Project Description: Analyzing Online Advertisement Clicks Objective The primary objective of this project is to analyze user behavior and identify factors influencing the likelihood of a user clicking on an online advertisement. By understanding these factors, we can improve ad targeting and optimize marketing strategies.

Dataset Description The dataset contains the following columns:

Daily Time Spent on Site: The amount of time (in minutes) a user spends on the website daily. Age: The age of the user. Area Income: The average income of the geographical area where the user resides. Daily Internet Usage: The amount of time (in minutes) a user spends on the internet daily. Ad Topic Line: The title or topic line of the advertisement. City: The city where the user is located. Male: A binary variable indicating the gender of the user (1 if male, 0 if female). Country: The country where the user is located. Timestamp: The exact time and date when the user clicked on the advertisement or visited the site. Clicked on Ad: A binary variable indicating whether the user clicked on the advertisement (1 if clicked, 0 if not).

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier,
GradientBoostingClassifier
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, roc_auc_score, confusion_matrix,
classification_report
import warnings
warnings.filterwarnings('ignore')
```

Read the Data

```
data=pd.read_csv(r"C:\Preet\advertising.csv")

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 10 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Daily Time Spent on Site  1000 non-null   float64
 1   Age                       1000 non-null   int64
 2   Area Income               1000 non-null   float64
 3   Daily Internet Usage      1000 non-null   float64
```

```
 4   Ad Topic Line             1000 non-null   object
 5   City                      1000 non-null   object
 6   Male                      1000 non-null   int64
 7   Country                   1000 non-null   object
 8   Timestamp                 1000 non-null   object
 9   Clicked on Ad             1000 non-null   int64
dtypes: float64(3), int64(3), object(4)
memory usage: 78.3+ KB
```

```
data.head()
```

```
   Daily Time Spent on Site  Age  Area Income  Daily Internet Usage  \
0                     68.95   35     61833.90                256.09
1                     80.23   31     68441.85                193.77
2                     69.47   26     59785.94                236.50
3                     74.15   29     54806.18                245.89
4                     68.37   35     73889.99                225.58

                           Ad Topic Line             City  Male
Country  \
0     Cloned 5thgeneration orchestration     Wrightburgh     0
Tunisia
1     Monitored national standardization       West Jodi     1
Nauru
2       Organic bottom-line service-desk        Davidton     0  San
Marino
3  Triple-buffered reciprocal time-frame  West Terrifurt     1
Italy
4          Robust logistical utilization    South Manuel     0
Iceland

              Timestamp  Clicked on Ad
0  2016-03-27 00:53:11              0
1  2016-04-04 01:39:02              0
2  2016-03-13 20:35:42              0
3  2016-01-10 02:31:19              0
4  2016-06-03 03:36:18              0
```

```
data.describe()
```

```
       Daily Time Spent on Site          Age   Area Income  \
count               1000.000000  1000.000000   1000.000000
mean                  65.000200    36.009000  55000.000080
std                   15.853615     8.785562  13414.634022
min                   32.600000    19.000000  13996.500000
25%                   51.360000    29.000000  47031.802500
50%                   68.215000    35.000000  57012.300000
75%                   78.547500    42.000000  65470.635000
max                   91.430000    61.000000  79484.800000
```

```
       Daily Internet Usage         Male  Clicked on Ad
count           1000.000000  1000.000000     1000.00000
mean             180.000100     0.481000        0.50000
std               43.902339     0.499889        0.50025
min              104.780000     0.000000        0.00000
25%              138.830000     0.000000        0.00000
50%              183.130000     0.000000        0.50000
75%              218.792500     1.000000        1.00000
max              269.960000     1.000000        1.00000
```

```
data.shape
```

```
(1000, 10)
```

```
data.isna().sum()
```

```
Daily Time Spent on Site    0
Age                         0
Area Income                 0
Daily Internet Usage        0
Ad Topic Line               0
City                        0
Male                        0
Country                     0
Timestamp                   0
Clicked on Ad               0
dtype: int64
```

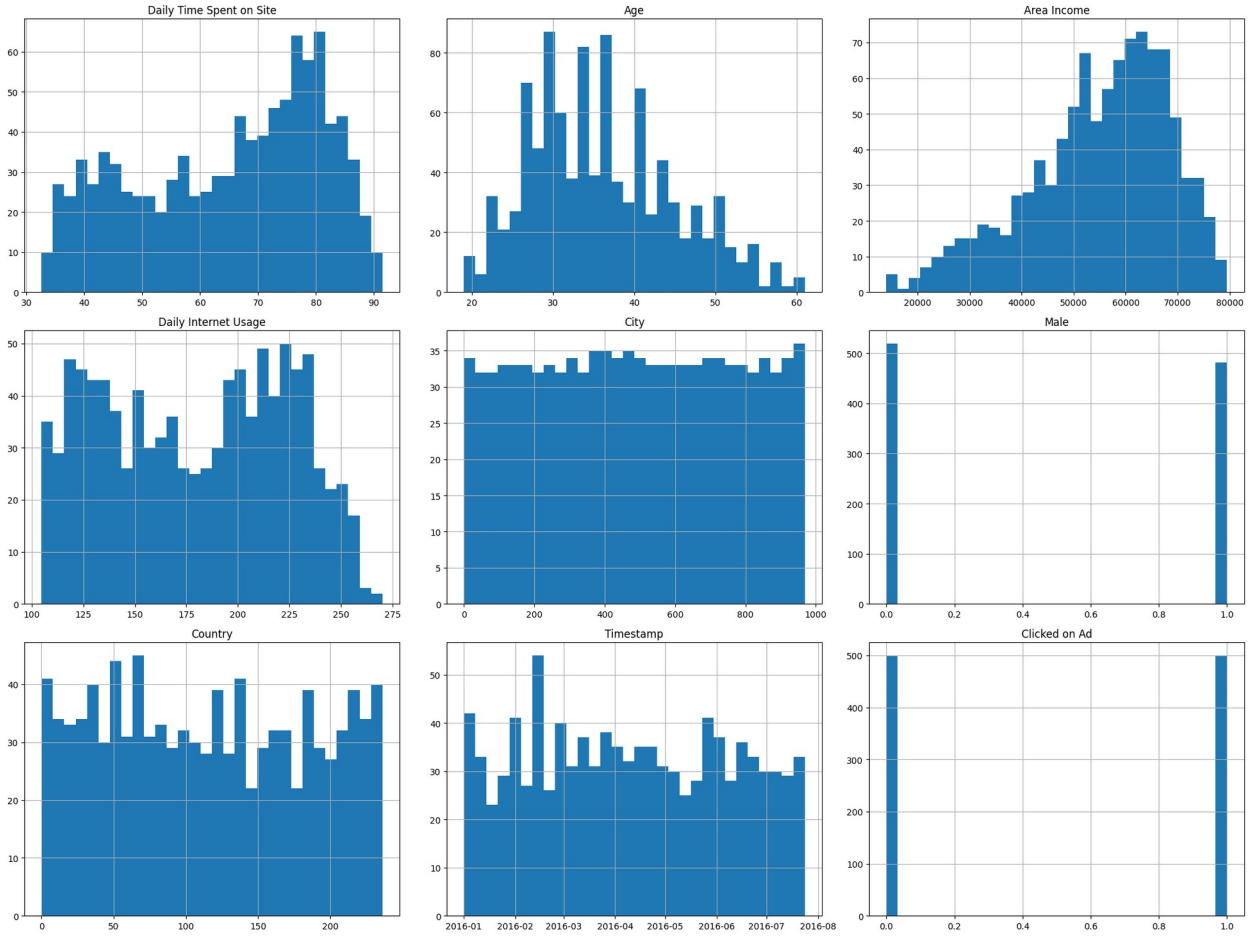
```
data.duplicated().sum()
```

```
0
```

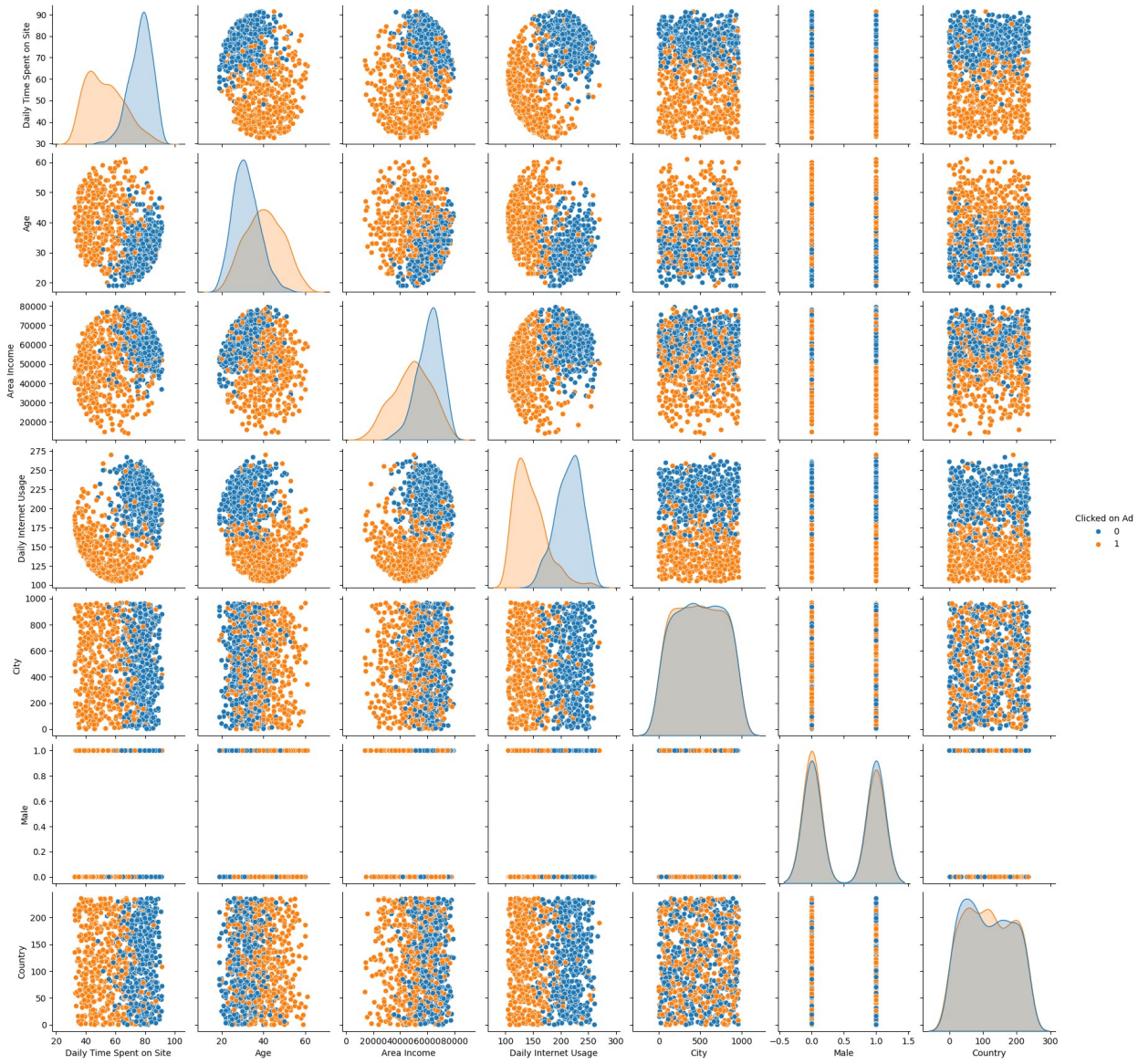
```
# Ensure all data types are correct
data['Timestamp'] = pd.to_datetime(data['Timestamp'])

# Encode categorical variables
label_encoder = LabelEncoder()
data['City'] = label_encoder.fit_transform(data['City'])
data['Country'] = label_encoder.fit_transform(data['Country'])
```

Explortary Data Analysis

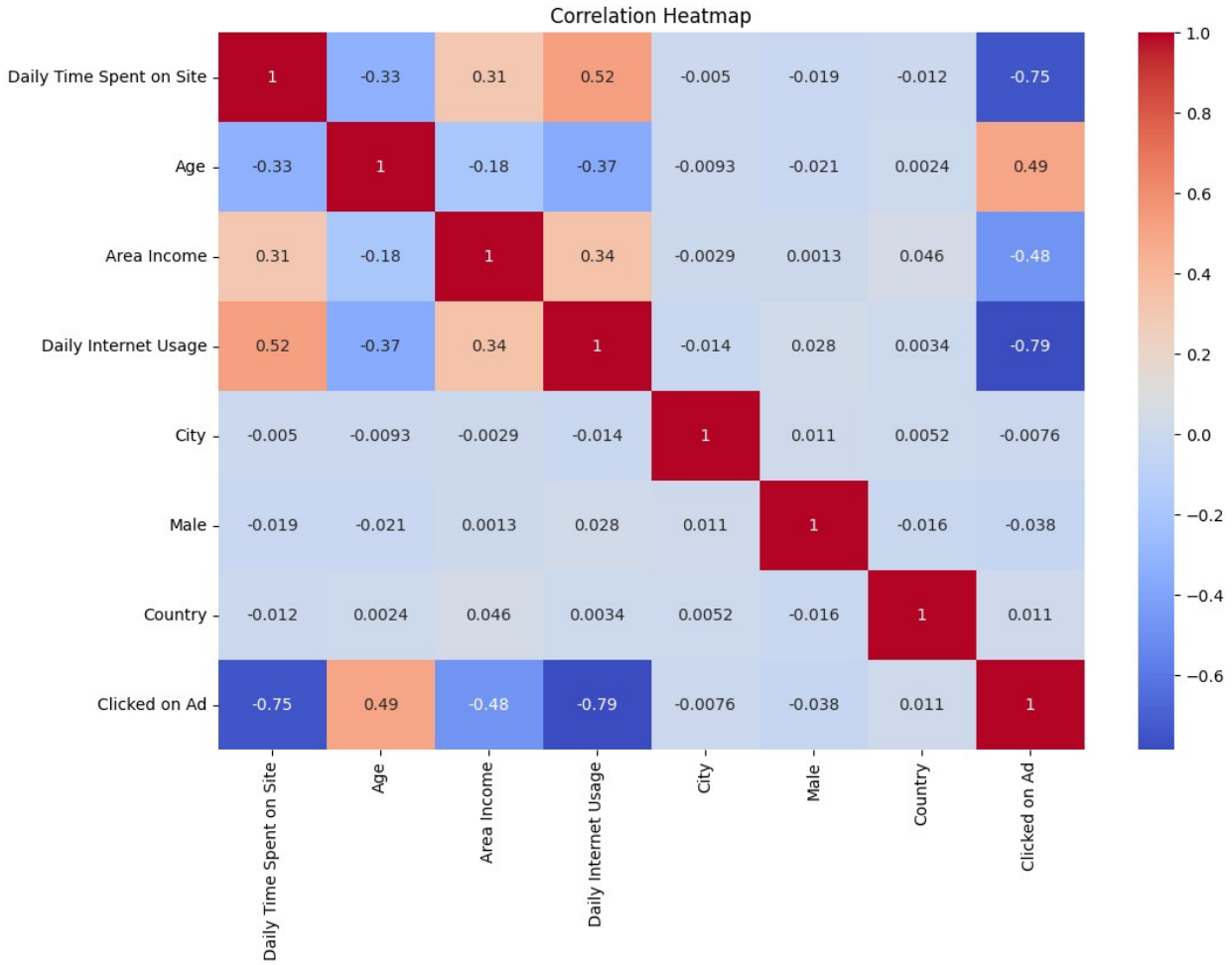
```
# Visualize the distribution of each feature
data.hist(bins=30, figsize=(20,15))
plt.tight_layout()
plt.show()
```




```
# Analyze the relationship between features and the target variable (Clicked on Ad)
sns.pairplot(data, hue='Clicked on Ad')
plt.show()
```




```
import seaborn as sns
import matplotlib.pyplot as plt

# Assuming 'data' is your DataFrame
numeric_data = data.select_dtypes(include='number')
plt.figure(figsize=(12, 8))
sns.heatmap(numeric_data.corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



Feature Engineering

```
# Create new features if necessary (e.g., extract hour from timestamp)
data['Hour'] = data['Timestamp'].dt.hour

# Normalize or standardize numerical features if needed
scaler = StandardScaler()
numerical_features = ['Daily Time Spent on Site', 'Age', 'Area
Income', 'Daily Internet Usage', 'Hour']
data[numerical_features] =
scaler.fit_transform(data[numerical_features])

# Drop the original Timestamp column as we have extracted useful
information from it
data = data.drop(columns=['Timestamp', 'Ad Topic Line'])
```

Modeling

```
# Split the data into training and testing sets
X = data.drop(columns=['Clicked on Ad'])
```

```
y = data['Clicked on Ad']

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)

 #Define the models
models = {
    'Logistic Regression': LogisticRegression(),
    'Decision Tree': DecisionTreeClassifier(),
    'Random Forest': RandomForestClassifier(),
    'Gradient Boosting': GradientBoostingClassifier()
}

# Train and evaluate the models
results = {}

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for model_name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    results[model_name] = {
        'Accuracy': accuracy_score(y_test, y_pred),
        'Precision': precision_score(y_test, y_pred),
        'Recall': recall_score(y_test, y_pred),
        'F1 Score': f1_score(y_test, y_pred),
        'AUC-ROC': roc_auc_score(y_test, y_pred)
    }
    print(f'{model_name} Classification Report:\n',
classification_report(y_test, y_pred))
    print(f'{model_name} Confusion Matrix:\n',
confusion_matrix(y_test, y_pred))

Logistic Regression Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.98      0.97       146
           1       0.98      0.96      0.97       154

    accuracy                           0.97       300
   macro avg       0.97      0.97      0.97       300
weighted avg       0.97      0.97      0.97       300

Logistic Regression Confusion Matrix:
 [[143   3]
 [  6 148]]
Decision Tree Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.92      0.93       146
```

```
           1       0.93      0.94      0.94       154

    accuracy                           0.93       300
   macro avg       0.93      0.93      0.93       300
weighted avg       0.93      0.93      0.93       300

Decision Tree Confusion Matrix:
 [[135  11]
 [  9 145]]
Random Forest Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.96      0.94       146
           1       0.96      0.93      0.94       154

    accuracy                           0.94       300
   macro avg       0.94      0.94      0.94       300
weighted avg       0.94      0.94      0.94       300

Random Forest Confusion Matrix:
 [[140   6]
 [ 11 143]]
Gradient Boosting Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.95      0.95       146
           1       0.95      0.94      0.95       154

    accuracy                           0.95       300
   macro avg       0.95      0.95      0.95       300
weighted avg       0.95      0.95      0.95       300

Gradient Boosting Confusion Matrix:
 [[139   7]
 [  9 145]]
```

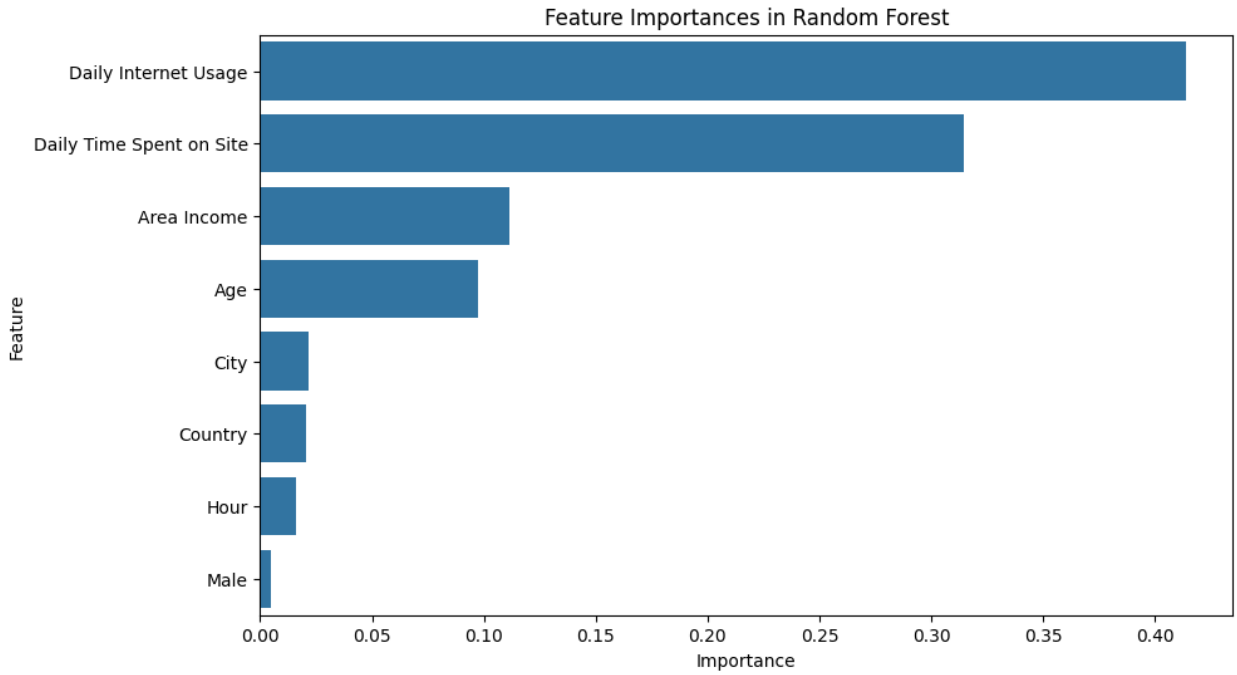
```python
# Display the results
results_df = pd.DataFrame(results).T
print(results_df)
```

```
                     Accuracy  Precision    Recall  F1 Score   AUC-ROC
Logistic Regression  0.970000   0.980132  0.961039  0.970492  0.970246
Decision Tree        0.933333   0.929487  0.941558  0.935484  0.933108
Random Forest        0.943333   0.959732  0.928571  0.943894  0.943738
Gradient Boosting    0.946667   0.953947  0.941558  0.947712  0.946807
```

```python
# Identify the most important features influencing ad clicks using
Random Forest
best_model = models['Random Forest']
importances = best_model.feature_importances_
feature_names = X.columns
```

```
feature_importance_df = pd.DataFrame({'Feature': feature_names,
'Importance': importances}).sort_values(by='Importance',
ascending=False)

# Plot the feature importances
plt.figure(figsize=(10,6))
sns.barplot(x='Importance', y='Feature', data=feature_importance_df)
plt.title('Feature Importances in Random Forest')
plt.show()
```




```
# Based on the findings, provide actionable insights
print("Recommendations:")
print("1. Focus on users with higher 'Daily Time Spent on Site' as
they are more likely to click on ads.")
print("2. Target ads to users within specific age ranges identified as
more likely to click.")
print("3. Optimize ad content to appeal to users with higher 'Daily
Internet Usage'.")
print("4. Use demographic information like 'Area Income' to better
tailor advertisements.")
```

```
Recommendations:
1. Focus on users with higher 'Daily Time Spent on Site' as they are
more likely to click on ads.
2. Target ads to users within specific age ranges identified as more
likely to click.
3. Optimize ad content to appeal to users with higher 'Daily Internet
Usage'.
```

```
4. Use demographic information like 'Area Income' to better tailor
advertisements.
```