Walmart Business Case Study

Importing Libraries for Data Analysis and Visualization

```
# Importing the Libraries:
import pandas as pd
import numpy as np
import scipy.stats as stats
from textblob import TextBlob
import seaborn as sns
import matplotlib.pyplot as plt
import math
from scipy.stats import chi2_contingency
from scipy.stats import ttest_ind
from scipy.stats import f_oneway
```

Uploading File to Google Colab Environment

```
# Upload the File
from google.colab import files
uploaded = files.upload()
```

```
Choose Files No file chosen      Upload widget is only available when the cell has been executed in
the current browser session. Please rerun this cell to enable.
Saving walmart_data.csv to walmart_data.csv
```

Loading Data from CSV File into DataFrame

```
# Loading Walmart Data from CSV File
Data = pd.read_csv('walmart_data.csv')
```

Creating a Copy of the DataFrame

```
# Creating a Copy of the Walmart Data
df = Data.copy()
```

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

```
# Previewing the First Five Rows of the DataFrame
df.head()
```

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

```
# Getting the Dimensions of the DataFrame
df.shape
```

```
(550068, 10)
```

```
# Displaying DataFrame Summary Information
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
```

```
# Checking for Missing Values in the DataFrame
df.isnull().sum()
```

	0
User_ID	0
Product_ID	0
Gender	0
Age	0
Occupation	0
City_Category	0
Stay_In_Current_City_Years	0
Marital_Status	0
Product_Category	0
Purchase	0

dtype: int64

```
# Listing Column Names in the DataFrame
df.columns
```

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

```
# Counting Duplicate Rows in the DataFrame
df.duplicated().sum()
```

```
0
```

```
# Counting Unique Values in Each Column of the DataFrame
df.nunique()
```

	0
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

```
# Statistical Summary of the DataFrame
df.describe()
```

	User_ID	Occupation	Marital_Status	Product_Category	Purchase
count	5.500680e+05	550068.000000	550068.000000	550068.000000	550068.000000
mean	1.003029e+06	8.076707	0.409653	5.404270	9263.968713
std	1.727592e+03	6.522660	0.491770	3.936211	5023.065394
min	1.000001e+06	0.000000	0.000000	1.000000	12.000000
25%	1.001516e+06	2.000000	0.000000	1.000000	5823.000000
50%	1.003077e+06	7.000000	0.000000	5.000000	8047.000000
75%	1.004478e+06	14.000000	1.000000	8.000000	12054.000000
max	1.006040e+06	20.000000	1.000000	20.000000	23961.000000

```python
# Transposed Statistical Summary of the DataFrame
df.describe().T
```

	count	mean	std	min	25%	50%
User_ID	550068.0	1.003029e+06	1727.591586	1000001.0	1001516.0	1003077.0
Occupation	550068.0	8.076707e+00	6.522660	0.0	2.0	7.0
Marital_Status	550068.0	4.096530e-01	0.491770	0.0	0.0	0.0
Product_Category	550068.0	5.404270e+00	3.936211	1.0	1.0	5.0
Purchase	550068.0	9.263969e+03	5023.065394	12.0	5823.0	8047.0

```python
# Transposed Statistical Summary of Categorical Columns in the DataFrame
df.describe(include = 'object').T
```

	count	unique	top	freq
Product_ID	550068	3631	P00265242	1880
Gender	550068	2	M	414259
Age	550068	7	26-35	219587
City_Category	550068	3	B	231173
Stay_In_Current_City_Years	550068	5	1	193821

```python
# Displaying the Data Types of Each Column in the DataFrame
df.dtypes
```

	0
User_ID	int64
Product_ID	object
Gender	object
Age	object
Occupation	int64
City_Category	object
Stay_In_Current_City_Years	object
Marital_Status	int64
Product_Category	int64
Purchase	int64

dtype: object

2. Detect Null Values and Outliers

a) Find the outliers for every continuous variable in the dataset

b) Remove/clip the data between the 5 percentile and 95 percentile

Identifying Continuous Variables::

```
# Identifying Continuous Variables:
Continuous_Vars = df.select_dtypes(include=['float64', 'int64']).columns
Continuous_Vars
```

```
Index(['User_ID', 'Occupation', 'Marital_Status', 'Product_Category',
       'Purchase'],
      dtype='object')
```

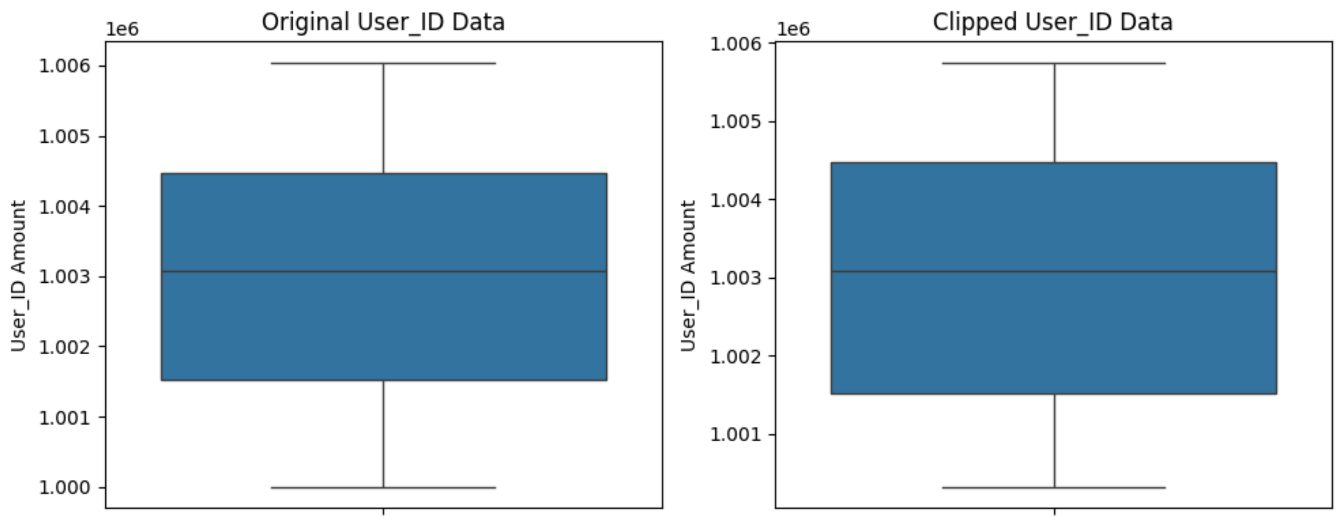
i) Outliers Dedection for User_ID:

```
# Outliers Dedection for User_ID:
# Calculate the 5th and 95th percentiles:
Lower_Bound = df['User_ID'].quantile(0.05)
Upper_Bound = df['User_ID'].quantile(0.95)

# Clip the data between the 5th and 95th percentiles:
df['User_ID_Clipped'] = np.clip(df['User_ID'], Lower_Bound, Upper_Bound)
```

```

# Display the first few rows of the modified DataFrame
print(df[['User_ID', 'User_ID_Clipped']])
```

```
        User_ID  User_ID_Clipped
0       1000001          1000329
1       1000001          1000329
2       1000001          1000329
3       1000001          1000329
4       1000002          1000329
...         ...              ...
550063  1006033          1005747
550064  1006035          1005747
550065  1006036          1005747
550066  1006038          1005747
550067  1006039          1005747

[550068 rows x 2 columns]
```

```
# Visualizing User_ID Amounts with a Boxplot to find the Outliers:

# Set up the matplotlib figure
plt.figure(figsize=(10, 4))

# Create a boxplot for the original User_ID data
plt.subplot(1, 2, 1)
sns.boxplot(y=df['User_ID'])
plt.title('Original User_ID Data')
plt.ylabel('User_ID Amount')

# Create a boxplot for the clipped User_ID data
plt.subplot(1, 2, 2)
sns.boxplot(y=df['User_ID_Clipped'])
plt.title('Clipped User_ID Data')
plt.ylabel('User_ID Amount')

# Adjust layout to prevent overlap and show the plots
plt.tight_layout()
plt.show()
```

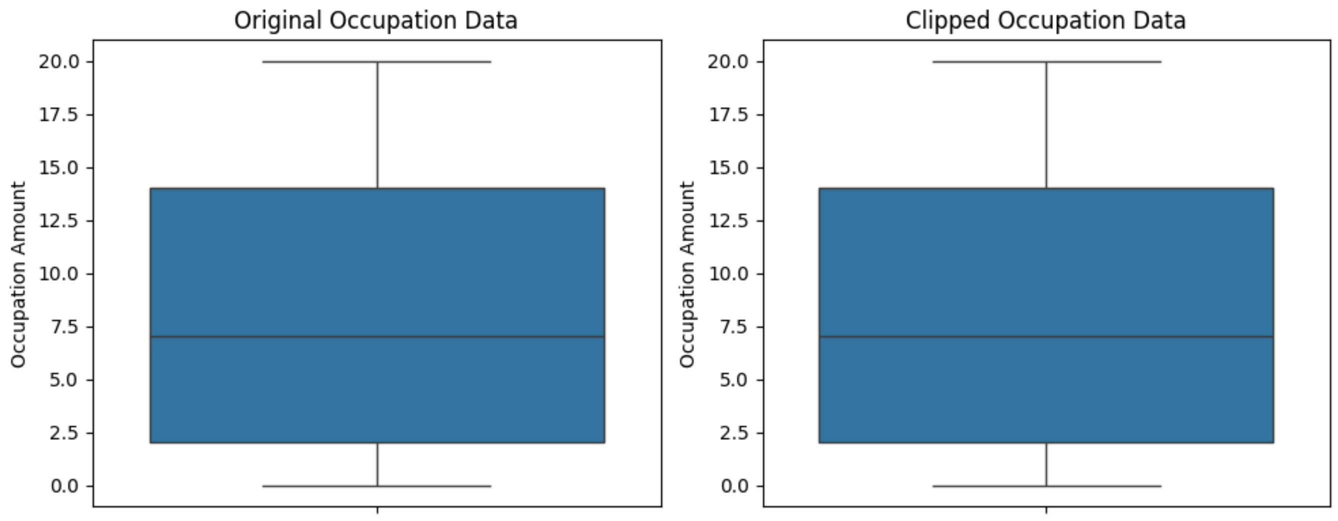


ii) Outliers Dedection for Occupation:

```
# Outliers Dedection for Occupation:
# Calculate the 5th and 95th percentiles:
Lower_Bound = df['Occupation'].quantile(0.05)
Upper_Bound = df['Occupation'].quantile(0.95)

# Clip the data between the 5th and 95th percentiles:
df['Occupation_Clipped'] = np.clip(df['Occupation'], Lower_Bound, Upper_Bound)

# Display the first few rows of the modified DataFrame
print(df[['Occupation', 'Occupation_Clipped']])
```

```
        Occupation  Occupation_Clipped
0               10                  10
1               10                  10
2               10                  10
3               10                  10
4               16                  16
...            ...                 ...
550063          13                  13
550064           1                   1
550065          15                  15
550066           1                   1
550067           0                   0

[550068 rows x 2 columns]
```

```python
# Visualizing Occupation Amounts with a Boxplot to find the Outliers:

# Set up the matplotlib figure
plt.figure(figsize=(10, 4))

# Create a boxplot for the original Occupation data
plt.subplot(1, 2, 1)
sns.boxplot(y=df['Occupation'])
plt.title('Original Occupation Data')
plt.ylabel('Occupation Amount')

# Create a boxplot for the clipped Occupation data
plt.subplot(1, 2, 2)
sns.boxplot(y=df['Occupation_Clipped'])
plt.title('Clipped Occupation Data')
plt.ylabel('Occupation Amount')

# Adjust layout to prevent overlap and show the plots
plt.tight_layout()
plt.show()
```



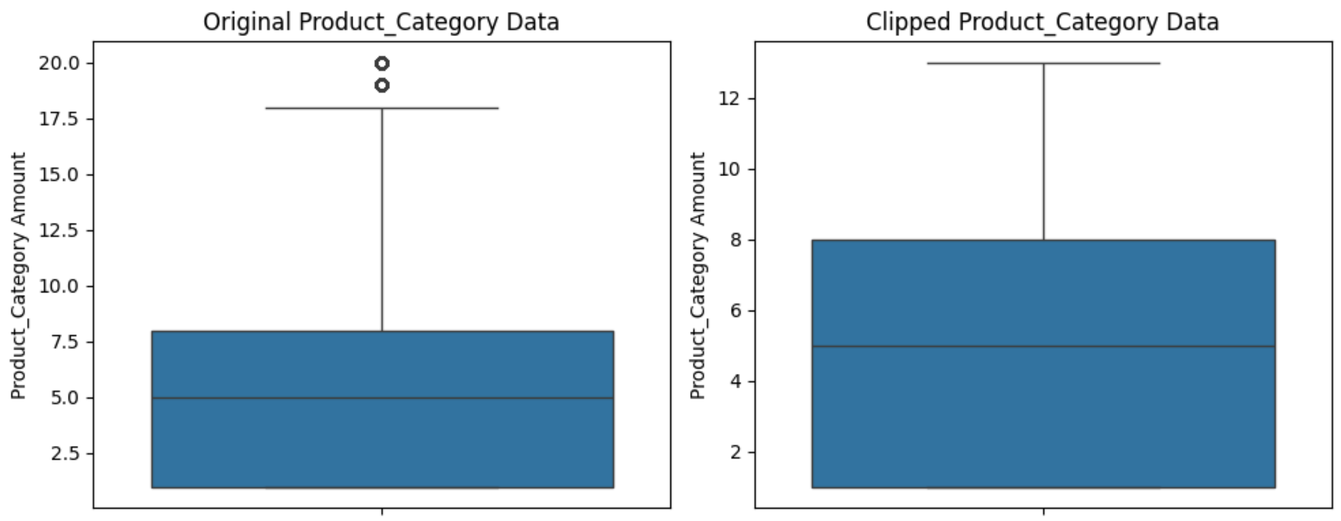
iii) Outliers Dedection for Product_Category:

```python
# Outliers Dedection for Occupation:
# Calculate the 5th and 95th percentiles:
Lower_Bound = df['Product_Category'].quantile(0.05)
Upper_Bound = df['Product_Category'].quantile(0.95)

```

```
# Clip the data between the 5th and 95th percentiles:
df['Product_Category_Clipped'] = np.clip(df['Product_Category'], Lower_Bound, Upper_Bour

# Display the first few rows of the modified DataFrame
print(df[['Product_Category', 'Product_Category_Clipped']])
```

```
        Product_Category  Product_Category_Clipped
0                      3                         3
1                      1                         1
2                     12                        12
3                     12                        12
4                      8                         8
...                  ...                       ...
550063                20                        13
550064                20                        13
550065                20                        13
550066                20                        13
550067                20                        13

[550068 rows x 2 columns]
```

```
# Visualizing Product_Category Amounts with a Boxplot to find the Outliers:

# Set up the matplotlib figure
plt.figure(figsize=(10, 4))

# Create a boxplot for the original Product_Category data
plt.subplot(1, 2, 1)
sns.boxplot(y=df['Product_Category'])
plt.title('Original Product_Category Data')
plt.ylabel('Product_Category Amount')

# Create a boxplot for the clipped Product_Category data
plt.subplot(1, 2, 2)
sns.boxplot(y=df['Product_Category_Clipped'])
plt.title('Clipped Product_Category Data')
plt.ylabel('Product_Category Amount')

# Adjust layout to prevent overlap and show the plots
plt.tight_layout()
plt.show()
```



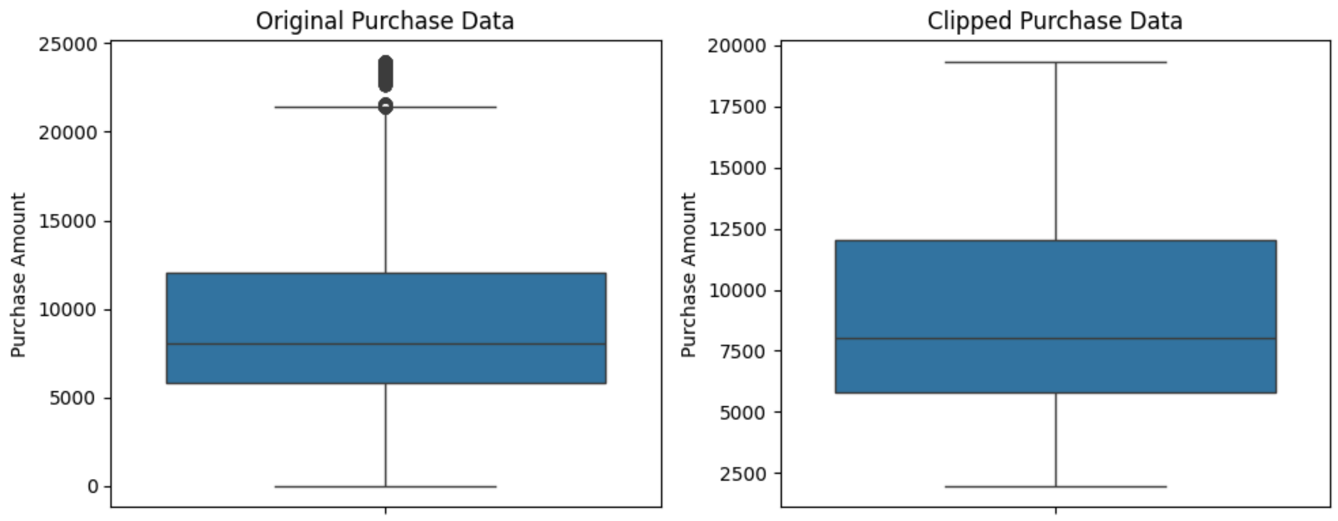
iv) Outliers Dedection for Purchase:

```
# Outliers Dedection for Purchase:
# Calculate the 5th and 95th percentiles:
Lower_Bound = df['Purchase'].quantile(0.05)
Upper_Bound = df['Purchase'].quantile(0.95)

# Clip the data between the 5th and 95th percentiles:
df['Purchase_Clipped'] = np.clip(df['Purchase'], Lower_Bound, Upper_Bound)

# Display the first few rows of the modified DataFrame
print(df[['Purchase', 'Purchase_Clipped']].head())
```

```
   Purchase  Purchase_Clipped
0      8370              8370
1     15200             15200
2      1422              1984
3      1057              1984
4      7969              7969
```

```
# Visualizing Purchase Amounts with a Boxplot to find the Outliers:

# Set up the matplotlib figure
plt.figure(figsize=(10, 4))

# Create a boxplot for the original Purchase data
plt.subplot(1, 2, 1)
sns.boxplot(y=df['Purchase'])
```

```
plt.title('Original Purchase Data')
plt.ylabel('Purchase Amount')

# Create a boxplot for the clipped Purchase data
plt.subplot(1, 2, 2)
sns.boxplot(y=df['Purchase_Clipped'])
plt.title('Clipped Purchase Data')
plt.ylabel('Purchase Amount')

# Adjust layout to prevent overlap and show the plots
plt.tight_layout()
plt.show()
```



Insights:

Improved Data Quality:

i) By clipping outliers, the data becomes more representative of the typical user, reducing the influence of extreme values.

ii) This improves the robustness and reliability of subsequent analyses.

Impact on Analysis:

i) Reducing outliers can stabilize algorithms sensitive to extreme values, like linear regression.

ii) Insights derived from the clipped data will be more reflective of the central trends rather than skewed by extreme anomalies.

Data Distribution:
i) Visualizing the data before and after clipping (e.g., with boxplots or histograms) can provide a clear picture of the outliers' impact and the data's distribution.
ii) This helps in understanding how much the outliers skew the data and how effective the clipping process is.

Further Steps:
i) After clipping, re-evaluate the data distribution and consider further transformations or normalizations if needed.
ii) Use the cleaned data for training predictive models or performing other statistical analyses to ensure higher accuracy and performance.

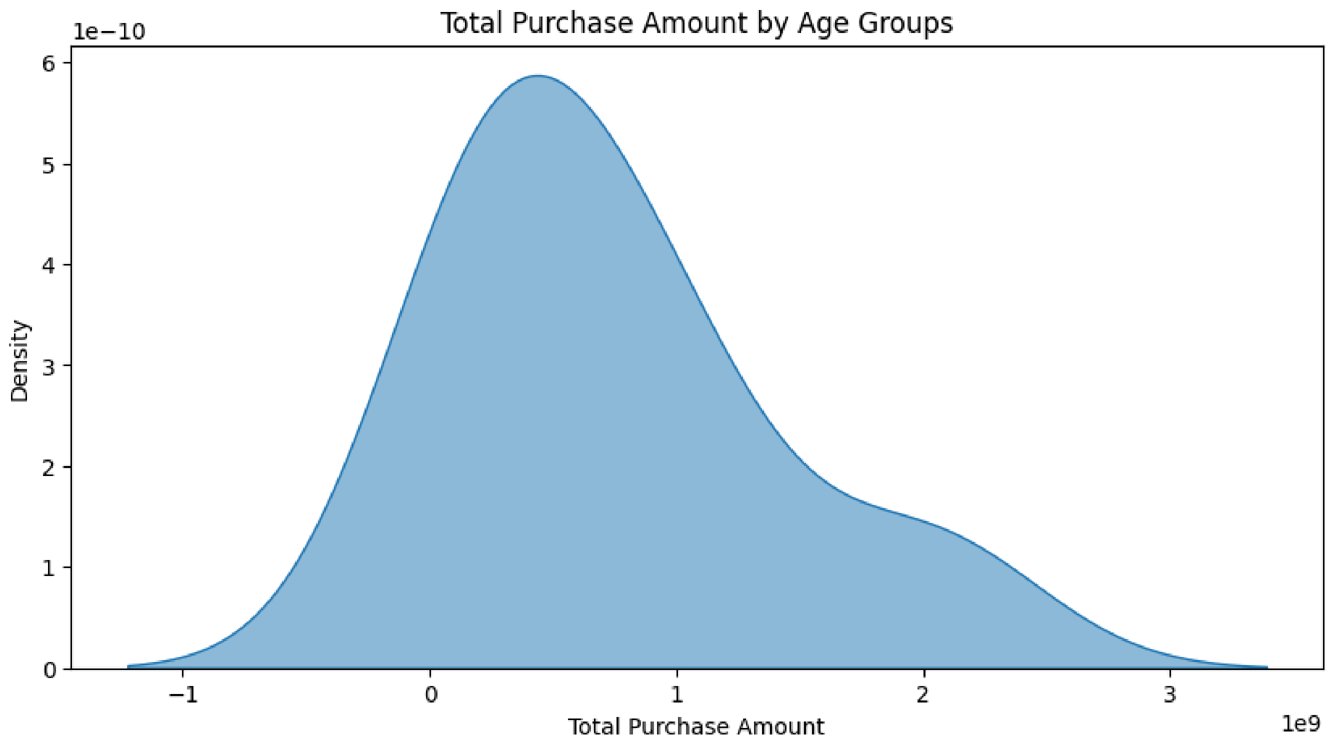
3. Data Exploration

a) What products are different age groups buying?

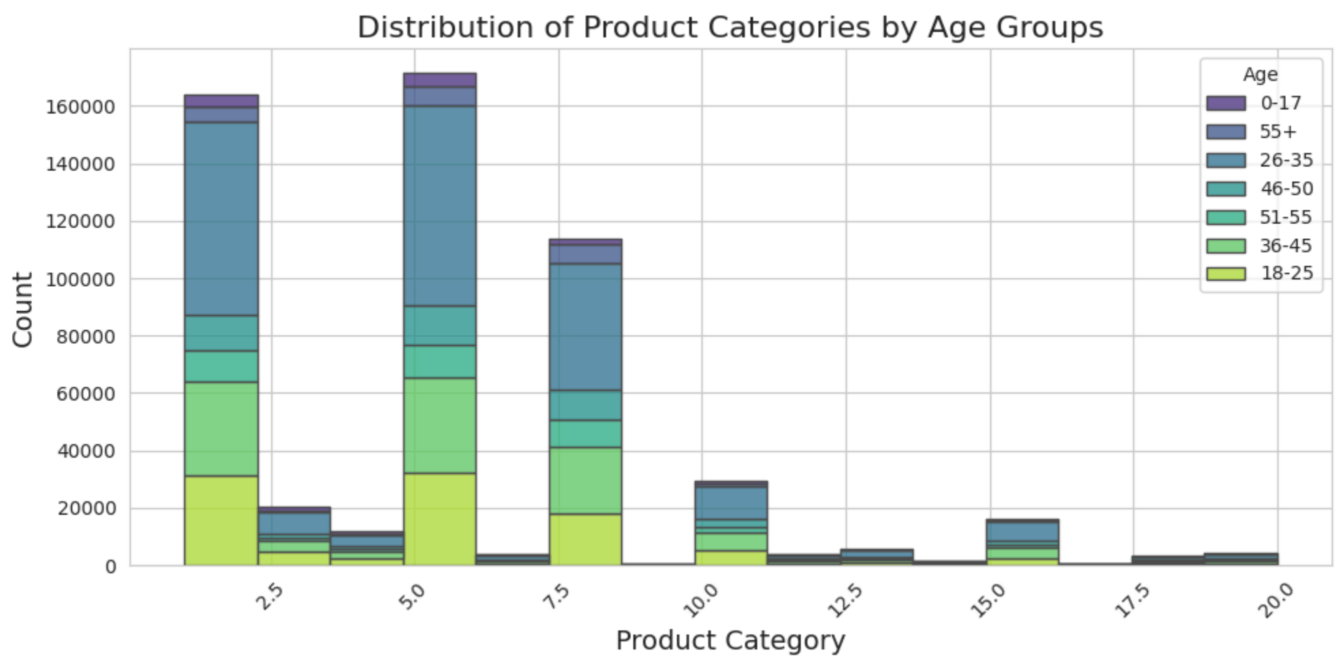
```
# Group by Age and Product_Category, then aggregate the total Purchase amounts:
# Age_Product_Purchase = df.groupby(['Age', 'Product_Category'])['Purchase'].sum().sort_
# print(Age_Product_Purchase)

Age_Product_Purchase = df.groupby('Age')['Purchase'].sum().sort_values(ascending=False).
print(Age_Product_Purchase)
```

```
     Age    Purchase
0  26-35  2031770578
1  36-45  1026569884
2  18-25   913848675
3  46-50   420843403
4  51-55   367099644
5    55+   200767375
6   0-17   134913183
```

```
# Create the KDE plot
plt.figure(figsize=(10, 5))

# Since Age_Product_Purchase contains the total purchase amounts by age,
sns.kdeplot(data=Age_Product_Purchase, x='Purchase', fill=True, alpha=0.5)

# Set title and labels
plt.title('Total Purchase Amount by Age Groups')
plt.xlabel('Total Purchase Amount')
plt.ylabel('Density')
plt.grid(False)
plt.show()
```



```
# Set the style of the plot
sns.set_style("whitegrid")

# Set up the figure size
plt.figure(figsize=(10, 5))

# Create a histplot to show the distribution of Product Categories by Age
sns.histplot(data=df, x='Product_Category', hue='Age', multiple='stack', palette='viridi

# Set plot title and labels
plt.title('Distribution of Product Categories by Age Groups', fontsize=16)
plt.xlabel('Product Category', fontsize=14)
plt.ylabel('Count', fontsize=14)

# Rotate x-axis labels for better readability
plt.xticks(rotation=45)

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



Insights:

Age Group Spending Patterns:

Analyze top-spending age groups to target high-value demographics effectively.

Product Category Popularity by Age:

Visualize which age groups prefer specific product categories to tailor offerings.

Strategic Marketing Insights:

Develop focused campaigns to engage key spending age groups for increased sales.

Inventory Management:

Optimize stock levels based on age-specific product preferences for better service.

Pricing Strategies:

Craft pricing models that reflect the varying spending powers of different age groups.

b) Is there a relationship between age, marital status, and the amount spent?

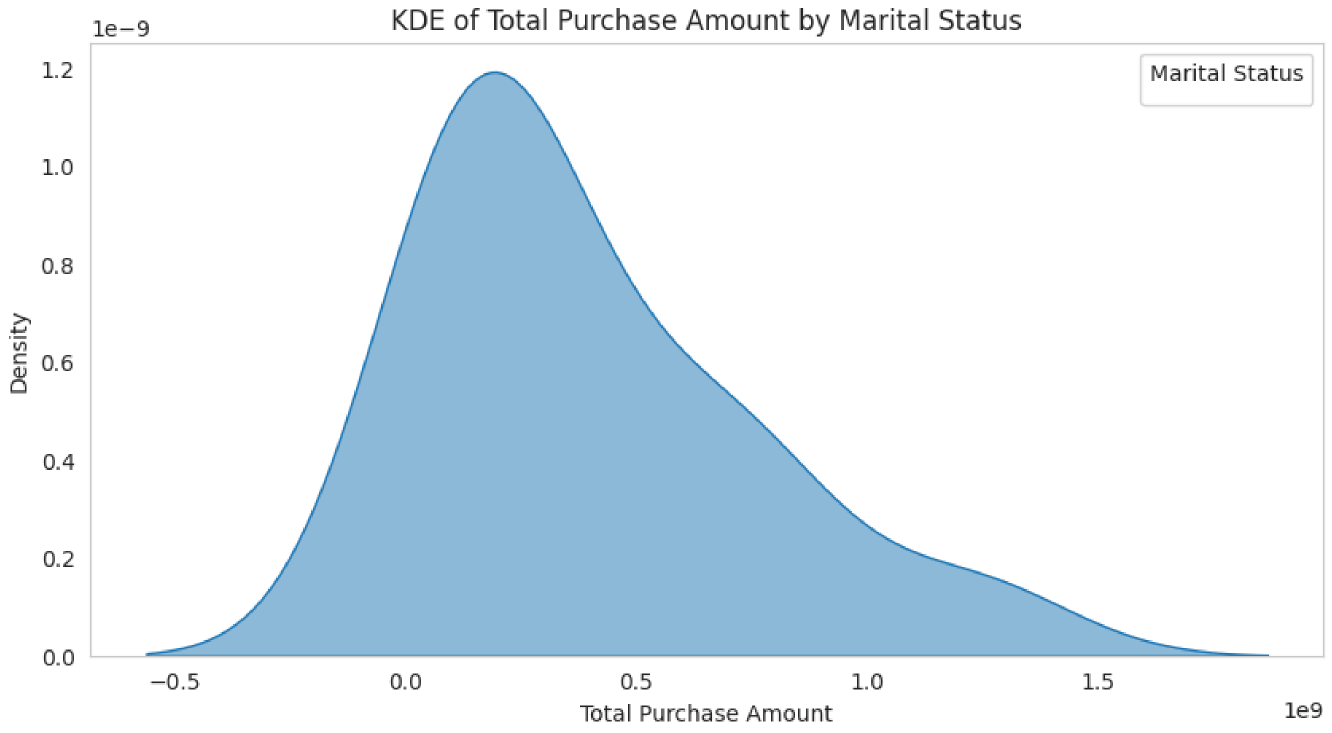
Multivariate Analysis Techniques

```
# b. Group Analysis with Aggregation
# Clean 'Stay_In_Current_City_Years' to make it numeric
df['Stay_In_Current_City_Years'] = df['Stay_In_Current_City_Years'].replace({'4+': 4})
Relationship_between_Age_Marital_Status = df.groupby(['Age', 'Marital_Status'])['Purchas
print(Relationship_between_Age_Marital_Status)
```

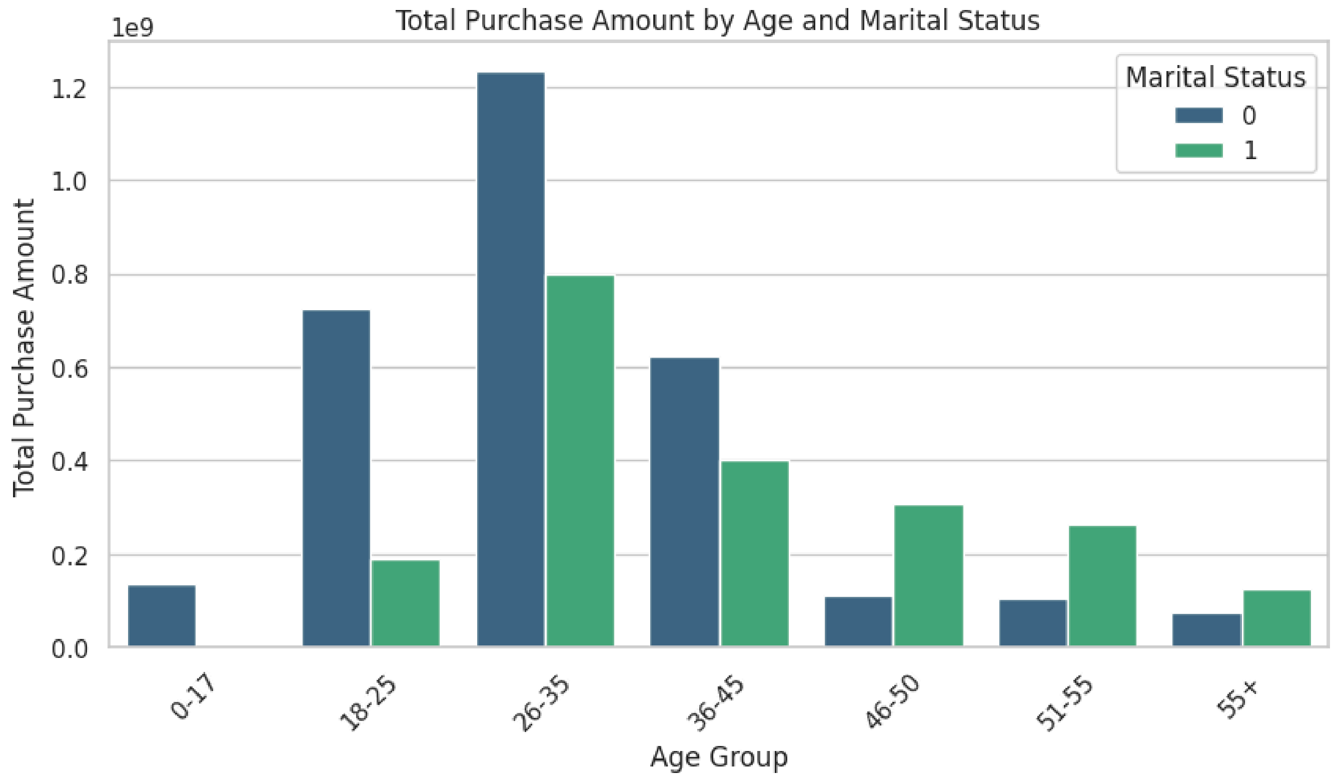
```
      Age  Marital_Status    Purchase
0    0-17               0   134913183
1   18-25               0   723920602
2   18-25               1   189928073
3   26-35               0  1233330102
4   26-35               1   798440476
5   36-45               0   624110760
6   36-45               1   402459124
7   46-50               0   113658360
8   46-50               1   307185043
9   51-55               0   103792394
10  51-55               1   263307250
11    55+               0    75202046
12    55+               1   125565329
```

```
# Create the KDE plot
plt.figure(figsize=(10, 5))
sns.kdeplot(data=Relationship_between_Age_Marital_Status, x='Purchase', fill=True, alpha

# Set title and labels
plt.title('KDE of Total Purchase Amount by Marital Status')
plt.xlabel('Total Purchase Amount')
plt.ylabel('Density')
plt.legend(title='Marital Status')
plt.grid(False)
plt.show()
```

```
WARNING:matplotlib.legend:No artists with labels found to put in legend.  Note that arti
```



```
sns.set(style="whitegrid")

# Create a bar plot
plt.figure(figsize=(10, 5))
sns.barplot(x='Age', y='Purchase', hue='Marital_Status', data=Relationship_between_Age_M

# Set title and labels
plt.title('Total Purchase Amount by Age and Marital Status')
plt.xlabel('Age Group')
plt.ylabel('Total Purchase Amount')
plt.legend(title='Marital Status')
plt.xticks(rotation=45)
plt.show()
```



Insights:

Age Group vs. Total Purchase:

The bar plot shows the total purchase amounts for different age groups. This helps identify which age groups are the biggest spenders.

Impact of Marital Status:

i) By introducing Marital_Status as a hue, the plot differentiates spending patterns between married and unmarried individuals within each age group.
ii) Noticeable differences indicate how marital status influences spending habits in various age groups.

Spending Trends:

i) Younger age groups might show varied spending habits based on their marital status. For example, unmarried individuals in the '18-25' group might spend differently compared to their married counterparts.

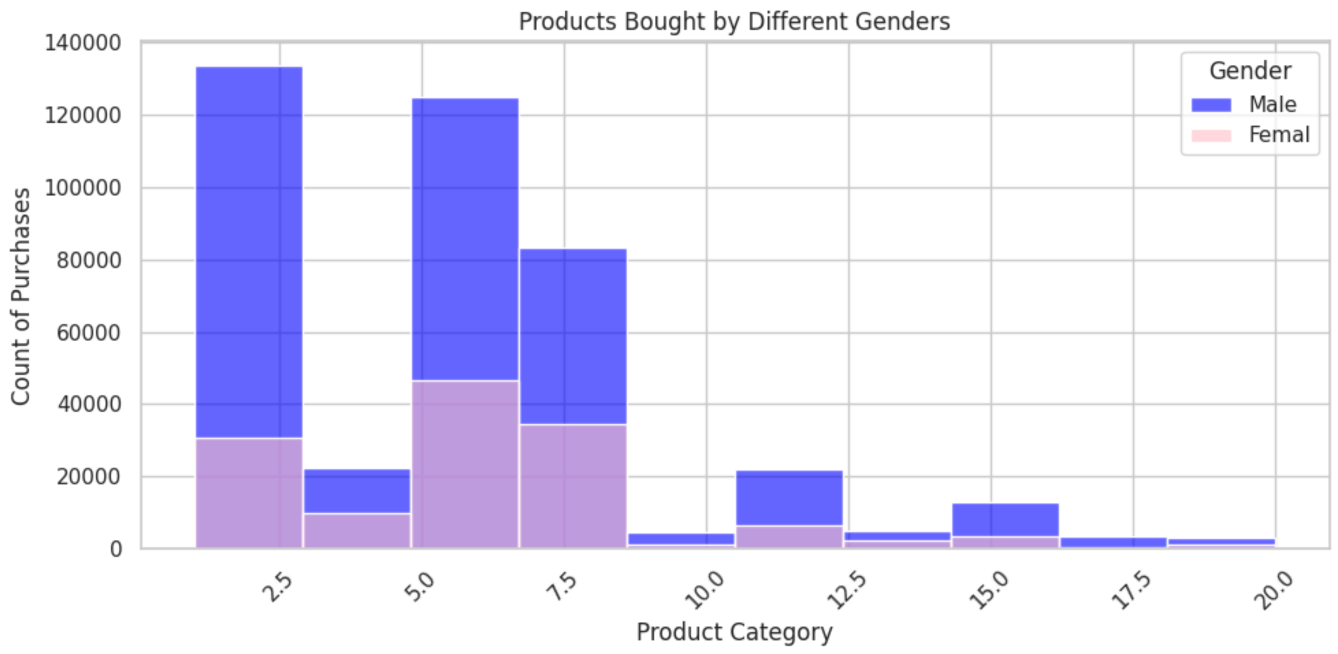
ii) In older age groups, you might observe more uniform spending patterns regardless of marital status, or even greater spending among married individuals due to family expenses.

c) Are there preferred product categories for different genders?

```
# These headings represent the product category and the count of each gender that purcha
Product_Cat_different_Gender = df.groupby(['Product_Category', 'Gender']).size().unstack
print(Product_Cat_different_Gender)
```

```
Gender  Product_Category      F       M
0                      1  24831  115547
1                      2   5658   18206
2                      3   6006   14207
3                      4   3639    8114
4                      5  41961  108972
5                      6   4559   15907
6                      7    943    2778
7                      8  33558   80367
8                      9     70     340
9                     10   1162    3963
10                    11   4739   19548
11                    12   1532    2415
12                    13   1462    4087
13                    14    623     900
14                    15   1046    5244
15                    16   2402    7426
16                    17     62     516
17                    18    382    2743
18                    19    451    1152
19                    20    723    1827
```

```
sns.set(style='whitegrid')
plt.figure(figsize=(10, 5))
# Create a histplot for Male & Femal users:
sns.histplot(data=df[df['Gender'] == 'M'], x='Product_Category', bins=10, color='blue',
sns.histplot(data=df[df['Gender'] == 'F'], x='Product_Category', bins=10, color='pink',

# Set title and labels
plt.title('Products Bought by Different Genders')
plt.xlabel('Product Category')
plt.ylabel('Count of Purchases')
plt.legend(title='Gender')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Insights:

Product Category Preferences by Gender:

i) The histplot visualization clearly shows the distribution of purchases for different product categories by male and female customers.
ii) By comparing the heights of the bars for each product category, you can identify which categories are more popular among men and women.

Gender-Specific Popular Categories:

i) If you notice higher bars for a certain product category under one gender, it indicates a stronger preference for that category.
ii) For example, if the "Electronics" category has a noticeably higher count for males, it suggests that male customers are more likely to purchase electronics.

Marketing Strategies:

i) Walmart can use these insights to tailor marketing strategies and promotions to specific gender preferences.
ii) For example, targeting females with promotions on categories where they have higher purchase

counts and males with different promotional offers based on their preferences.

Inventory Management:
i) Knowing the preferred product categories for different genders can help in better inventory management.
ii) Ensuring that popular products for each gender are well-stocked can improve customer satisfaction and sales.

Personalized Shopping Experience:
i) Walmart can enhance the shopping experience by offering personalized recommendations based on gender-specific preferences.
ii) Personalized emails or app notifications can include product suggestions that align with the purchasing patterns of each gender.

4. How does gender affect the amount spent?

a. From the above calculated CLT answer the following questions
i. Is the confidence interval computed using the entire dataset wider for one of the genders? Why is this the case?
ii. How is the width of the confidence interval affected by the sample size?
iii. Do the confidence intervals for different sample sizes overlap? iv. How does the sample size affect the shape of the distributions of the means?

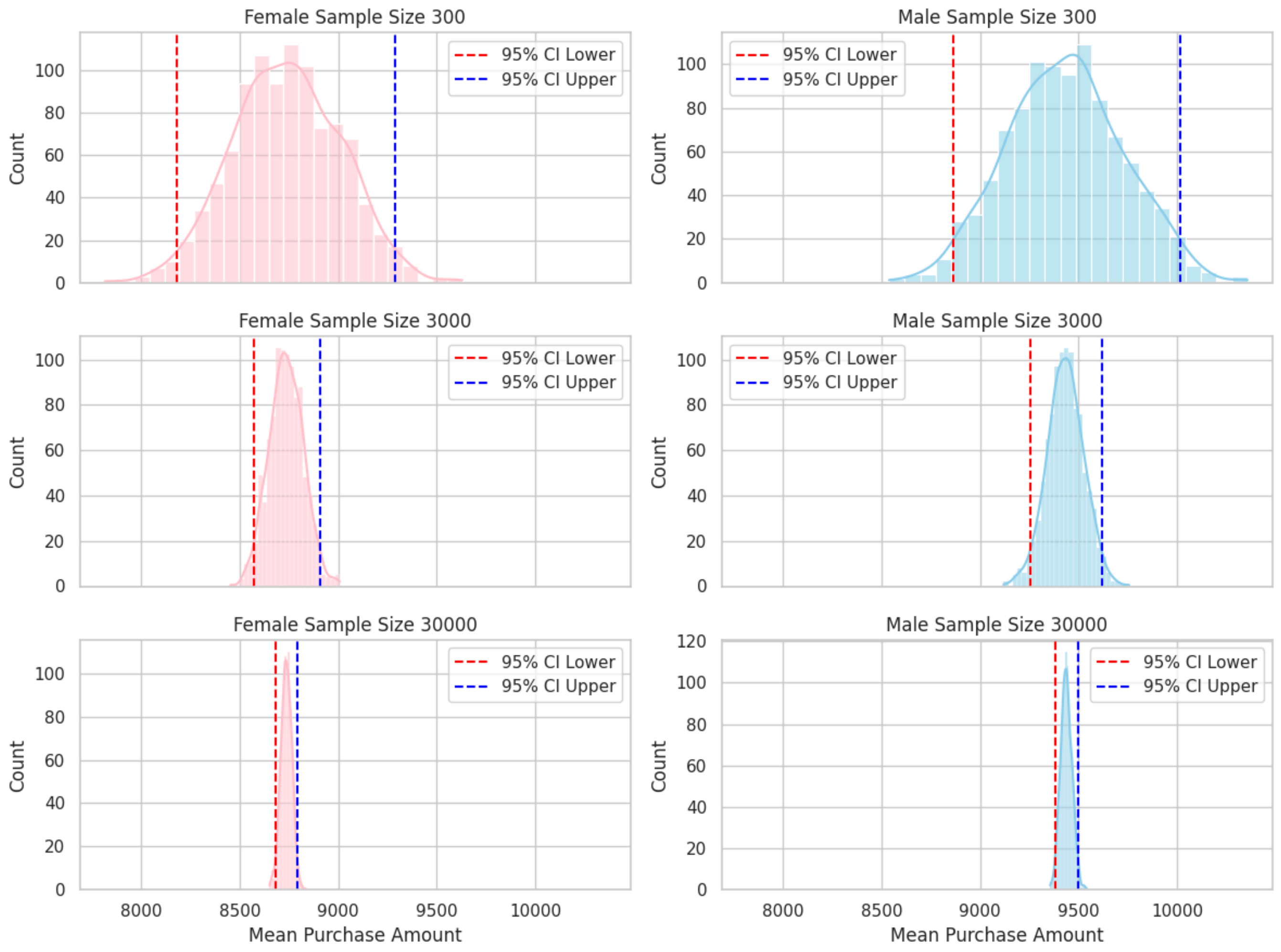
```
df.head(2)
```

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

```
# Function to calculate bootstrap confidence intervals
def bootstrap_confidence_intervals(data, sample_size, n_bootstraps=1000, confidence=0.9
    bootstrapped_means = []
    for _ in range(n_bootstraps):
        sample = data.sample(n=sample_size, replace=True)
        bootstrapped_means.append(sample['Purchase'].mean())
    # Compute confidence interval from the bootstrapped means
    lower_bound = np.percentile(bootstrapped_means, (1 - confidence) / 2 * 100)
    upper_bound = np.percentile(bootstrapped_means, (1 + confidence) / 2 * 100)
    return lower_bound, upper_bound

# Function to calculate bootstrap sample means for plotting
def bootstrap_sample_means(data, sample_size, n_bootstraps=1000):
    bootstrapped_means = []
    for _ in range(n_bootstraps):
        sample = data.sample(n=sample_size, replace=True)
        bootstrapped_means.append(sample['Purchase'].mean())
    return bootstrapped_means

# Sample sizes to evaluate
sample_sizes = [300, 3000, 30000]
ci_results = {}
sample_means_data = {}
```

```
for size in sample_sizes:
    # Calculate confidence intervals for both genders
    ci_results[f'Female_{size}'] = bootstrap_confidence_intervals(df[df['Gender'] == 'F'
    ci_results[f'Male_{size}'] = bootstrap_confidence_intervals(df[df['Gender'] == 'M'],

    # Generate bootstrapped means for histograms
    sample_means_data[f'Female_{size}'] = bootstrap_sample_means(df[df['Gender'] == 'F']
    sample_means_data[f'Male_{size}'] = bootstrap_sample_means(df[df['Gender'] == 'M'],
```

```
# Plot the Distribution of Sample Means with Confidence Intervals:
fig, axes = plt.subplots(3, 2, figsize=(12, 9), sharex = True)

for idx, size in enumerate(sample_sizes):
    # Female sample means and confidence interval plot
    sns.histplot(sample_means_data[f'Female_{size}'], kde=True, ax=axes[idx, 0], color='
    ci_female = ci_results[f'Female_{size}']
    axes[idx, 0].axvline(ci_female[0], color='red', linestyle='--', label=f"95% CI Lower
    axes[idx, 0].axvline(ci_female[1], color='blue', linestyle='--', label=f"95% CI Uppe
    axes[idx, 0].set_title(f"Female Sample Size {size}")
    axes[idx, 0].set_xlabel("Mean Purchase Amount")
    axes[idx, 0].legend()

    # Male sample means and confidence interval plot
    sns.histplot(sample_means_data[f'Male_{size}'], kde=True, ax=axes[idx, 1], color='sk
    ci_male = ci_results[f'Male_{size}']
    axes[idx, 1].axvline(ci_male[0], color='red', linestyle='--', label=f"95% CI Lower")
    axes[idx, 1].axvline(ci_male[1], color='blue', linestyle='--', label=f"95% CI Upper"
    axes[idx, 1].set_title(f"Male Sample Size {size}")
    axes[idx, 1].set_xlabel("Mean Purchase Amount")
    axes[idx, 1].legend()

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


Female Sample Size 300
Male Sample Size 300
Female Sample Size 3000
Male Sample Size 3000
Female Sample Size 30000
Male Sample Size 30000
95% CI Lower
95% CI Upper
Count
Mean Purchase Amount
8000
8500
9000
9500
10000

Insights:

Confidence Interval Width:

i) The confidence interval calculated using the entire dataset might be wider for one gender if there is higher variability in spending patterns within that gender.
ii) A wider confidence interval indicates more uncertainty around the mean, suggesting that the spending behavior within that gender is less consistent.

Effect of Sample Size on Confidence Interval Width:

i) As the sample size increases, the width of the confidence interval generally decreases.
ii) Larger sample sizes provide more precise estimates of the average spending, reducing the uncertainty around the mean.

Overlap of Confidence Intervals:

i) If the confidence intervals for different sample sizes overlap, it suggests that the average spending between the two genders is not significantly different.
ii) Non-overlapping confidence intervals would indicate significant differences in average spending between genders.

Effect of Sample Size on Distribution Shape:

i) Larger sample sizes tend to produce a more normal distribution of the sample means, thanks to the Central Limit Theorem.
ii) This normality allows for more accurate and reliable confidence interval estimates.

Recommendations for Walmart:

Targeted Marketing Strategies:

Gender-Specific Promotions: Develop targeted marketing campaigns and promotions based on the spending patterns of each gender. For instance, if males show higher spending in certain categories, tailor promotions to attract more male customers.

Personalized Shopping Experience:

Utilize the confidence interval insights to offer personalized recommendations and deals to customers. This can enhance customer satisfaction and loyalty by catering to individual preferences.

Inventory Management:

Use the insights on spending patterns to optimize inventory levels. Ensure that popular products among each gender are adequately stocked to prevent stockouts and meet customer demand effectively.

Pricing Strategies:

Develop pricing strategies that reflect the spending power and preferences of different genders.

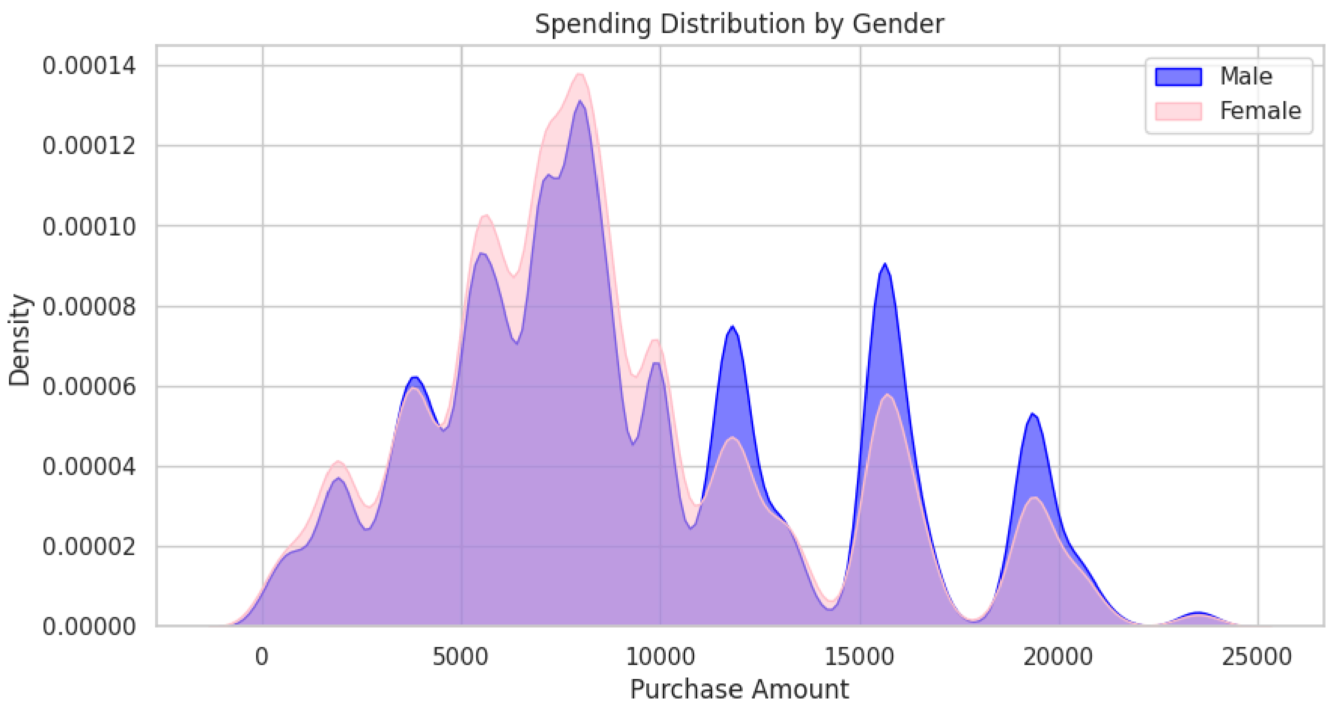
For example, offer premium products or bundled deals to genders showing higher spending patterns.

1) Gender-Based Spending Hypothesis Test

```
# Separate data for males and females
male_spending = df[df['Gender'] == 'M']['Purchase']
female_spending = df[df['Gender'] == 'F']['Purchase']

# Perform two-sample t-test
t_stat, p_value = stats.ttest_ind(male_spending, female_spending, equal_var=False)

print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}\n")

# Conclusion
if p_value < 0.05:
    print("Reject the null hypothesis: There is a significant difference in spending bet
else:
    print("Fail to reject the null hypothesis: No significant difference in spending bet
```

```
T-statistic: 46.358248669626064
P-value: 0.0

Reject the null hypothesis: There is a significant difference in spending between males
```

```
# KDE Plot for Spending Distribution by Gender
plt.figure(figsize=(10, 5))
sns.kdeplot(data=male_spending, fill=True, color="blue", label="Male", alpha=0.5)
sns.kdeplot(data=female_spending, fill=True, color="pink", label="Female", alpha=0.5)
plt.title("Spending Distribution by Gender")
plt.xlabel("Purchase Amount")
plt.ylabel("Density")
plt.legend()
plt.show()
```



Insights and Interpretation

Hypothesis Test Result:

If the p-value < 0.05: This indicates a significant difference in spending between males and females. It means Walmart can create gender-specific marketing campaigns based on this finding.

KDE Plot Analysis:

KDE (Kernel Density Estimate) Plot: This helps Walmart visually understand the spending distribution trends. For example, they can see which spending ranges are more common for males and females, aiding in better-targeted marketing strategies.

2) Marital Status and Product Category using Chi-Square Test

```
# Create a contingency table
Contingency_Table = pd.crosstab(df['Marital_Status'], df['Product_Category'])

# Perform Chi-Square Test
chi2_stat, p_value, dof, expected = stats.chi2_contingency(Contingency_Table)
print(f"Chi2 Stat: {chi2_stat}, P-value: {p}")
```

```
Chi2 Stat: 539.4762103623166, P-value: 2.8475938150382975e-102
```

Insights

1) Chi-Square Test Statistic (Chi2 Stat): This value represents the difference between the observed and expected frequencies in each category of the contingency table. A higher chi-square value generally suggests a stronger association.
2) P-value: If the p-value is less than the chosen significance level (typically 0.05), it indicates a significant association between marital status and product category. This means married and unmarried customers show different purchasing behaviors in certain product categories.
3) Degrees of Freedom (dof): This tells us how many independent values are free to vary in the table, although it does not directly impact our interpretation of the association.

Recommendations

For Significant Association (p-value < 0.05):
Targeted Product Marketing: Walmart can design product-specific campaigns targeting married or unmarried customers. For example, if married customers have a higher preference for certain household or family-related items, Walmart can promote these items more actively to married individuals.
Personalized Promotions: Walmart could leverage marital status to create personalized promotions. For example, products preferred by unmarried individuals could be promoted during events or seasons when single individuals might shop more.
For No Significant Association (p-value >= 0.05):
Generalized Marketing: If there's no significant association, Walmart can approach marketing strategies without segmenting by marital status, as the product preferences are similar across both groups.

Unified Inventory Management: Since both married and unmarried groups would show similar purchasing trends, Walmart could maintain a uniform stock level for these product categories without needing to differentiate by marital status.

3) Chi-square Test for Association between Gender and Marital Status

```
Gender_by_Marital_Status = pd.crosstab(index=df['Gender'], columns=df['Marital_Status'])

chi_stat, p_value, df, exp_feq = chi2_contingency(Gender_by_Marital_Status)
print('chi_stat :', chi_stat)
print('p_value :', p_value)
print('DOF :', df)
print('exp_feq :', exp_feq)
```

```
chi_stat : 74.00272697523472
p_value : 7.800918945407 45e-18
DOF : 1
exp_feq : [[ 80174.43730412  55634.56269588]
 [244556.56269588 169702.43730412]]
```

```
alpha = 0.5
if p_value < alpha:
  print('Reject H0')
  print('Gender impacts Marital Status')
else:
  print('Fail to Reject H0')
  print('Gender does not impact Marital Status')
```

```
Reject H0
Gender impacts Marital Status
```

Insights

1) If the p-value is less than 0.5 (your chosen alpha level), you would reject the null hypothesis (H0), which states that there is no relationship between gender and marital status. In this case, you conclude that gender does impact marital status.

2) If the p-value is greater than or equal to 0.5, you fail to reject the null hypothesis, indicating that there is no significant impact of gender on marital status.

Recommendations

If you reject H0:

1) Targeted Marketing: Use the insights to tailor marketing strategies based on gender demographics, potentially creating gender-specific campaigns for different marital statuses.

2) Product Development: Consider developing products or services that cater specifically to the preferences of different gender and marital status combinations.

If you reject H0:

1) Focus on Other Factors:

2) Broaden Analysis: Consider including additional demographic factors (e.g., age, income, education) in your analysis to gain a more comprehensive understanding of customer behavior and preferences.

4) Gender and Purchase Amounts Analysis using Two-Sample t-test

```
# Separate Purchase data by Gender
Male_Purchase = df[df['Gender'] == 'M']['Purchase']
Female_Purchase = df[df['Gender'] == 'F']['Purchase']

# Perform Two-Sample t-test
t_stat, p_value = ttest_ind(Male_Purchase, Female_Purchase)
print(f"T-statistic: {t_stat}, P-value: {p_value}")
```

```
T-statistic: 44.837957934353966, P-value: 0.0
```

Insights and Recommendations

If you fail to reject H 0 (i.e., no significant difference):

- Uniform Marketing Approach: Since there is no significant difference, consider a unified marketing strategy that does not heavily focus on gender.
- Explore Other Factors: Look into other demographic or behavioral factors that might influence purchasing behavior. Expanding your analysis to include variables like age, income, or location may reveal more insights.

If you reject H 0(i.e., significant difference):

- Marketing Strategies: Tailor marketing campaigns based on gender preferences if a significant difference in purchasing behavior is found. For example, if males spend significantly more, consider promotions targeted toward female customers to boost their purchasing.
- Product Development: Use insights from the data to design products or services that cater specifically to the purchasing patterns of each gender.

5) Chi-square Test for Association between Gender and Purchase

```
Gender_by_City_Category = pd.crosstab(index=df['Gender'], columns=df['City_Category'])
chi_stat, p_value, df, exp_feq = chi2_contingency(Gender_by_City_Category)
print('chi_stat :', chi_stat)
print('p_value :', p_value)
print('DOF : ', df)
print('exp_feq :', exp_feq)
```

```
chi_stat : 33.58382571304351
p_value : 5.097590042852447e-08
DOF :  2
exp_feq : [[ 36471.3189642  57075.4415036  42262.2395322]
 [111248.6810358 174097.5584964 128912.7604678]]
```

```
alpha = 0.5
if p_value < alpha:
  print('Reject H0')
  print('Gender impacts City_Category')
else:
  print('Fail to Reject H0')
  print('Gender does not impact City_Category')
```

```
Reject H0
Gender impacts City_Category
```

Insights

1) If you reject H0 (if p_value < 0.5): This indicates that there is a significant association between gender and city category. It suggests that males and females might have different distributions across the city categories.
2) If you fail to reject H0 (if p_value >= 0.5): This indicates that there is no significant

association between gender and city category. In this case, gender does not appear to affect the distribution across city categories.

Recommendations

If you reject H0:

1) Tailored Marketing Strategies: Utilize the insights from the association to develop gender-specific marketing campaigns targeted at specific city categories. For example, if certain city categories have a higher concentration of a particular gender, marketing efforts can be directed accordingly.

2) Location-Based Promotions: Consider implementing promotions or product offerings based on gender preferences in different city categories. This could enhance customer engagement and sales.

If you reject H0:

1) Reassess Target Markets: Since gender does not significantly influence city category preferences, consider looking at other factors such as age, income, or lifestyle preferences that might impact customer behavior.

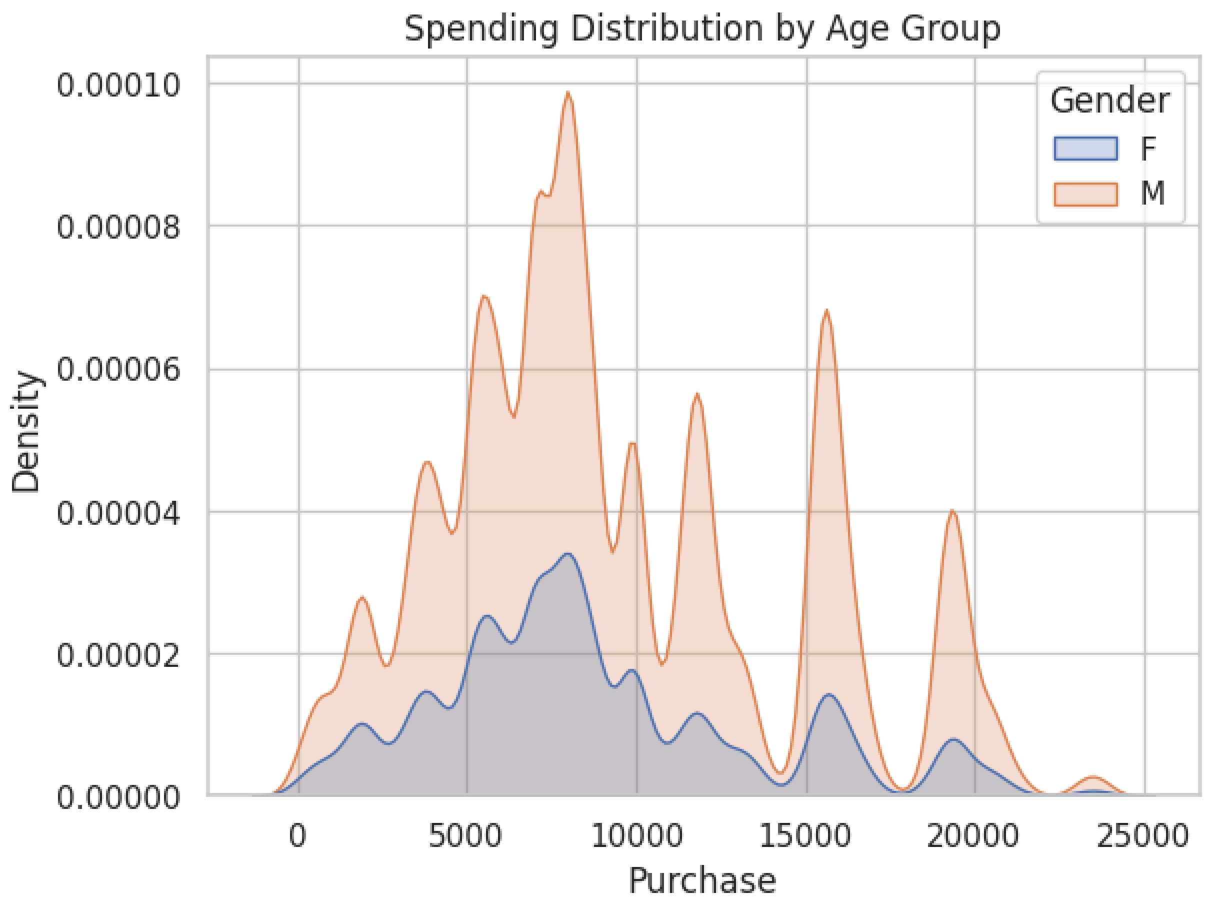
2) Broadening the Analysis: Expand your analysis to include additional demographic and psychographic variables to gain a more holistic understanding of your customers. This can help uncover other significant patterns that might inform business strategies.

6) Age Group Preferences using ANOVA

```python
# Group purchases by Age
age_groups = [df[df['Age'] == age]['Purchase'] for age in df['Age'].unique()]

# Perform One-Way ANOVA
f_stat, p_value = f_oneway(*age_groups)

print(f"F-statistic: {f_stat}, P-value: {p_value}")
```

```
F-statistic: 40.57579909450408, P-value: 1.053563939251671e-49
```

```python
# KDE plot for spending distribution by Age
sns.kdeplot(data=df, x='Purchase', hue='Gender', fill='bule')
plt.title('Spending Distribution by Age Group')
plt.show()
```



Insights

If you reject $H0$ (significant differences):

- This suggests that age plays a role in how much individuals spend, and there could be specific age groups that differ significantly from others in terms of purchasing behavior.

If you fail to reject $H0$(no significant differences):

- This indicates that, across age groups, the average spending does not vary significantly. The purchasing behavior may be consistent across ages.

Recommendations If you reject $H0$:

- Targeted Marketing Campaigns: Develop age-specific marketing strategies, such as promotions or products that cater to the spending habits of the age groups that spend significantly more.
- Segmentation Analysis: Perform deeper analysis on the age groups that differ significantly to understand their preferences and tailor your offerings to those segments.

If you fail to rejectH0:

- Unified Marketing Approach: Since spending is consistent across age groups, consider a broad approach in your marketing strategy that doesn't focus solely on age.

- Explore Additional Factors: Investigate other potential factors (e.g., gender, income, location) that might influence purchasing behavior, as they could reveal other segments worth exploring.

5. How does Marital_Status affect the amount spent?

a. From the above calculated CLT answer the following questions.

i. Is the confidence interval computed using the entire dataset wider for one of the genders? Why is this the case?

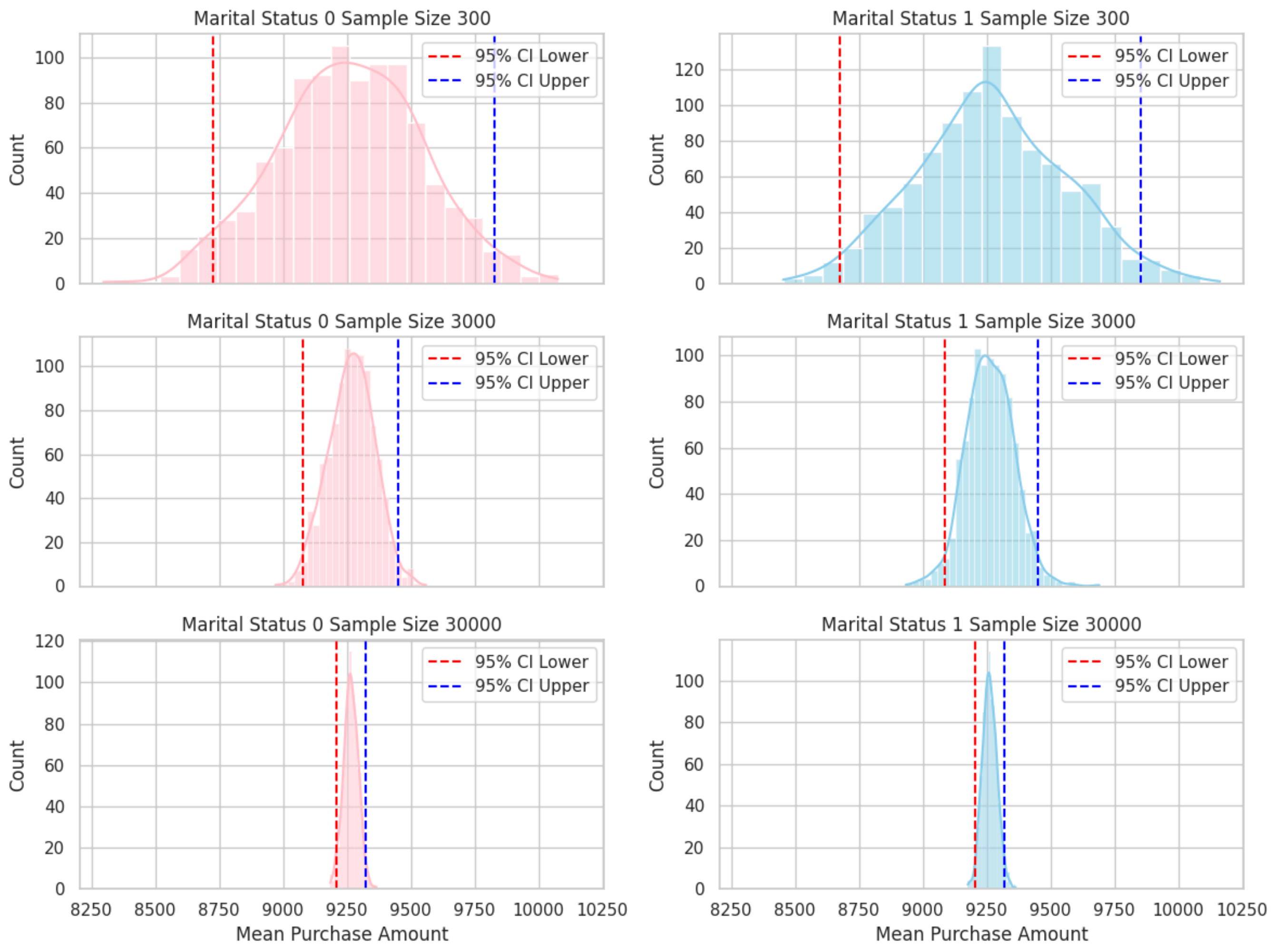
ii. How is the width of the confidence interval affected by the sample size?

iii. Do the confidence intervals for different sample sizes overlap?

iv. How does the sample size affect the shape of the distributions of the means?

```
# Loop through sample sizes and calculate confidence intervals for Marital_Status
for size in sample_sizes:
    for marital_status in [0, 1]:
        # Filter data based on Marital_Status
        filtered_data = df[df['Marital_Status'] == marital_status]

        # Calculate confidence intervals
        ci_key = f'MaritalStatus_{marital_status}_{size}'
        ci_results[ci_key] = bootstrap_confidence_intervals(filtered_data, size)

        # Generate bootstrapped means for histograms
        sample_means_key = f'MaritalStatus_{marital_status}_{size}'
        sample_means_data[sample_means_key] = bootstrap_sample_means(filtered_data, size
```

```
# Plot the Distribution of Sample Means with Confidence Intervals
fig, axes = plt.subplots(3, 2, figsize=(12, 9), sharex=True)

for idx, size in enumerate(sample_sizes):
    # Sample means for Marital Status 0
    sns.histplot(sample_means_data[f'MaritalStatus_0_{size}'], kde=True, ax=axes[idx, 0]
    ci_marital_0 = ci_results[f'MaritalStatus_0_{size}']
    axes[idx, 0].axvline(ci_marital_0[0], color='red', linestyle='--', label="95% CI Low
    axes[idx, 0].axvline(ci_marital_0[1], color='blue', linestyle='--', label="95% CI Up
    axes[idx, 0].set_title(f"Marital Status 0 Sample Size {size}")
    axes[idx, 0].set_xlabel("Mean Purchase Amount")
    axes[idx, 0].legend()

    # Sample means for Marital Status 1
    sns.histplot(sample_means_data[f'MaritalStatus_1_{size}'], kde=True, ax=axes[idx, 1]
    ci_marital_1 = ci_results[f'MaritalStatus_1_{size}']
    axes[idx, 1].axvline(ci_marital_1[0], color='red', linestyle='--', label="95% CI Low
    axes[idx, 1].axvline(ci_marital_1[1], color='blue', linestyle='--', label="95% CI Up
    axes[idx, 1].set_title(f"Marital Status 1 Sample Size {size}")
    axes[idx, 1].set_xlabel("Mean Purchase Amount")
    axes[idx, 1].legend()

plt.tight_layout()
plt.show()

```


Marital Status 0 Sample Size 300
Marital Status 1 Sample Size 300
Marital Status 0 Sample Size 3000
Marital Status 1 Sample Size 3000
Marital Status 0 Sample Size 30000
Marital Status 1 Sample Size 30000
95% CI Lower
95% CI Upper
Count
Mean Purchase Amount
8250
8500
8750
9000
9250
9500
9750
10000
10250

Insights:

Confidence Interval Width:

i) Entire Dataset: The confidence interval calculated using the entire dataset may be wider for one marital status group if there is greater variability in spending patterns within that group. A wider confidence interval indicates less consistency in spending behavior.
ii) Reason: Higher variability within a group leads to greater uncertainty around the mean, thus a wider confidence interval.

Effect of Sample Size on Confidence Interval Width:

i) Smaller Sample Sizes: Confidence intervals are typically wider due to higher variability and less information about the population.
ii) Larger Sample Sizes: The width of the confidence interval generally decreases, providing a more precise estimate of the average spending.

Overlap of Confidence Intervals:

i) Overlap: If the confidence intervals for different sample sizes overlap, it suggests no significant difference in average spending between married and unmarried individuals.
ii) Non-Overlap: Non-overlapping intervals indicate significant differences in spending behavior between the groups.

Effect of Sample Size on Distribution Shape:

i) Smaller Samples: Distributions of sample means may not follow a normal distribution due to limited data points.
ii) Larger Samples: Distributions tend to be more normal and stable due to the Central Limit Theorem, leading to more reliable confidence interval estimates.

Recommendations for Walmart:

Targeted Marketing Strategies:

i) Married Individuals: If significant differences are observed, develop targeted marketing campaigns focusing on products and promotions that resonate more with married individuals.
ii) Unmarried Individuals: Similarly, tailor promotions and advertising for unmarried customers, addressing their specific needs and preferences.

Personalized Shopping Experience:

i) Customized Offers: Use insights from the analysis to offer personalized recommendations and deals based on marital status. This can improve customer satisfaction and boost sales.

Inventory Management:

i) Demand Forecasting: Adjust inventory levels based on the spending patterns of married and unmarried customers. Ensure popular products for each group are well-stocked.

Pricing Strategies:
i) Reflecting Spending Power: Develop pricing models that consider the spending power and preferences of married and unmarried customers. Offer premium products or bundled deals accordingly.

6. How does Age affect the amount spent?

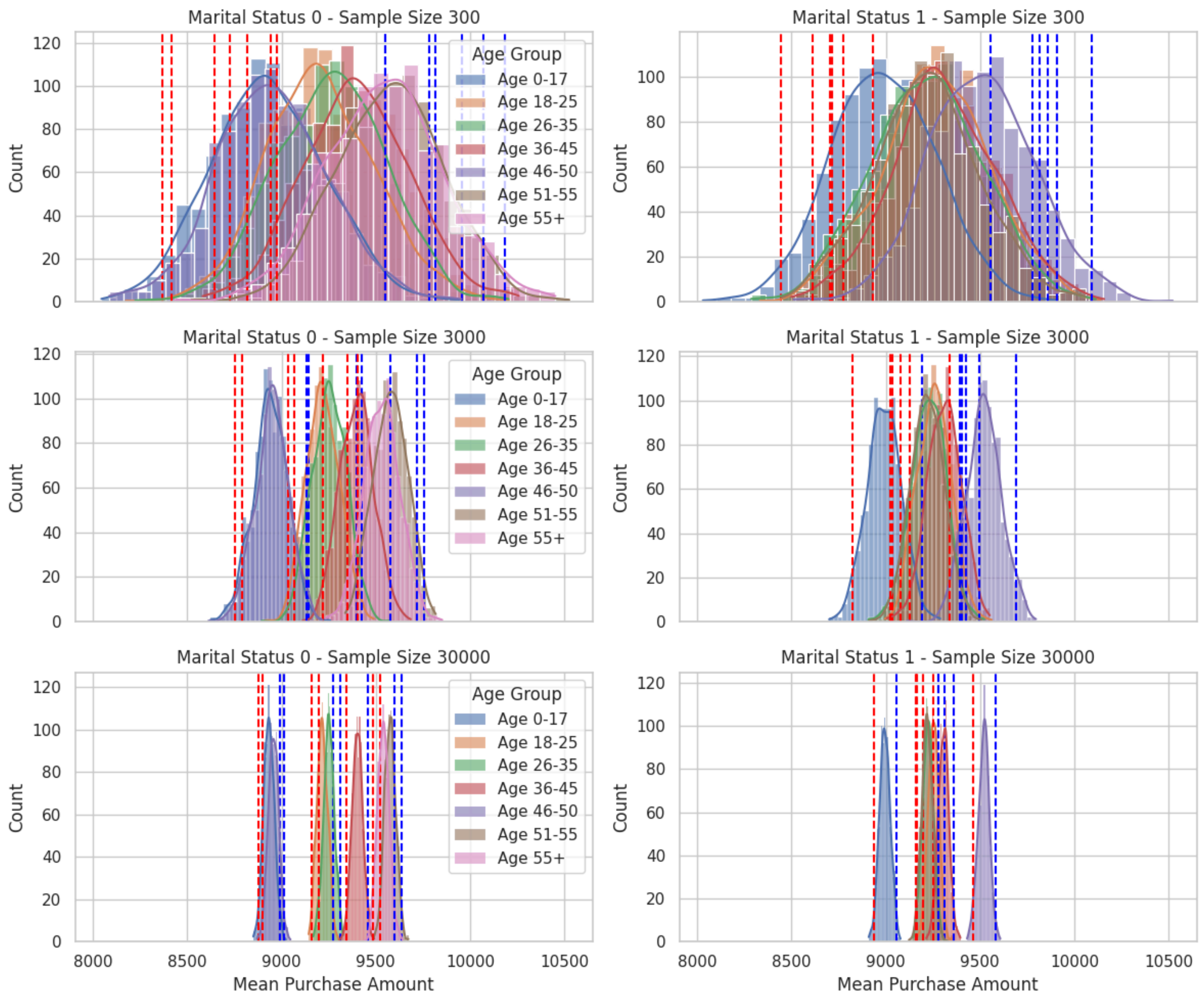
a. From the above calculated CLT answer the following questions.
i. Is the confidence interval computed using the entire dataset wider for one of the genders? Why is this the case?
ii. How is the width of the confidence interval affected by the sample size?
iii. Do the confidence intervals for different sample sizes overlap?
iv. How does the sample size affect the shape of the distributions of the means?

```
# Function to calculate bootstrap confidence intervals
def bootstrap_confidence_intervals(data, sample_size, n_bootstraps=1000, confidence=0.95
    bootstrapped_means = []
    for _ in range(n_bootstraps):
        sample = data.sample(n=sample_size, replace=True)
        bootstrapped_means.append(sample['Purchase'].mean())
    # Compute confidence interval from the bootstrapped means
    lower_bound = np.percentile(bootstrapped_means, (1 - confidence) / 2 * 100)
    upper_bound = np.percentile(bootstrapped_means, (1 + confidence) / 2 * 100)
    return lower_bound, upper_bound

# Function to calculate bootstrap sample means for plotting
def bootstrap_sample_means(data, sample_size, n_bootstraps=1000):
    bootstrapped_means = []
    for _ in range(n_bootstraps):
        sample = data.sample(n=sample_size, replace=True)
        bootstrapped_means.append(sample['Purchase'].mean())
    return bootstrapped_means

# Sample sizes to evaluate
sample_sizes = [300, 3000, 30000]
ci_results = {}
sample_means_data = {}
```

```
# Age categories to evaluate
age_groups = ["0-17", "18-25", "26-35", "36-45", "46-50", "51-55", "55+"]

# Loop through sample sizes, Marital_Status, and Age groups
```

```
for size in sample_sizes:
    for marital_status in [0, 1]:
        for age_group in age_groups:
            # Filter data based on Marital_Status and Age
            filtered_data = df[(df['Marital_Status'] == marital_status) & (df['Age'] ==

            if not filtered_data.empty:
                # Calculate confidence intervals
                ci_key = f'MaritalStatus_{marital_status}_Age_{age_group}_{size}'
                ci_results[ci_key] = bootstrap_confidence_intervals(filtered_data, size)

                # Generate bootstrapped means for histograms
                sample_means_key = f'MaritalStatus_{marital_status}_Age_{age_group}_{siz
                sample_means_data[sample_means_key] = bootstrap_sample_means(filtered_da
```

```
# Define the layout of the plots
fig, axes = plt.subplots(len(sample_sizes), 2, figsize=(12, 10), sharex=True)

# Loop through each sample size and plot Marital_Status = 0 and Marital_Status = 1 in se
for idx, size in enumerate(sample_sizes):
    for marital_status in [0, 1]:
        col_idx = marital_status  # Set column index for marital status

        # Filter and plot for each age group
        for age_group in age_groups:
            sample_means_key = f'MaritalStatus_{marital_status}_Age_{age_group}_{size}'
            ci_key = f'MaritalStatus_{marital_status}_Age_{age_group}_{size}'

            # Check if data exists for the current combination
            if sample_means_key in sample_means_data and ci_key in ci_results:

                sns.histplot(sample_means_data[sample_means_key], kde=True, ax=axes[idx,

                # Plot confidence interval lines
                ci_lower, ci_upper = ci_results[ci_key]
                axes[idx, col_idx].axvline(ci_lower, color='red', linestyle='--')
                axes[idx, col_idx].axvline(ci_upper, color='blue', linestyle='--')

        # Set title and label once for each subplot
        axes[idx, col_idx].set_title(f"Marital Status {marital_status} - Sample Size {si
        axes[idx, col_idx].set_xlabel("Mean Purchase Amount")

    # Add a single legend for each row
    axes[idx, 0].legend(title="Age Group")

# Final adjustments for layout
plt.tight_layout()
plt.show()

```


Marital Status 0 - Sample Size 300
Marital Status 1 - Sample Size 300
Marital Status 0 - Sample Size 3000
Marital Status 1 - Sample Size 3000
Marital Status 0 - Sample Size 30000
Marital Status 1 - Sample Size 30000
Count
Mean Purchase Amount
Age Group
Age 0-17
Age 18-25
Age 26-35
Age 36-45
Age 46-50
Age 51-55
Age 55+
8000
8500
9000
9500
10000
10500

Insights

Confidence Interval Width by Gender:
In the full dataset, the confidence interval might be wider for one gender if there is more variability in spending in that group. For example, if one gender has more extreme purchase values or larger standard deviations, their confidence interval would be wider, reflecting greater uncertainty in the mean estimate.

Effect of Sample Size on Confidence Interval Width:
As sample size increases, the width of the confidence interval decreases. This happens because larger samples provide a more precise estimate of the population mean, reducing the variability of the mean in each bootstrap sample.

Overlap of Confidence Intervals for Different Sample Sizes:
Confidence intervals from smaller samples may differ significantly from those of larger samples due to increased variance. However, as sample size grows, intervals should stabilize and may start overlapping, reflecting more accurate estimates.

Sample Size and Shape of Mean Distributions:
According to the Central Limit Theorem, as sample size increases, the distribution of the sample means will tend to approximate a normal distribution, even if the underlying data is not normally distributed. Smaller samples might show more skewed or non-normal distributions of means, especially in skewed age or marital status groups, but larger samples will appear more symmetrical.

Recommendations:

Targeting Marketing Strategies:
For age groups with higher spending levels, tailor marketing strategies based on marital status and age to maximize revenue. Since spending habits appear to vary by marital status, understanding which groups show more variability in spending can help refine targeted strategies.

Optimal Sample Size for Analysis:
When studying the population in-depth, a sample size of around 3000-30000 balances precision with computation time, giving reliable confidence intervals without unnecessary computational complexity.

Predictive Modeling for Spending Behavior:
Based on the confidence intervals and the CLT insights, consider using predictive modeling for

spending patterns among different age and marital status groups to forecast and optimize future campaigns.

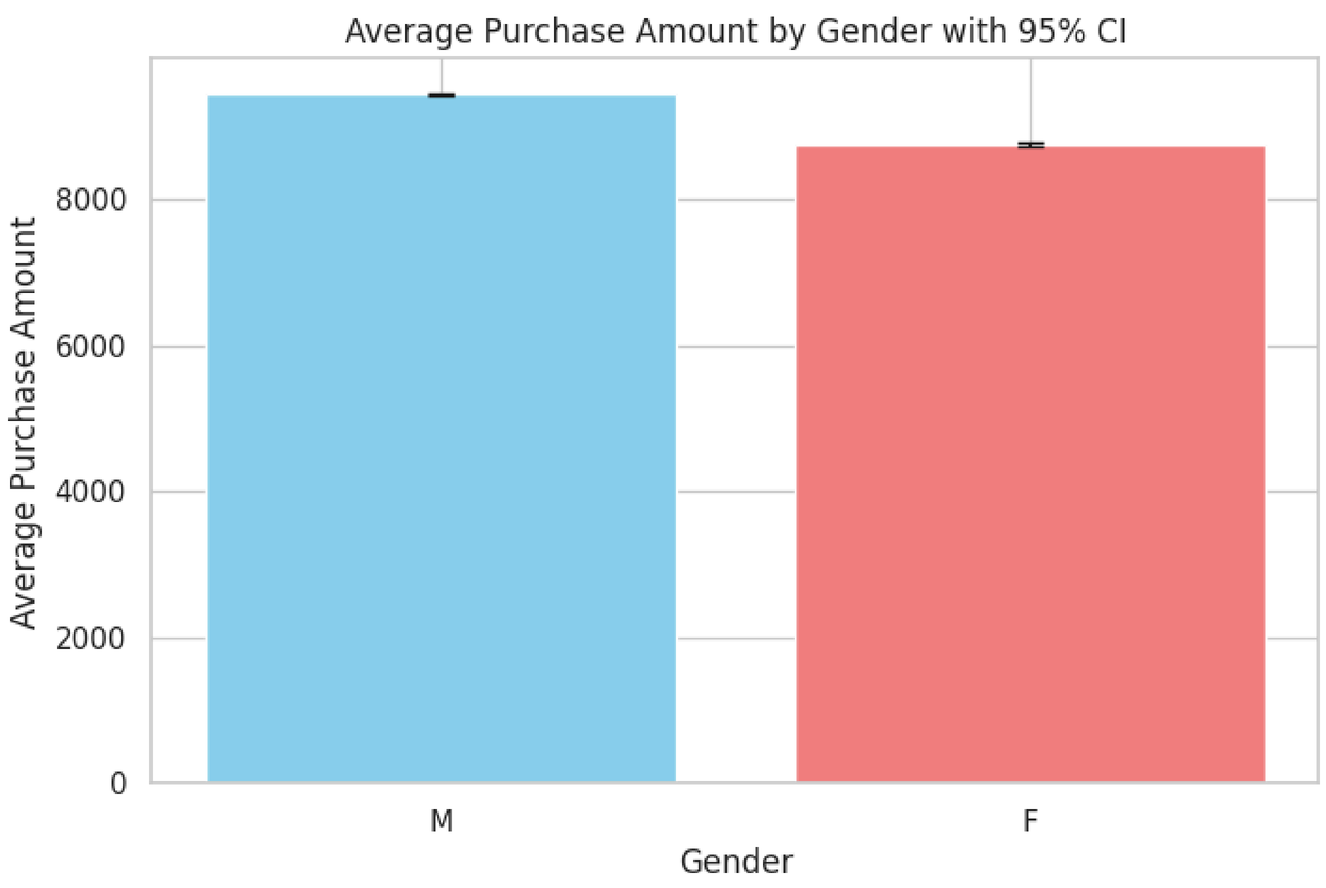
7. Create a report

a. Report whether the confidence intervals for the average amount spent by males and females (computed using all the data) overlap. How can Walmart leverage this conclusion to make changes or improvements?

```
# Calculate mean, std, and sample size for males and females
m, f = df[df['Gender'] == 'M']['Purchase'], df[df['Gender'] == 'F']['Purchase']
z = 1.96  # Z-score for 95% CI

# Confidence intervals
m_ci = (m.mean() - z * (m.std() / len(m)**0.5), m.mean() + z * (m.std() / len(m)**0.5))
f_ci = (f.mean() - z * (f.std() / len(f)**0.5), f.mean() + z * (f.std() / len(f)**0.5))

# Check for overlap
overlap = not (m_ci[1] < f_ci[0] or f_ci[1] < m_ci[0])

# Output results
print(f"Male 95% CI: {m_ci} \nFemale 95% CI: {f_ci} \nOverlap: {overlap}")
```

```
Male 95% CI: (9422.019162420047, 9453.032918524483)
Female 95% CI: (8709.211081242413, 8759.920449068539)
Overlap: False
```

```
# Calculate mean and 95% CI for male and female purchases
genders = ['M', 'F']
means = [m.mean(), f.mean()]
errors = [z * (m.std() / np.sqrt(len(m))), z * (f.std() / np.sqrt(len(f)))]

# Plot
plt.figure(figsize=(8, 5))
plt.bar(genders, means, yerr=errors, capsize=5, color=['skyblue', 'lightcoral'])
plt.xlabel('Gender')
plt.ylabel('Average Purchase Amount')
plt.title('Average Purchase Amount by Gender with 95% CI')
plt.show()
```



Insights:

Spending Trends by Gender:

If the confidence intervals overlap, it suggests that males and females spend similar amounts on average, indicating that both genders could be targeted similarly in terms of promotions and product recommendations.

If the confidence intervals do not overlap, it suggests a statistically significant difference in spending behavior between males and females. For instance, if males spend more, they may respond well to premium or high-value product promotions, whereas females might show more interest in other segments.

Implications for Marketing Strategy:

No Overlap: Walmart could tailor gender-specific marketing campaigns based on the observed spending patterns, like promoting different products, offers, or discounts targeted at each gender.

Overlap: Walmart might focus more on general promotions rather than gender-specific campaigns, ensuring inclusivity and broader reach without differentiating between male and female spending patterns.

Recommendations:

Gender-Specific Promotions:
If significant spending differences exist (no overlap), Walmart should consider gender-focused promotions to cater to each gender's specific purchasing power and preferences.

Example: If males show higher spending, Walmart could promote electronics or premium items more heavily to male customers. If females show higher spending, marketing could focus on categories where they tend to spend more, such as home goods or beauty products.

Optimized Inventory and Product Selection:
Insights from spending patterns can help Walmart optimize inventory. For example, if one gender spends significantly more in specific categories, Walmart can adjust stock levels to meet demand and focus on promoting related items.

Personalized Marketing:
If gender differences in spending exist, Walmart can leverage this information for personalized recommendations in their app or website, increasing the relevance of product suggestions based on gender preferences.

Broad Reach Campaigns:
If no significant difference is found, Walmart could adopt a unified strategy that doesn’t require segmenting by gender. This would simplify campaigns, potentially lowering marketing costs, and ensuring that both male and female shoppers are reached uniformly.

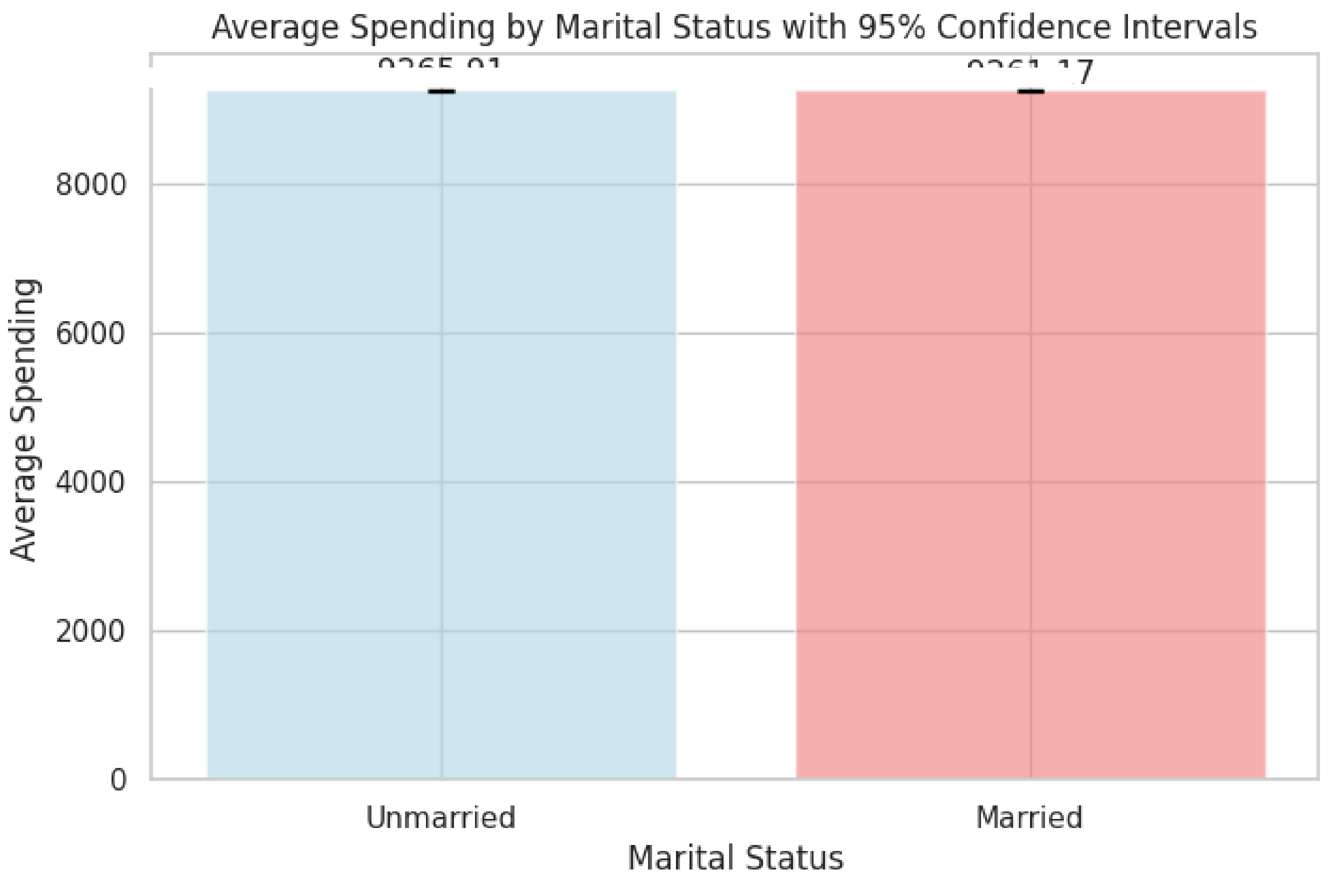
b. Report whether the confidence intervals for the average amount spent by married and unmarried (computed using all the data) overlap. How can Walmart leverage this conclusion to make changes or improvements?

```
# Check the unique values in 'Marital_Status' column
print(df['Marital_Status'].unique())

# If 'Marital_Status' is integer
if df['Marital_Status'].dtype == 'int':
    unmarried_data = df[df['Marital_Status'] == 0]['Purchase']
    married_data = df[df['Marital_Status'] == 1]['Purchase']
else:  # If 'Marital_Status' is string
    unmarried_data = df[df['Marital_Status'] == '0']['Purchase']
    married_data = df[df['Marital_Status'] == '1']['Purchase']

# Continue with the calculations as before
if unmarried_data.empty or married_data.empty:
    print("One of the categories has no data. Please check your data.")
else:
    # Calculate statistics
    unmarried_mean = unmarried_data.mean()
    married_mean = married_data.mean()
    unmarried_std = unmarried_data.std()
    married_std = married_data.std()
    unmarried_sample_size = len(unmarried_data)
    married_sample_size = len(married_data)

    # Z-score for 95% CI
    z = 1.96

    # Calculate confidence intervals
    unmarried_ic_lower = unmarried_mean - z * (unmarried_std / np.sqrt(unmarried_sample_
    unmarried_ic_upper = unmarried_mean + z * (unmarried_std / np.sqrt(unmarried_sample_
    married_ic_lower = married_mean - z * (married_std / np.sqrt(married_sample_size))
    married_ic_upper = married_mean + z * (married_std / np.sqrt(married_sample_size))

    # Check for overlap
    overlap = not(unmarried_ic_upper < married_ic_lower or married_ic_upper < unmarried_

    print("Unmarried 95% CI:", (unmarried_ic_lower, unmarried_ic_upper))
    print("Married 95% CI:", (married_ic_lower, married_ic_upper))
    print("Do the CIs overlap?", overlap)

    if overlap:
        print("The confidence intervals overlap, suggesting no significant difference ir
        print("Walmart can consider similar marketing strategies for both groups.")
    else:
        print("The confidence intervals do not overlap, indicating a difference in spenc
        print("Walmart should consider targeted marketing strategies for married and unm
```

```
[0 1]
Unmarried 95% CI: (9248.61610045097, 9283.199137392043)
Married 95% CI: (9240.460046422771, 9281.889101741976)
Do the CIs overlap? True
The confidence intervals overlap, suggesting no significant difference in average spendi
Walmart can consider similar marketing strategies for both groups.
```

```
# Sample data for means, confidence intervals
categories = ['Unmarried', 'Married']
```

```
means = [unmarried_mean, married_mean]
lower_bounds = [unmarried_ic_lower, married_ic_lower]
upper_bounds = [unmarried_ic_upper, married_ic_upper]

# Plotting the means with error bars for confidence intervals
plt.figure(figsize=(8, 5))
bars = plt.bar(categories, means, color=['lightblue', 'lightcoral'], alpha=0.6, capsize=

# Add error bars for confidence intervals
plt.errorbar(x=categories, y=means,
             yerr=[np.array(means) - np.array(lower_bounds),
                    np.array(upper_bounds) - np.array(means)],
             fmt='none', c='black', capsize=5)

# Adding labels and title
plt.title('Average Spending by Marital Status with 95% Confidence Intervals')
plt.ylabel('Average Spending')
plt.xlabel('Marital Status')

# Add labels on the bars
for bar, mean in zip(bars, means):
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2, yval, f'{mean:.2f}', ha='center', va='bc
plt.show()
```



Insights:

Spending Differences by Marital Status:
If the confidence intervals overlap, it suggests that the average spending between married and unmarried individuals is not significantly different. This would imply that marital status does not play a substantial role in influencing the amount spent by customers at Walmart.

If the confidence intervals do not overlap, it suggests a statistically significant difference in spending behavior between married and unmarried individuals, indicating that Walmart may benefit from understanding and targeting these two groups differently.

Implications for Marketing and Inventory:

Overlap: If married and unmarried customers spend similarly, Walmart can apply broad, inclusive marketing campaigns that appeal to both groups without specific segmentation by marital status.

No Overlap: If there is a clear difference in spending between the two groups, Walmart could leverage this information for targeted marketing. For example, married customers might be more likely to respond to family-oriented product promotions, whereas unmarried customers might respond better to individual convenience items or smaller package sizes.

Recommendations:

Personalized Marketing:

If a spending gap exists, Walmart could develop tailored promotions for each group. For instance, targeting married customers with promotions on household items, bulk purchases, and family-centric products, while promoting single-serving options, convenience products, and lifestyle items to unmarried customers.

Product Placement and Inventory Optimization:

For stores in areas where one group is predominant, Walmart can adjust inventory and product placement based on the identified spending trends of that group. For example, in family-dense areas, Walmart could stock more family-size packages and household items, while in areas with higher single populations, it might prioritize products for individual use and convenience.

Enhanced Customer Experience:

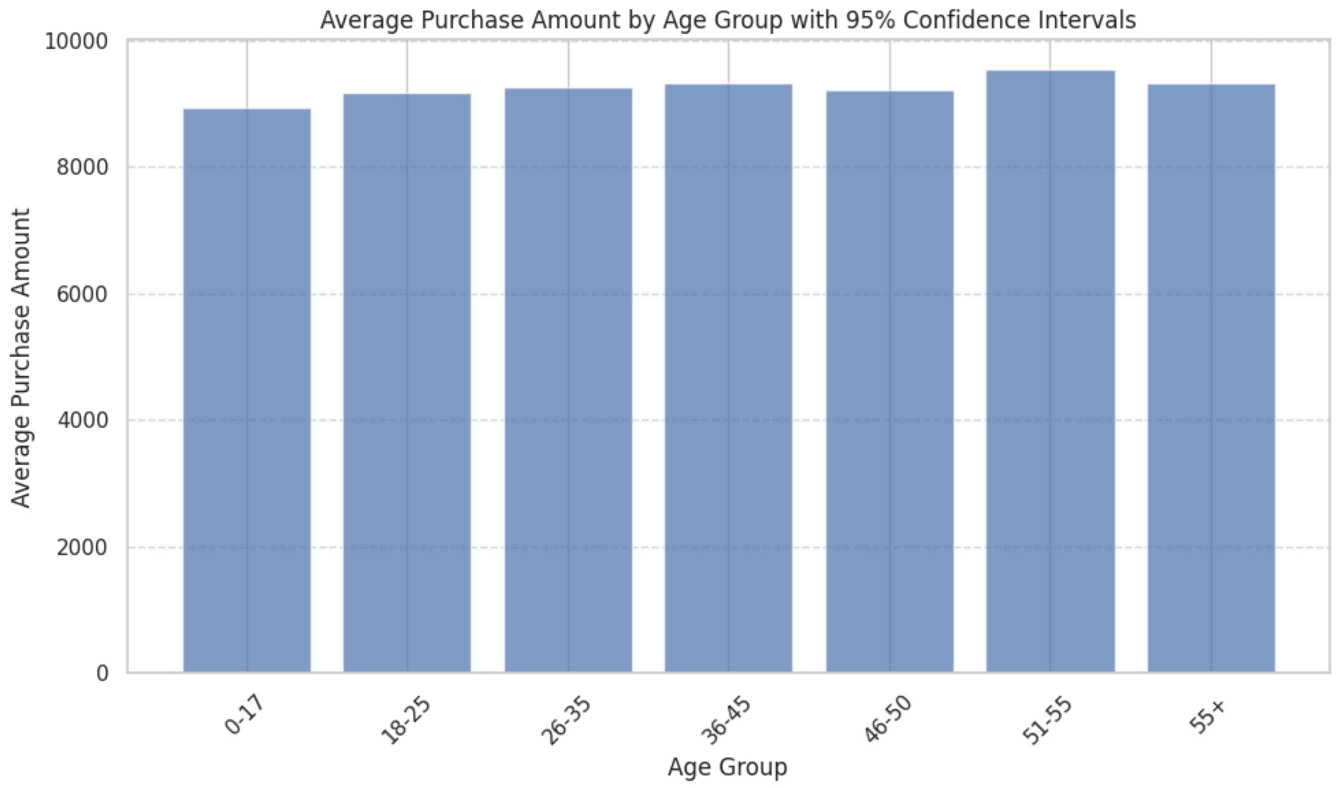
By leveraging insights into spending behavior, Walmart can further personalize shopping experiences both online and in-store, possibly integrating tailored product recommendations, exclusive deals, and marketing content that speaks to the unique needs and preferences of each marital status group.

c. Report whether the confidence intervals for the average amount spent by different age groups (computed using all the data) overlap. How can Walmart leverage this conclusion to make changes or improvements?

```
# Calculate mean, std, and count for each age group
age_group_stats = df.groupby('Age')['Purchase'].agg(['mean', 'std', 'count'])

# Calculate the 95% confidence intervals
z_score = stats.norm.ppf(0.975)
age_group_stats['margin_of_error'] = z_score * (age_group_stats['std'] / np.sqrt(age_grc
age_group_stats['CI_lower'] = age_group_stats['mean'] - age_group_stats['margin_of_error
age_group_stats['CI_upper'] = age_group_stats['mean'] + age_group_stats['margin_of_error

# Check for overlap
for i in range(len(age_group_stats) - 1):
    overlap = age_group_stats['CI_upper'].iloc[i] >= age_group_stats['CI_lower'].iloc[i
    print(f"Age group {age_group_stats.index[i]} and {age_group_stats.index[i + 1]} over
print(age_group_stats[['mean', 'CI_lower', 'CI_upper']])
```

```
Age group 0-17 and 18-25 overlap: False
Age group 18-25 and 26-35 overlap: False
Age group 26-35 and 36-45 overlap: False
Age group 36-45 and 46-50 overlap: True
Age group 46-50 and 51-55 overlap: False
Age group 51-55 and 55+ overlap: True
              mean     CI_lower     CI_upper
Age
0-17   8933.464640  8851.947971  9014.981310
18-25  9169.663606  9138.407949  9200.919264
26-35  9252.690633  9231.733676  9273.647589
36-45  9331.350695  9301.669411  9361.031979
46-50  9208.625697  9163.085143  9254.166252
51-55  9534.808031  9483.991473  9585.624589
55+    9336.280459  9269.298834  9403.262084
```

```
# Plotting the confidence intervals
plt.figure(figsize=(10, 6))
plt.bar(age_group_stats.index, age_group_stats['mean'], alpha=0.7)
plt.xticks(rotation=45)
plt.title('Average Purchase Amount by Age Group with 95% Confidence Intervals')
plt.xlabel('Age Group')
plt.ylabel('Average Purchase Amount')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



Insights:

Spending Trends Across Age Groups:

If confidence intervals overlap between age groups, it suggests that the spending behavior is similar across those groups, indicating no significant difference in average spending based on age. In this case, age may not be a key determinant of spending patterns at Walmart.

If confidence intervals do not overlap, this indicates distinct spending behaviors across certain age groups, suggesting that age does play a role in purchase behavior, with some age groups potentially spending more or less than others.

Implications for Targeted Marketing:

Overlap: If there is no significant difference in spending across age groups, Walmart could consider broader marketing strategies that do not focus specifically on age, such as general discount campaigns or store-wide promotions that appeal to a wide audience.

No Overlap: If distinct spending patterns exist among age groups, Walmart can create more age-specific marketing strategies. For example, younger age groups might respond well to promotions on trendy or tech-related products, while older age groups may prefer promotions on necessities or household items.

Personalization Opportunities:

Higher Spending Age Groups: Walmart could offer loyalty rewards or personalized discounts for age groups that tend to spend more, encouraging them to continue shopping and increasing brand loyalty.

Engagement with Lower Spending Groups: For age groups that tend to spend less, Walmart might consider special deals, promotions, or bundled offers to encourage higher spending and drive interest in specific products.

Recommendations:

Marketing Strategies by Age:

For groups with distinct spending behaviors, tailor promotions and advertising to their unique preferences. For example, if younger groups spend less, attract them with discount offers on products that appeal to their lifestyle, such as electronics or fashion. If older groups have higher average spending, focus on value-based promotions on household essentials and family-related items.

Customized Product Offerings:

Adjust product inventory and offerings based on the age demographics of specific store locations. For example, stores in areas with a higher proportion of younger shoppers might stock more trend-oriented items, while stores with older demographics may benefit from a wider selection of household and health products.

Enhanced Customer Engagement:

If certain age groups show higher spending, Walmart can leverage this by implementing age-targeted loyalty programs or discounts to build customer loyalty and encourage repeat visits

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