```
# Import necessary libraries
In [1]:
         import pandas as pd
         import matplotlib.pyplot as plt
         import seaborn as sns
In [2]:
         # Load the dataset
         df = pd.read_csv('bikes_sales_dataset.csv')
         df.head()
In [3]:
Out[3]:
                                                                                                                         Age Purchas
                                                                                            Commute
                   Martial
                                                                               Home
                            Gender Income Children Education Occupation
                                                                                                       Region Age
                                                                                      Cars
                                                                              Owner
                                                                                             Distance
                                                                                                                     Brackets
                                                                                                                                    В
                    Status
                                                                       Skilled
                                                                                                                      Middle
                            Female $40,000
                                                                                             0-1 Miles Europe
         0 12496 Married
                                                        Bachelors
                                                                                                                42
                                                                                 Yes
                                                                      Manual
                                                                                                                         Age
                                                           Partial
                                                                                                                       Middle
         1 24107 Married
                                                    3
                                                                      Clerical
                                                                                             0-1 Miles Europe
                                                                                                                43
                              Male $30,000
                                                                                 Yes
                                                         College
                                                                                                                         Age
                                                           Partial
                                                    5
                                                                  Professional
                                                                                             2-5 Miles
                                                                                                                         Old
         2 14177 Married
                              Male $80,000
                                                                                  No
                                                                                                       Europe
                                                                                                                 60
                                                          College
                                                                                                                       Middle
                                                                                                 5-10
         3 24381
                     Single
                              Male $70,000
                                                        Bachelors Professional
                                                                                 Yes
                                                                                                        Pacific
                                                                                                                41
                                                                                                Miles
                                                                                                                         Age
                                                                                                                      Middle
         4 25597
                     Single
                              Male $30,000
                                                       Bachelors
                                                                      Clerical
                                                                                             0-1 Miles Europe
                                                                                                                36
                                                                                  No
                                                                                                                         Age
         df.info()
In [4]:
```

```
<class 'pandas.core.frame.DataFrame'>
       RangeIndex: 1000 entries, 0 to 999
       Data columns (total 14 columns):
            Column
                              Non-Null Count Dtype
           -----
                              -----
        0
            TD
                              1000 non-null
                                             int64
           Martial Status
                              1000 non-null
                                             object
        2
            Gender
                              1000 non-null
                                             object
                                             object
            Income
                              1000 non-null
            Children
                              1000 non-null
                                             int64
                                             object
            Education
                             1000 non-null
           Occupation
                                             object
                             1000 non-null
           Home Owner
                                             object
                             1000 non-null
                                             int64
            Cars
                              1000 non-null
        9
            Commute Distance 1000 non-null
                                             object
           Region
                                             object
        10
                              1000 non-null
           Age
        11
                             1000 non-null
                                             int64
        12 Age Brackets
                             1000 non-null
                                             object
        13 Purchased Bike
                                             object
                             1000 non-null
       dtypes: int64(4), object(10)
       memory usage: 109.5+ KB
In [5]: # Convert Income to numeric
        df['Income'] = df['Income'].replace('[\$,]', '', regex=True).astype(float)
        df.info()
In [6]:
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 14 columns):

#	Column	Non-Null Count	Dtype			
0	ID	1000 non-null	int64			
1	Martial Status	1000 non-null	object			
2	Gender	1000 non-null	object			
3	Income	1000 non-null	float64			
4	Children	1000 non-null	int64			
5	Education	1000 non-null	object			
6	Occupation	1000 non-null	object			
7	Home Owner	1000 non-null	object			
8	Cars	1000 non-null	int64			
9	Commute Distance	1000 non-null	object			
10	Region	1000 non-null	object			
11	Age	1000 non-null	int64			
12	Age Brackets	1000 non-null	object			
13	Purchased Bike	1000 non-null	object			
dtynes float64(1) int64(4) object(9)						

dtypes: float64(1), int64(4), object(9)

memory usage: 109.5+ KB

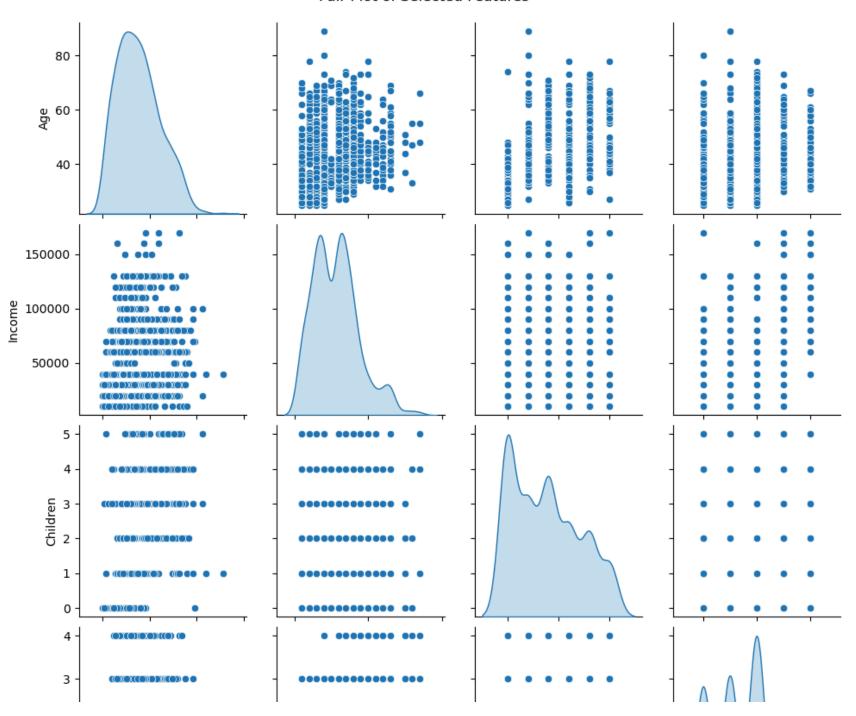
In [7]: df.describe()

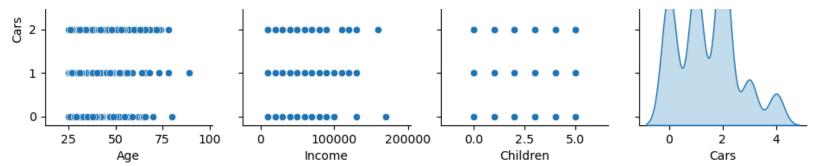
Out[7]:

	ID	Income	Children	Cars	Age
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000
mean	19965.992000	56360.000000	1.898000	1.442000	44.163000
std	5347.333948	31085.635215	1.628572	1.125123	11.364488
min	11000.000000	10000.000000	0.000000	0.000000	25.000000
25%	15290.750000	30000.000000	0.000000	1.000000	35.000000
50%	19744.000000	60000.000000	2.000000	1.000000	43.000000
75%	24470.750000	70000.000000	3.000000	2.000000	52.000000
max	29447.000000	170000.000000	5.000000	4.000000	89.000000

```
sns.pairplot(df[['Age', 'Income', 'Children', 'Cars', 'Purchased Bike']], diag_kind='kde')
 # Display the plot
 plt.suptitle('Pair Plot of Selected Features', y=1.02) # Add a title to the pair plot
 plt.show()
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\ oldcore.py:1119: FutureWarning: use inf as na option is deprecate
d and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option context('mode.use inf as na', True):
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecate
d and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option context('mode.use inf as na', True):
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\ oldcore.py:1119: FutureWarning: use inf as na option is deprecate
d and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option context('mode.use inf as na', True):
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\ oldcore.py:1119: FutureWarning: use inf as na option is deprecate
d and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option context('mode.use inf as na', True):
```





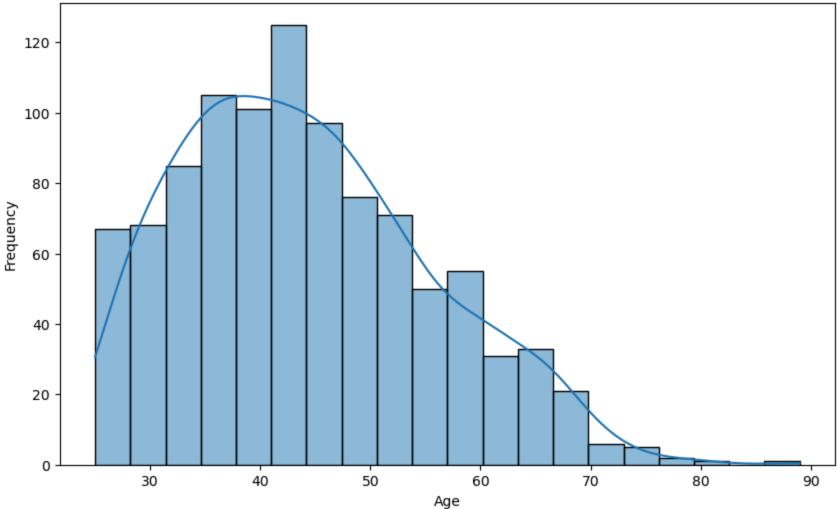


## Distribution of Age

```
In [9]: plt.figure(figsize=(10, 6))
    sns.histplot(df['Age'], bins=20, kde=True)
    plt.title('Distribution of Age')
    plt.xlabel('Age')
    plt.ylabel('Frequency')
    plt.show()
```

C:\ProgramData\anaconda3\Lib\site-packages\seaborn\\_oldcore.py:1119: FutureWarning: use\_inf\_as\_na option is deprecate
d and will be removed in a future version. Convert inf values to NaN before operating instead.
 with pd.option\_context('mode.use\_inf\_as\_na', True):

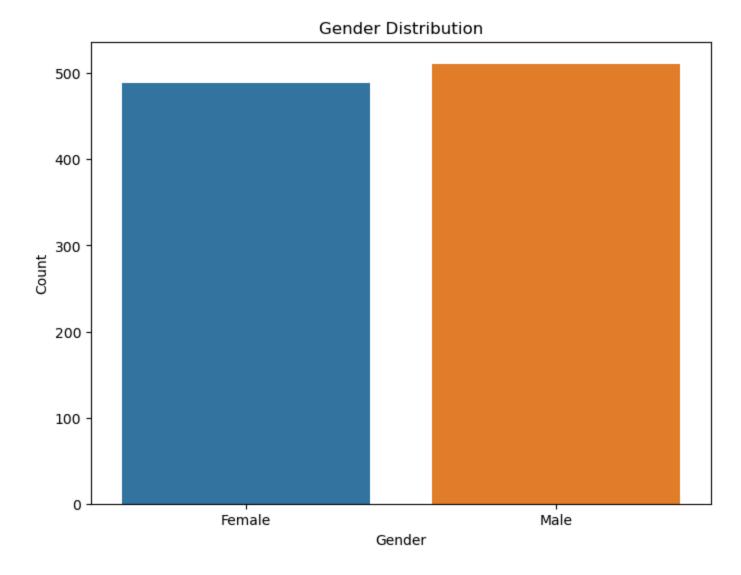




- The age distribution appears to be roughly normal, with a majority of customers falling within a certain age range.
- The dataset includes a diverse range of ages, which may help in understanding the buying patterns across different age groups.

## **Gender Distribution**

```
In [10]: plt.figure(figsize=(8, 6))
    sns.countplot(data=df, x='Gender')
    plt.title('Gender Distribution')
    plt.xlabel('Gender')
    plt.ylabel('Count')
    plt.show()
```



## Observation:

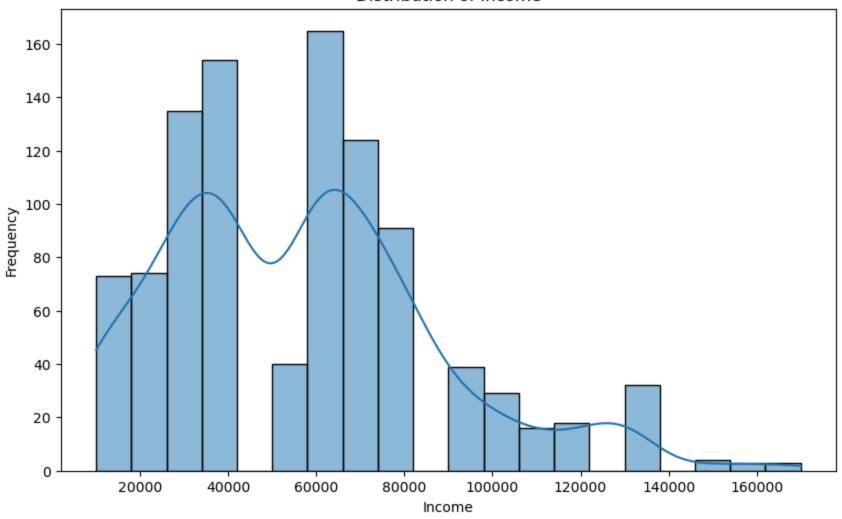
- The dataset includes a roughly balanced number of male and female customers.
- This balance can help in analyzing if there are significant differences in purchasing behaviors between genders.

## **Income Distribution**

```
In [11]: plt.figure(figsize=(10, 6))
    sns.histplot(df['Income'], bins=20, kde=True)
    plt.title('Distribution of Income')
    plt.xlabel('Income')
    plt.ylabel('Frequency')
    plt.show()
```

C:\ProgramData\anaconda3\Lib\site-packages\seaborn\\_oldcore.py:1119: FutureWarning: use\_inf\_as\_na option is deprecate
d and will be removed in a future version. Convert inf values to NaN before operating instead.
 with pd.option\_context('mode.use\_inf\_as\_na', True):



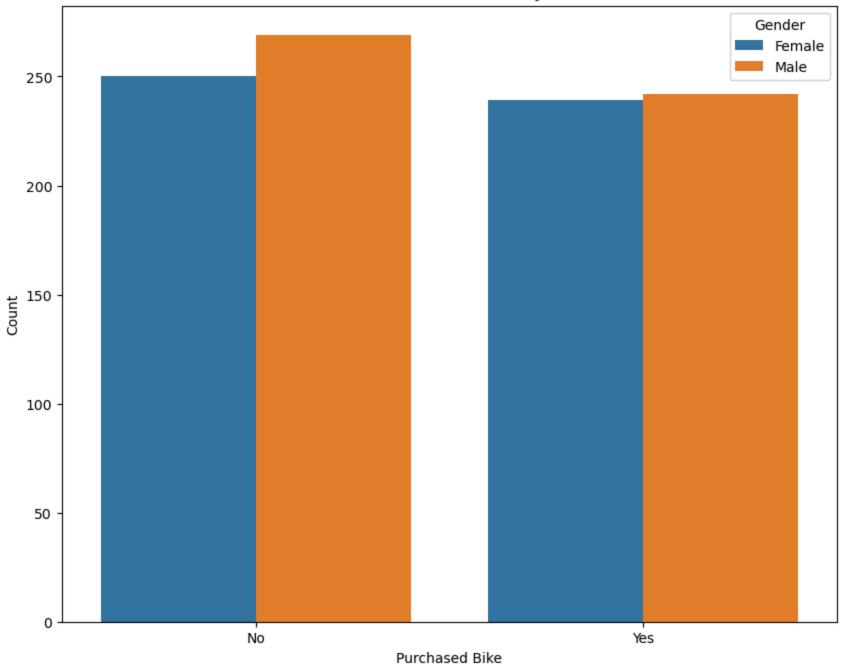


- The income distribution shows a wide range, indicating that the dataset includes customers from various economic backgrounds.
- The presence of high-income customers might influence the purchasing behavior towards bikes.

# Number of Bikes Purchased by Gender

```
In [12]: plt.figure(figsize=(10, 8))
    sns.countplot(data=df, x='Purchased Bike', hue='Gender')
    plt.title('Number of Bikes Purchased by Gender')
    plt.xlabel('Purchased Bike')
    plt.ylabel('Count')
    plt.show()
```



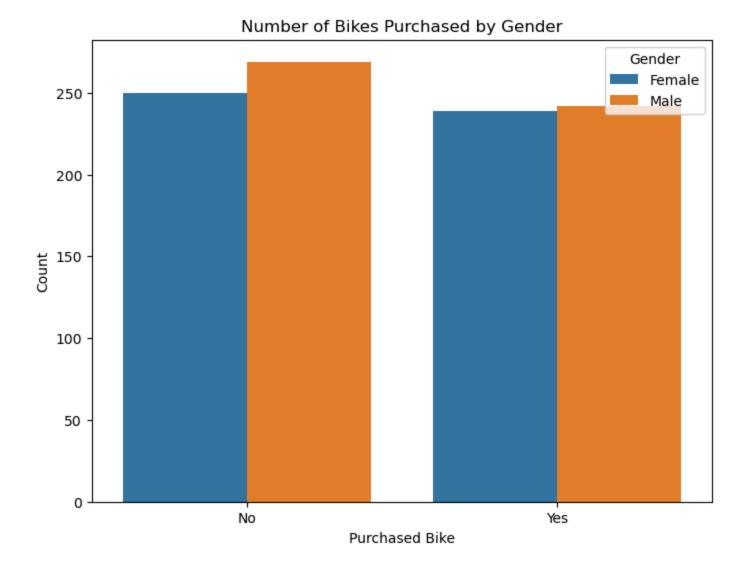


#### Observation:

- The visualization indicates whether there are significant differences in bike purchases between male and female customers.
- This can be useful in targeting marketing efforts towards the more likely gender group to purchase bikes.

# **Average Income by Occupation**

```
In [13]: # Number of Bikes Purchased by Gender
plt.figure(figsize=(8, 6))
sns.countplot(data=df, x='Purchased Bike', hue='Gender')
plt.title('Number of Bikes Purchased by Gender')
plt.xlabel('Purchased Bike')
plt.ylabel('Count')
plt.show()
```



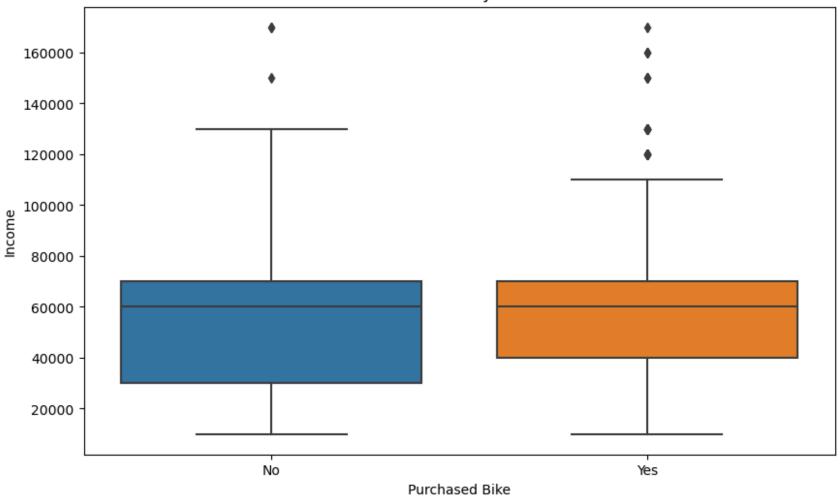
## Observation:

- Different occupations have varying average incomes.
- Higher-income occupations might be more likely to purchase bikes, especially higher-end models.

# Income Distribution by Bike Purchase

```
In [14]: plt.figure(figsize=(10, 6))
    sns.boxplot(data=df, x='Purchased Bike', y='Income')
    plt.title('Income Distribution by Bike Purchase')
    plt.xlabel('Purchased Bike')
    plt.ylabel('Income')
    plt.show()
```

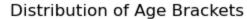
#### Income Distribution by Bike Purchase

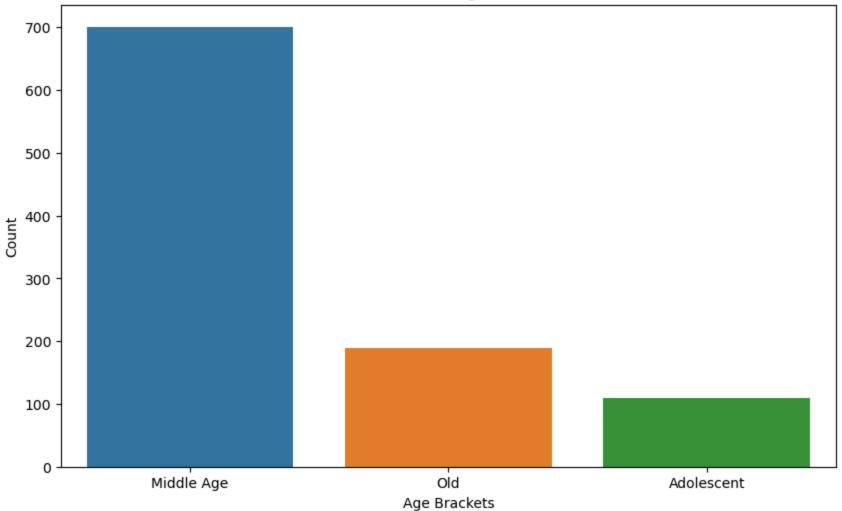


- Customers who purchased bikes might show different income patterns compared to those who did not.
- This can help in understanding if income is a significant factor in the decision to purchase a bike.

# **Age Brackets Distribution**

```
In [15]: plt.figure(figsize=(10, 6))
    sns.countplot(data=df, x='Age Brackets')
    plt.title('Distribution of Age Brackets')
    plt.xlabel('Age Brackets')
    plt.ylabel('Count')
    plt.show()
```





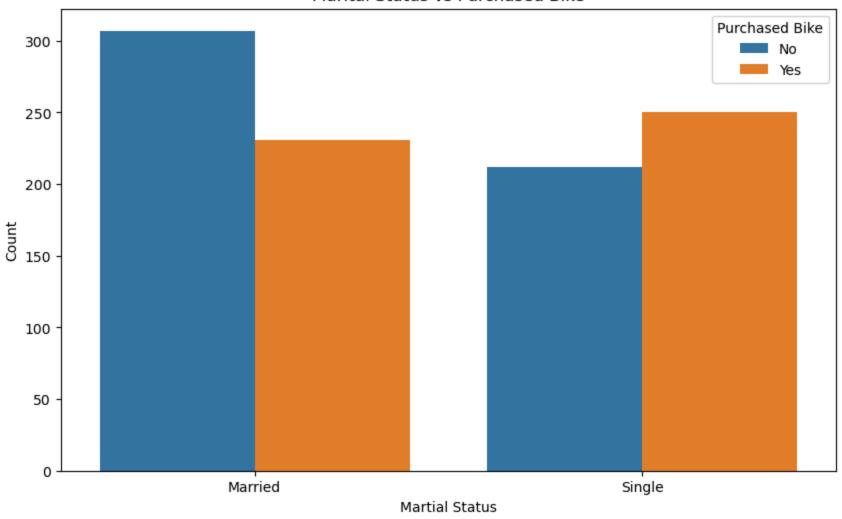
### Observation:

- The dataset includes various age brackets, showing the age diversity of the customer base.
- Analyzing purchasing behaviors across different age brackets can help in segmenting the market effectively.

### Marital Status vs Purchased Bike

```
In [16]: plt.figure(figsize=(10, 6))
    sns.countplot(data=df, x='Martial Status', hue='Purchased Bike')
    plt.title('Marital Status vs Purchased Bike')
    plt.xlabel('Martial Status')
    plt.ylabel('Count')
    plt.show()
```

#### Marital Status vs Purchased Bike

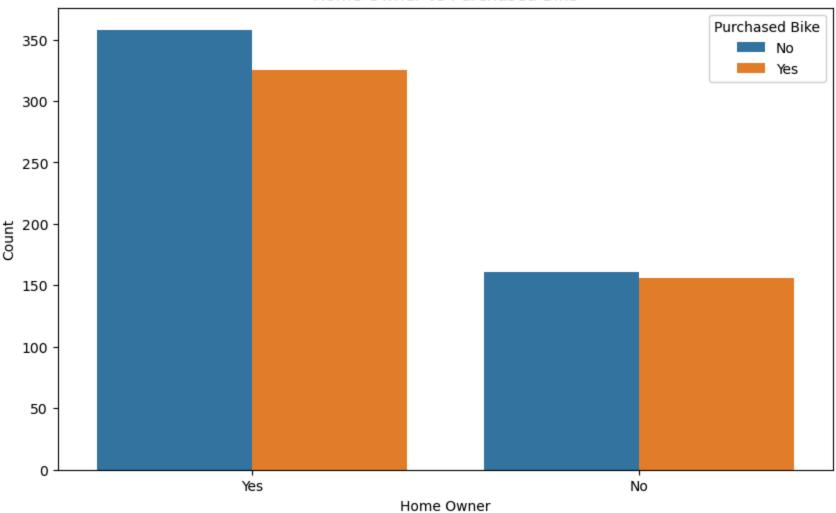


- There might be observable differences in bike purchasing behavior based on marital status.
- Understanding this can help in tailoring marketing campaigns to target specific marital status groups more effectively.

#### Home Owner vs Purchased Bike

```
In [17]: plt.figure(figsize=(10, 6))
    sns.countplot(data=df, x='Home Owner', hue='Purchased Bike')
    plt.title('Home Owner vs Purchased Bike')
    plt.xlabel('Home Owner')
    plt.ylabel('Count')
    plt.show()
```





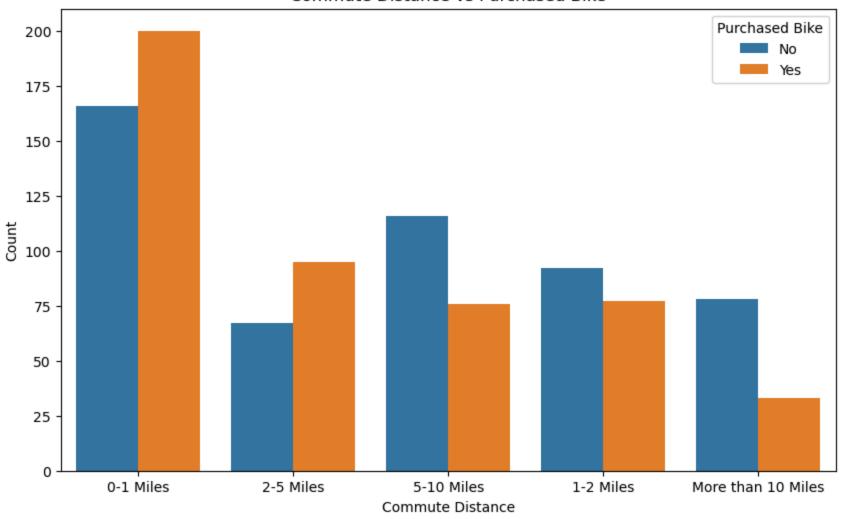
### Observation:

- Homeownership might be an indicator of financial stability, which could influence bike purchasing decisions.
- Customers who own homes might have a higher likelihood of purchasing bikes.

### Commute Distance vs Purchased Bike

```
In [18]: plt.figure(figsize=(10, 6))
    sns.countplot(data=df, x='Commute Distance', hue='Purchased Bike')
    plt.title('Commute Distance vs Purchased Bike')
    plt.xlabel('Commute Distance')
    plt.ylabel('Count')
    plt.show()
```

#### Commute Distance vs Purchased Bike



- The distance customers commute could influence their decision to purchase a bike.
- Customers with shorter commute distances might be more inclined to buy bikes for convenience.

# **Contact Information**

For any queries or further information, please feel free to reach out to me through the following platforms:

• LinkedIn: Vinay Kumar Panika

• **GitHub**: Vinaypanika