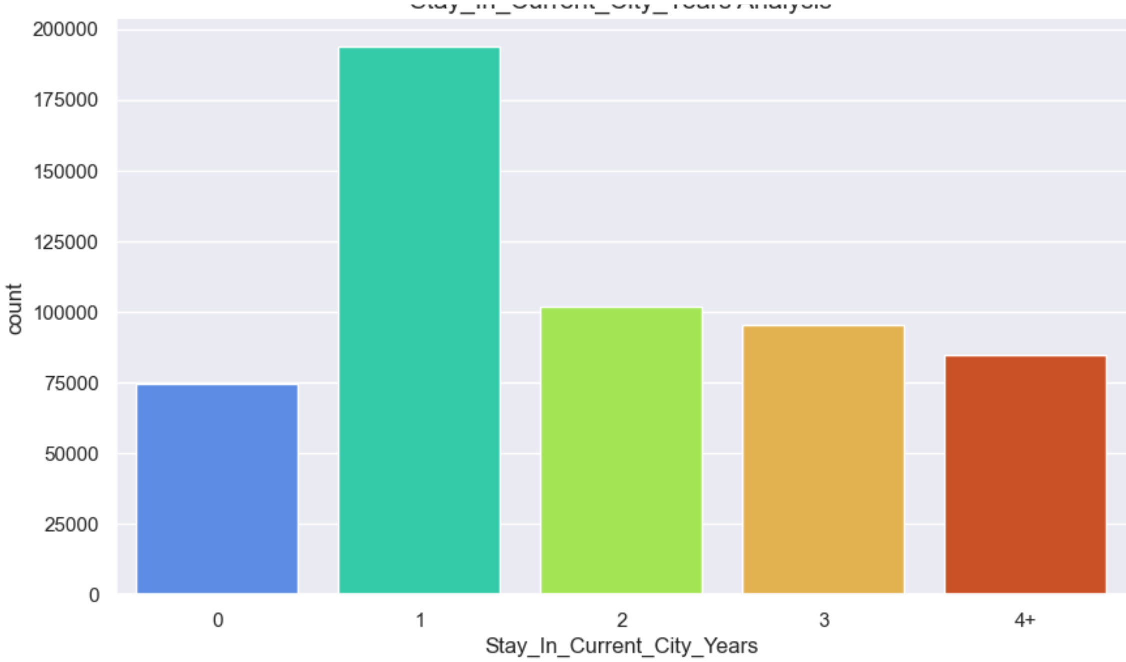
In [22]:
```
plt.figure(figsize=(10,40))
sns.set(style='darkgrid')

# Plot each categorical column
for i, col in enumerate(category, 1):
    plt.subplot(6, 1, i)
    sns.countplot(data=df, x=col, hue=col, palette='turbo', legend=False)
    sns.despine()
    plt.title(f'{col} Analysis', fontsize=14, fontfamily='sans-serif')

# Show the plot
plt.show()
```



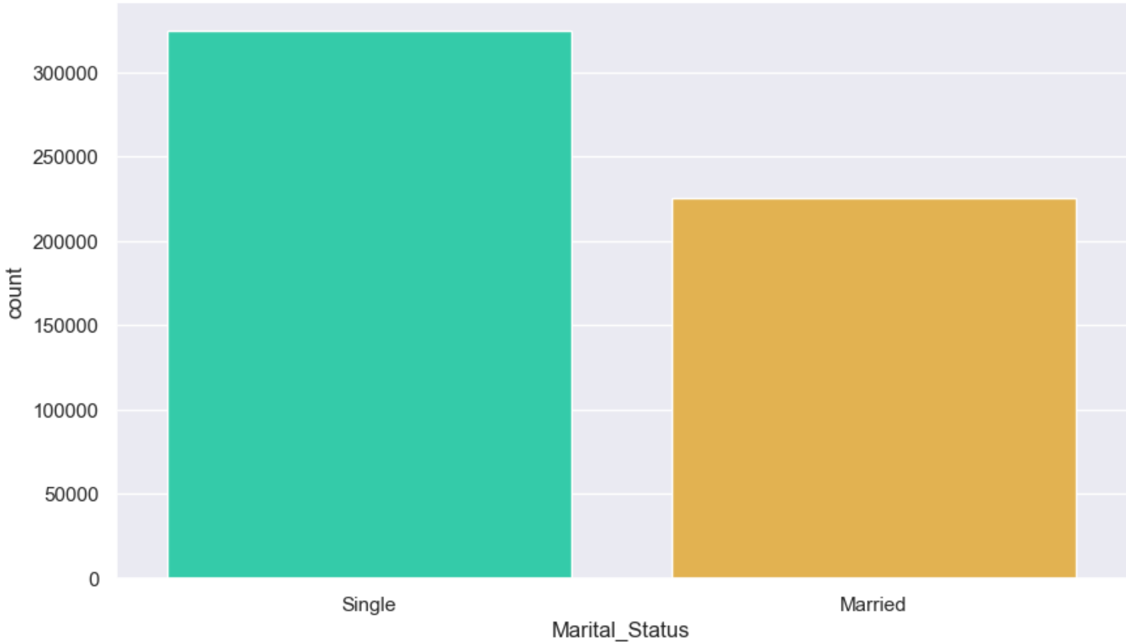




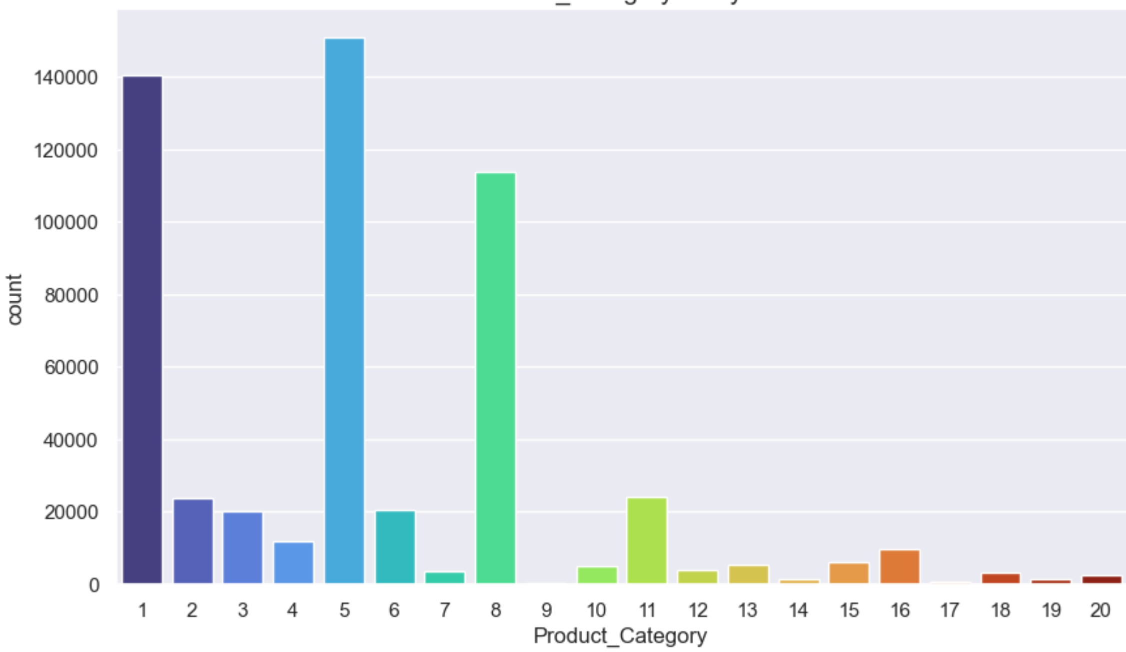
Stay_In_Current_City_Years Analysis



Marital_Status Analysis



Product_Category Analysis



Insights:

Age Group Distribution:

- The age group '26-35' has the highest count, indicating that customers in this age range make the most purchases. It is followed by the age groups '36-45' and '18-25'.

Occupation Analysis:

- Occupation '4' has the highest count, suggesting that customers with occupation '4' have the highest representation in the dataset. Occupations '0', '7', and '1' also have significant counts.

City Category Distribution:

- City_Category 'B' has the highest count, indicating that customers from City_Category 'B' have made the most purchases. City_Category 'C' and 'A' follow in terms of count.

Marital Status Impact:

- Customers with a marital status of 'Single' have a higher count compared to those who are 'Married', suggesting that single individuals make more purchases in the dataset.

City Residence Duration Impact:

- Customers who have stayed in their current city for more than 1 year show a higher purchase tendency, suggesting a positive correlation between the duration of stay and purchasing behavior.

Product Category Purchase Analysis:

- Product categories '1' and '5' exhibit higher purchase amounts, indicating that these categories contribute significantly to the overall sales revenue.

Bivariate Analysis

In [23]:
```
pivot = lambda index: df.pivot_table(index=df[index], columns='Gender', agg
```

In [24]:
```
pivot('Age')
```

Out[24]:

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 [25]:
```
pivot('Occupation')
```

Out[25]:

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 [26]:
```
pivot('City_Category')
```

Out[26]:

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

In [27]:
```
pivot('Stay_In_Current_City_Years')
```

Out[27]:

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

In [28]:
```
pivot('Marital_Status')
```

Out[28]:

Gender	F	M
Marital_Status		
Single	78821	245910
Married	56988	168349

In [29]:
```
df.columns
```

Out[29]:
```
Index(['User_ID', 'Product_ID', 'Gender', 'Age', 'Occupation', 'City_Categ
ory',
       'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category',
       'Purchase'],
      dtype='object')
```

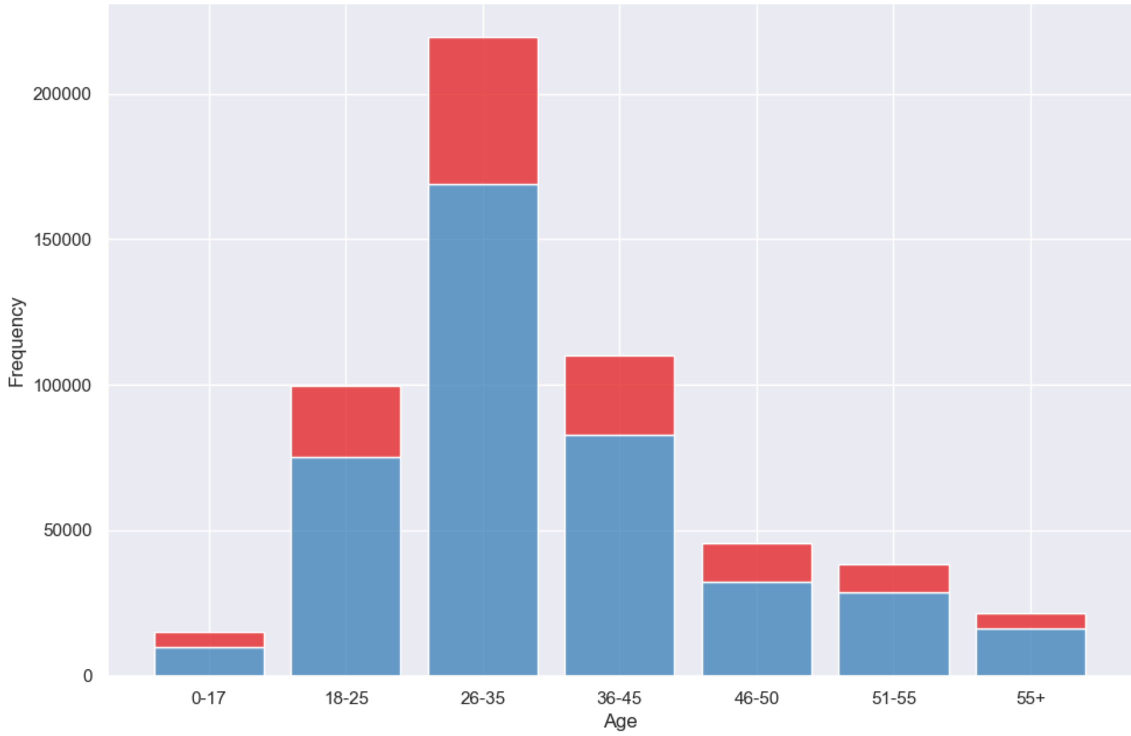
In [30]:
```
pivot('Product_Category')
```

Out[30]:

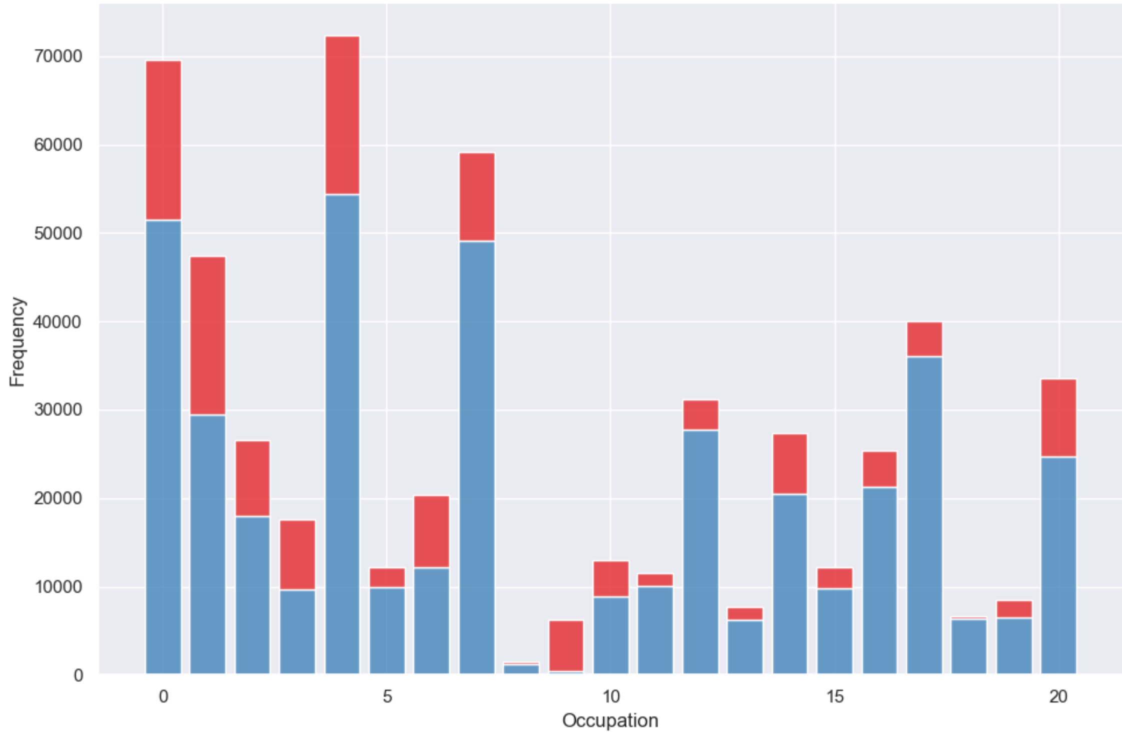
Gender Product_Category	F	M
1	24831	115547
2	5658	18206
3	6006	14207
4	3639	8114
5	41961	108972
6	4559	15907
7	943	2778
8	33558	80367
9	70	340
10	1162	3963
11	4739	19548
12	1532	2415
13	1462	4087
14	623	900
15	1046	5244
16	2402	7426
17	62	516
18	382	2743
19	451	1152
20	723	1827

In [31]:
```
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=df, x=col, hue='Gender', palette='Set1', legend=False
    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='

    plt.tight_layout()

plt.show()
```

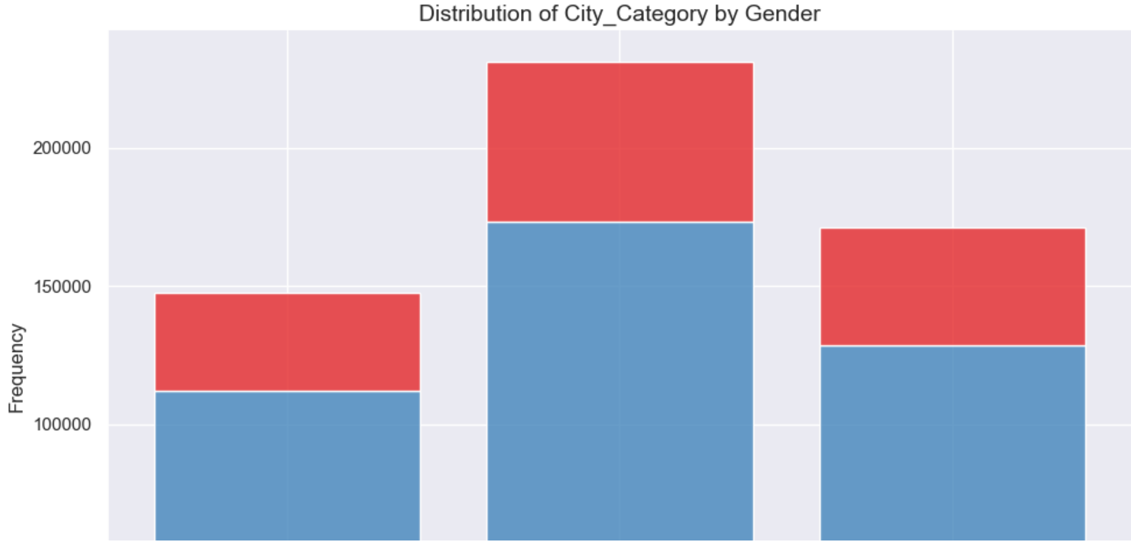
Distribution of Age by Gender

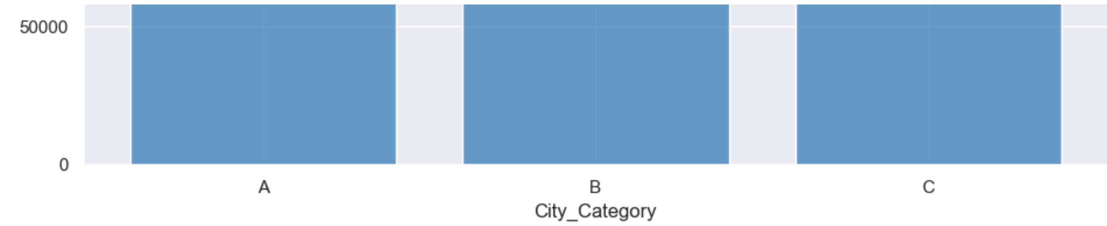


Distribution of Occupation by Gender

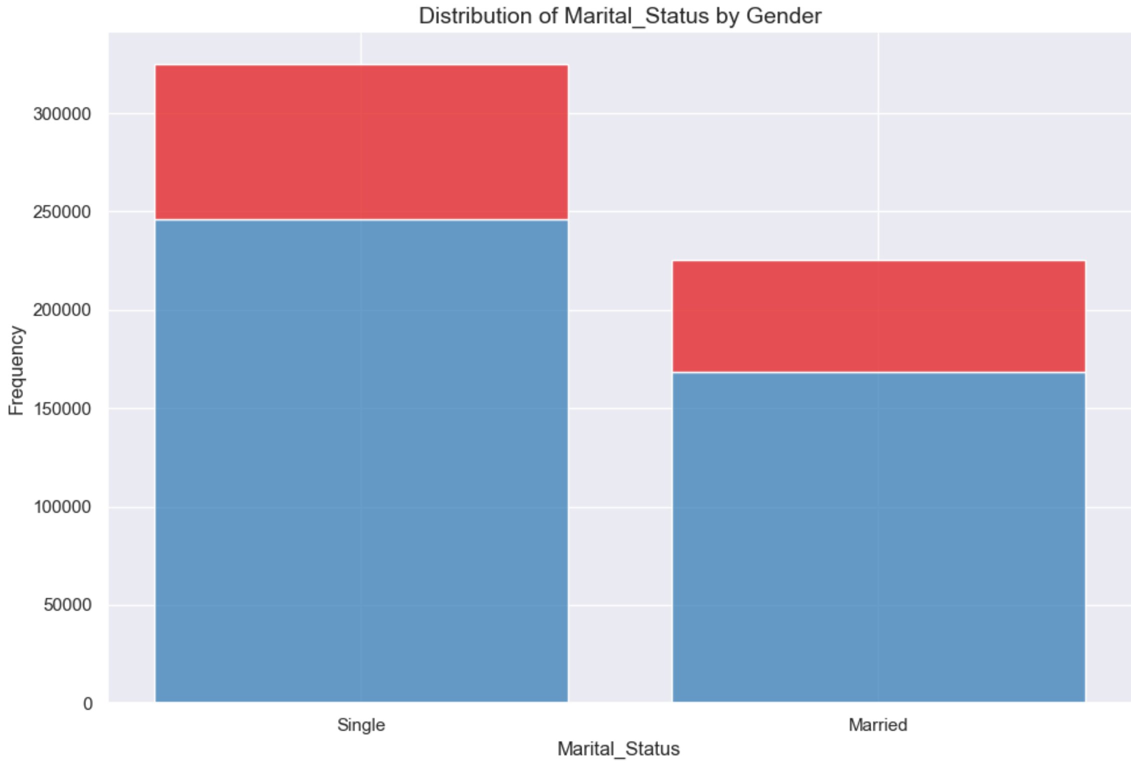


Distribution of City_Category by Gender

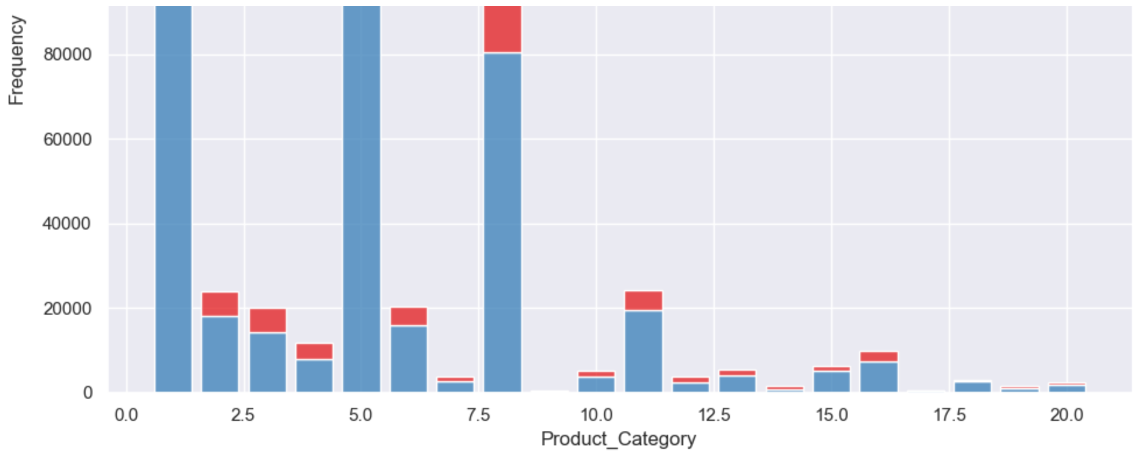



50000
0
A
B
C
City_Category


Distribution of Stay_In_Current_City_Years by Gender
Frequency
200000
175000
150000
125000
100000
75000
50000
25000
0
0
1
2
3
4+
Stay_In_Current_City_Years


Distribution of Marital_Status by Gender
Frequency
300000
250000
200000
150000
100000
50000
0
Single
Married
Marital_Status


Distribution of Product_Category by Gender
140000
120000
100000



Insights:

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.

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.

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'.

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.

Marital Status-Related Purchase Analysis:

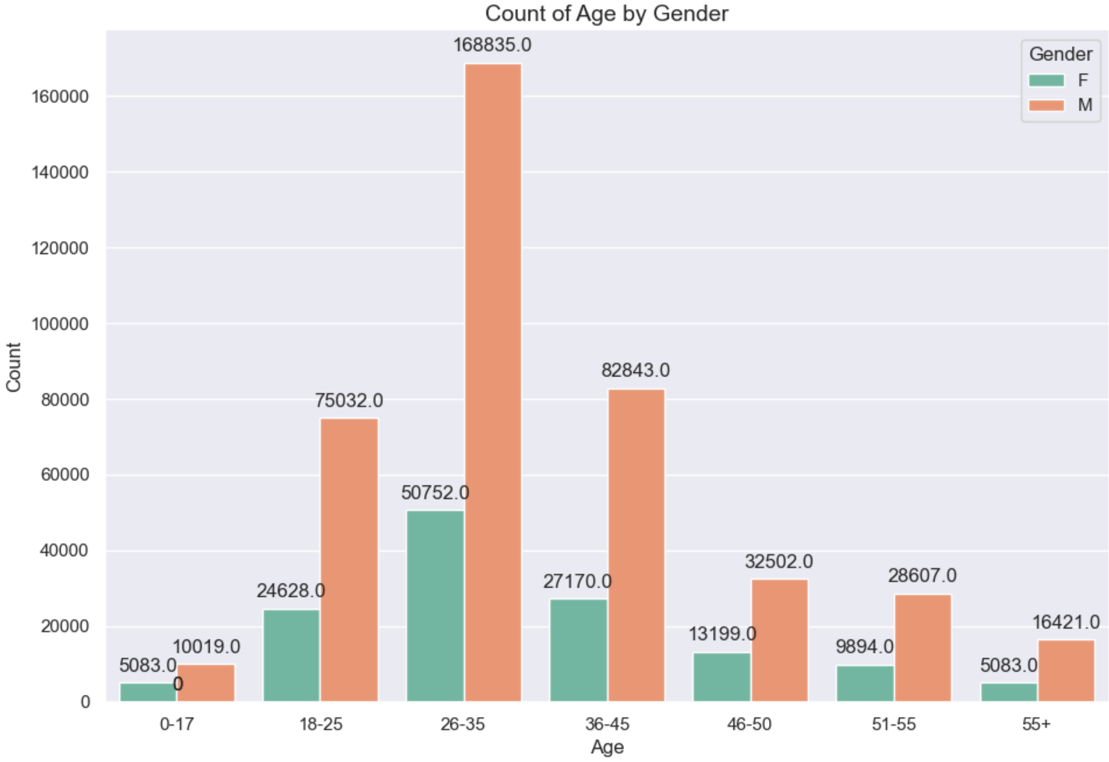
- Individuals with a marital status of 'Single' have higher purchase counts compared to those who are 'Married', indicating that single individuals contribute more to overall sales.

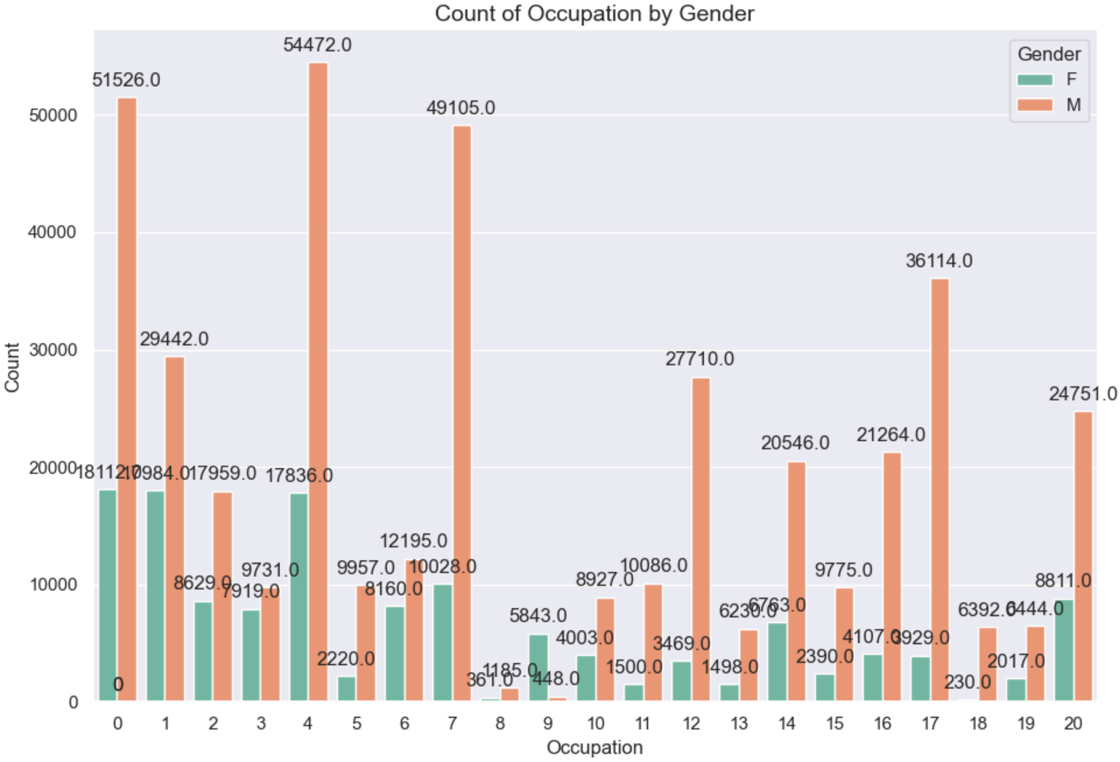
Product Category-Related Purchase Analysis:

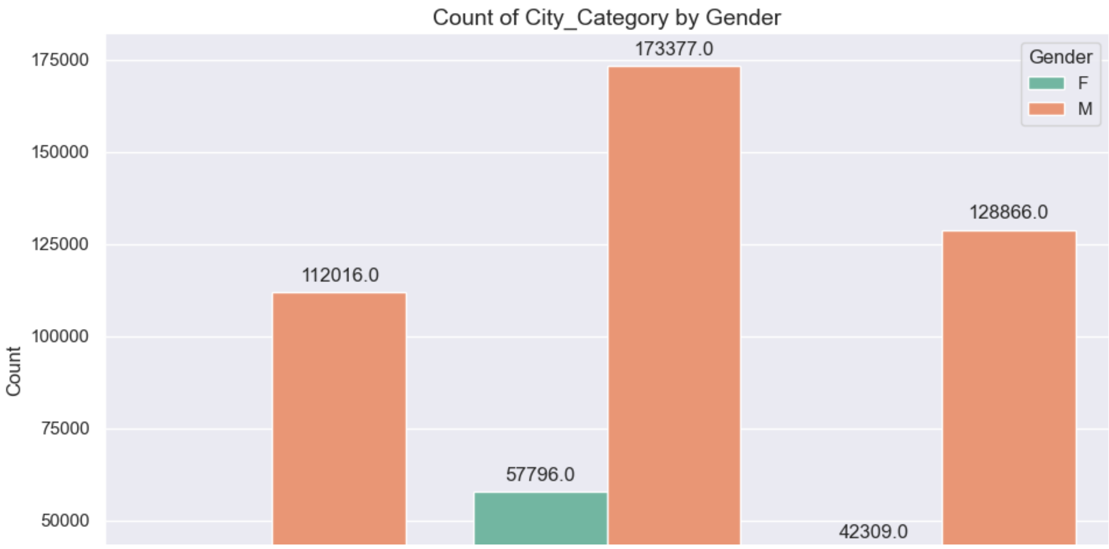
- Product Category '1' has the highest purchase counts, indicating that it significantly contributes to overall sales. Product Categories '5' and '8' also show notable purchase counts.

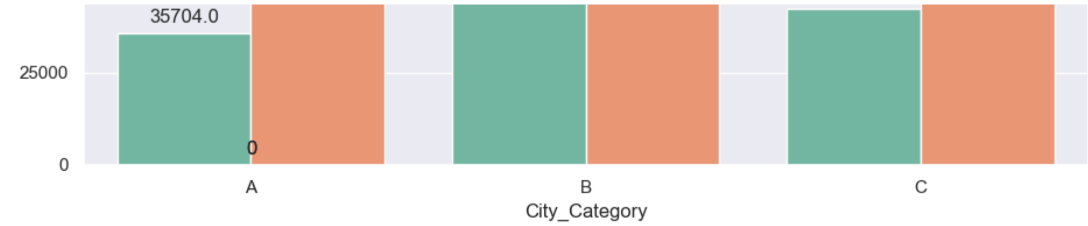
Multivariate Analysis

In [32]:
```
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=df, x=col, hue='Gender', palette='Set2')
    sns.despine()

    plt.title(f'Count of {col} by Gender', fontsize=14, fontfamily='sans-se
    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
Gender
F
M
Count
Age
0-17
18-25
26-35
36-45
46-50
51-55
55+
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

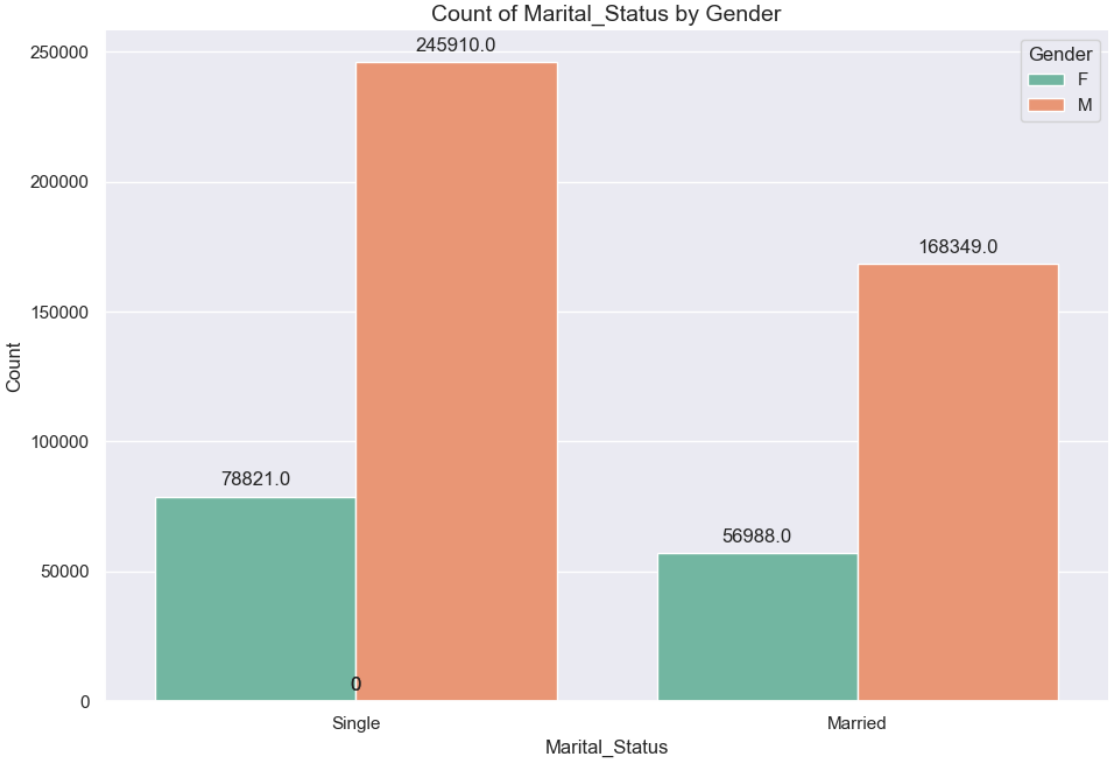

Count of Occupation by Gender
Gender
F
M
Count
Occupation
51526.0
29442.0
54472.0
49105.0
36114.0
27710.0
24751.0
20546.0
21264.0
17959.0
17836.0
12195.0
9731.0
9957.0
10028.0
8160.0
8927.0
10086.0
9775.0
8811.0
5843.0
4003.0
3469.0
2220.0
1500.0
1498.0
2390.0
1185.0
448.0
230.0
2017.0


Count of City_Category by Gender
Gender
F
M
Count
112016.0
173377.0
128866.0
57796.0
42309.0

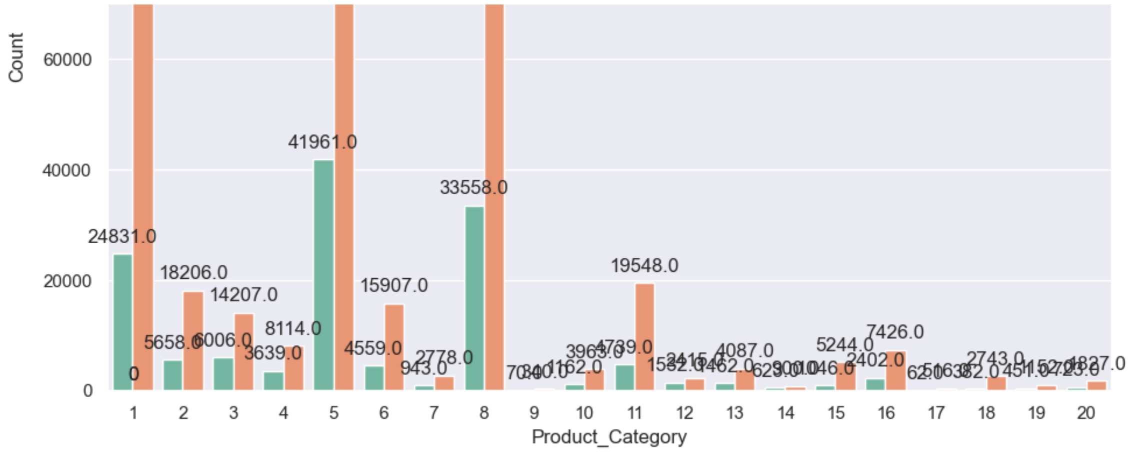


Count of Stay_In_Current_City_Years by Gender

Count of Marital_Status by Gender



Count of Product_Category by Gender



In [33]:
```
import warnings

warnings.simplefilter(action='ignore', category=FutureWarning)
```

Balck friday Sales analysis on gender

In [34]:
```
avg_purchase = df.groupby('Gender')[['Purchase']].mean().reset_index().roun
avg_purchase
```

Out[34]:

	Gender	Purchase
0	F	8734.57
1	M	9437.53

In [35]:
```
df_male = df[df['Gender']=='M']
df_female = df[df['Gender']=='F']
```

In [36]:
```
print(f'Male customers - {len(df_male)}')
print(f'Female customers - {len(df_female)}')
```

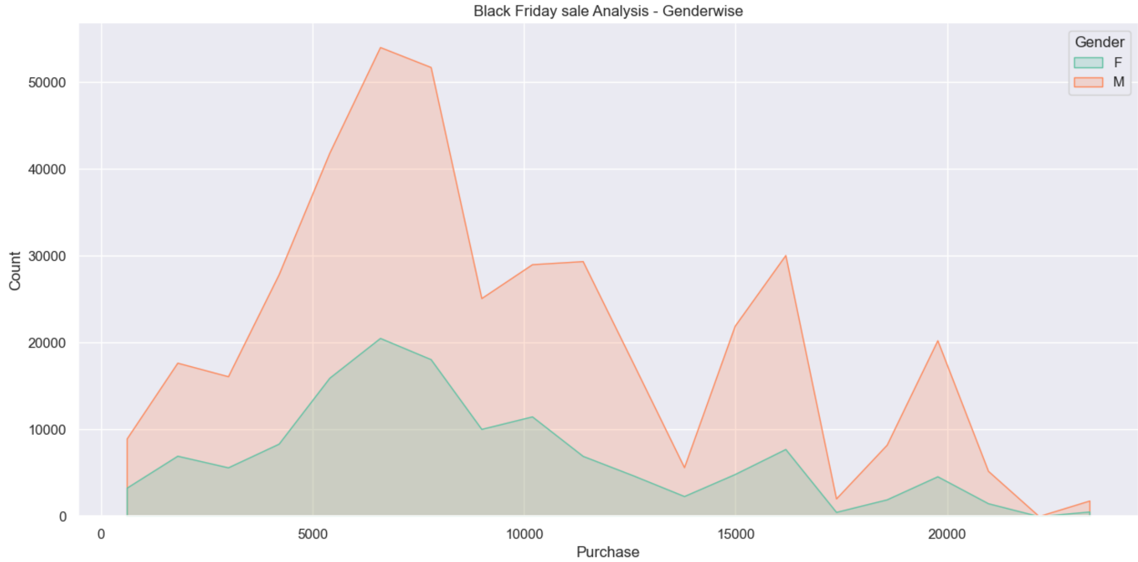
```
Male customers - 414259
Female customers - 135809
```

In [37]:
```
df.groupby('Gender')['Purchase'].describe().T
```

Out[37]:

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 [38]:
```
plt.figure(figsize=(15,7))
sns.set(style='darkgrid')
sns.histplot(data=df, x = "Purchase", bins=20, hue = "Gender",element='poly
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 [39]:
```
# Calculates the 95% confidence interval and width for a specified category

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_m

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

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

In [40]:
```
# Calculates the 95% confidence interval and width for a specified category

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

    # 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}')
```

Confidence intervals for the Average amount spent per gender.

95% confidence interval of Entire Dataset

In [41]:
```
data_ci(df, 'Gender', 'M')
```

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

In [42]:
```
data_ci(df, 'Gender', 'F')
```

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

95% confidence interval of 300 samples

In [43]:
```
sample_ci(df, 'Gender', 'M', 300)
```

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

In [44]:
```
sample_ci(df, '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 [45]:
```
sample_ci(df, 'Gender', 'M', 3000)
```

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

In [46]:
```
sample_ci(df, 'Gender', 'F', 3000)
```

```
Sample Size: 3000
F 95% confidence interval: (8630.48138780842, 8982.545945524911)
F Width: 352.0645577164905
```

95% confidence interval of 30000 samples

In [47]:
```
sample_ci(df, 'Gender', 'M', 30000)
```

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

In [48]:
```
sample_ci(df, 'Gender', 'M', 30000)
```

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

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 [49]:
```
data_ci(df, 'Marital_Status', 'Married')
```

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

In [50]:
```
data_ci(df, 'Marital_Status', 'Single')
```

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

95% confidence interval of 300 samples

In [51]:
```
sample_ci(df, 'Marital_Status', 'Married', 300)
```

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

In [52]:
```
sample_ci(df, '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 [53]:
```
sample_ci(df, 'Marital_Status', 'Married', 3000)
```

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

In [54]:
```
sample_ci(df, '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 [55]:
```
sample_ci(df, 'Marital_Status', 'Married', 30000)
```

```
Sample Size: 30000
Married 95% confidence interval: (9198.156166015178, 9312.029900651487)
Married Width: 113.87373463630865
```

In [56]:
```
sample_ci(df, '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.

95% confidence interval of Entire Dataset

In [57]:
```
data_ci(df, 'City_Category', 'A')
```

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

In [58]:
```
data_ci(df, 'City_Category', 'B')
```

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

In [59]:
```
data_ci(df, 'City_Category', 'C')
```

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

95% confidence interval of 300 samples

In [60]:
```
sample_ci(df, 'City_Category', 'A', 300)
```

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

In [61]:
```
sample_ci(df, 'City_Category', 'B', 300)
```

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

In [62]:
```
sample_ci(df, '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 [63]:
```
sample_ci(df, 'City_Category', 'A', 3000)
```

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

In [64]:
```
sample_ci(df, 'City_Category', 'B', 3000)
```

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

In [65]:
```
sample_ci(df, '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 [66]:
```
sample_ci(df, 'City_Category', 'A', 30000)
```

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

In [67]:
```
sample_ci(df, 'City_Category', 'B', 30000)
```

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

In [68]:
```
sample_ci(df, '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.

Business Recommendations:

1. **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.

2. **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.

3. **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.

4. **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.

5. **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.

6. **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.

7. **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.

8. **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.

9. **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.

10. **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.