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In [1]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, accuracy_score, roc_auc_score

# Load data
df = pd.read_csv("Ecommerce_Consumer_Behavior_Analysis_Data.csv")

# Inspect data
print(df.head())
print(df.info())
print(df.describe())

# Handle missing values
df = df.dropna() # Simple approach, can be refined

# Define features and target (replace 'target_column' with actual column name)
target_column = "your_target_column_name_here"
X = df.drop(columns=[target_column])
y = df[target_column]

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

# Identify numerical and categorical features
num_features = X.select_dtypes(include=["int64", "float64"]).columns.tolist()
cat_features = X.select_dtypes(include=["object"]).columns.tolist()

# Preprocessing: Scaling & Encoding
preprocessor = ColumnTransformer([
    ("num", StandardScaler(), num_features),
    ("cat", OneHotEncoder(handle_unknown="ignore"), cat_features)
])

# Logistic Regression Baseline Model
log_reg_pipeline = Pipeline([
    ("preprocessor", preprocessor),
    ("classifier", LogisticRegression(max_iter=1000))
])
log_reg_pipeline.fit(X_train, y_train)
y_pred_log = log_reg_pipeline.predict(X_test)

def evaluate_model(name, y_true, y_pred):
    print(f"\n{name} Performance:")
    print(classification_report(y_true, y_pred))

evaluate_model("Logistic Regression", y_test, y_pred_log)

# Decision Tree with Hyperparameter Tuning
dt_pipeline = Pipeline([
    ("preprocessor", preprocessor),
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    ("classifier", DecisionTreeClassifier(random_state=42))
])

param_grid = {
    "classifier__max_depth": [3, 5, 10],
    "classifier__min_samples_split": [2, 5, 10]
}

grid_search = GridSearchCV(dt_pipeline, param_grid, cv=5, scoring="accuracy")
grid_search.fit(X_train, y_train)

y_pred_tree = grid_search.best_estimator_.predict(X_test)
evaluate_model("Decision Tree (Tuned)", y_test, y_pred_tree)

# Feature Importance Analysis
best_tree = grid_search.best_estimator_.named_steps["classifier"]
importances = best_tree.feature_importances_
feature_names = preprocessor.get_feature_names_out()

sns.barplot(x=importances, y=feature_names)
plt.title("Feature Importance in Decision Tree")
plt.xlabel("Importance")
plt.ylabel("Feature")
plt.show()
```

	Customer_ID	Age	Gender	Income_Level	Marital_Status	Education_Level	\
0	37-611-6911	22	Female	Middle	Married	Bachelor's	
1	29-392-9296	49	Male	High	Married	High School	
2	84-649-5117	24	Female	Middle	Single	Master's	
3	48-980-6078	29	Female	Middle	Single	Master's	
4	91-170-9072	33	Female	Middle	Widowed	High School	

	Occupation	Location	Purchase_Category	Purchase_Amount	...	\
0	Middle	Évry	Gardening & Outdoors	\$333.80	...	
1	High	Huocheng	Food & Beverages	\$222.22	...	
2	High	Huzhen	Office Supplies	\$426.22	...	
3	Middle	Wiwilí	Home Appliances	\$101.31	...	
4	Middle	Nara	Furniture	\$211.70	...	

	Customer_Satisfaction	Engagement_with_Ads	Device_Used_for_Shopping	\
0		7	NaN	Tablet
1		5	High	Tablet
2		7	Low	Smartphone
3		1	NaN	Smartphone
4		10	NaN	Smartphone

	Payment_Method	Time_of_Purchase	Discount_Used	\
0	Credit Card	3/1/2024	True	
1	PayPal	4/16/2024	True	
2	Debit Card	3/15/2024	True	
3	Other	10/4/2024	True	
4	Debit Card	1/30/2024	False	

	Customer_Loyalty_Program_Member	Purchase_Intent	Shipping_Preference	\
0	False	Need-based	No Preference	
1	False	Wants-based	Standard	
2	True	Impulsive	No Preference	
3	True	Need-based	Express	
4	False	Wants-based	No Preference	

	Time_to_Decision
0	2
1	6
2	3
3	10
4	4

```
[5 rows x 28 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 28 columns):
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#	Column	Non-Null Count	Dtype
0	Customer_ID	1000 non-null	object
1	Age	1000 non-null	int64
2	Gender	1000 non-null	object
3	Income_Level	1000 non-null	object
4	Marital_Status	1000 non-null	object
5	Education_Level	1000 non-null	object
6	Occupation	1000 non-null	object
7	Location	1000 non-null	object
8	Purchase_Category	1000 non-null	object
9	Purchase_Amount	1000 non-null	object
10	Frequency_of_Purchase	1000 non-null	int64
11	Purchase_Channel	1000 non-null	object

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12 Brand_Loyalty          1000 non-null    int64
13 Product_Rating        1000 non-null    int64
14 Time_Spent_on_Product_Research(hours) 1000 non-null    float64
15 Social_Media_Influence 753 non-null     object
16 Discount_Sensitivity   1000 non-null    object
17 Return_Rate            1000 non-null    int64
18 Customer_Satisfaction  1000 non-null    int64
19 Engagement_with_Ads    744 non-null     object
20 Device_Used_for_Shopping 1000 non-null    object
21 Payment_Method         1000 non-null    object
22 Time_of_Purchase       1000 non-null    object
23 Discount_Used          1000 non-null    bool
24 Customer_Loyalty_Program_Member 1000 non-null    bool
25 Purchase_Intent        1000 non-null    object
26 Shipping_Preference    1000 non-null    object
27 Time_to_Decision       1000 non-null    int64

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dtypes: bool(2), float64(1), int64(7), object(18)

memory usage: 205.2+ KB

None

	Age	Frequency_of_Purchase	Brand_Loyalty	Product_Rating \
count	1000.000000	1000.000000	1000.000000	1000.000000
mean	34.304000	6.945000	3.026000	3.033000
std	9.353238	3.147361	1.416803	1.436654
min	18.000000	2.000000	1.000000	1.000000
25%	26.000000	4.000000	2.000000	2.000000
50%	34.500000	7.000000	3.000000	3.000000
75%	42.000000	10.000000	4.000000	4.000000
max	50.000000	12.000000	5.000000	5.000000

	Time_Spent_on_Product_Research(hours)	Return_Rate \
count	1000.000000	1000.000000
mean	1.013030	0.954000
std	0.791802	0.810272
min	0.000000	0.000000
25%	0.000000	0.000000
50%	1.000000	1.000000
75%	2.000000	2.000000
max	2.000000	2.000000

	Customer_Satisfaction	Time_to_Decision
count	1000.000000	1000.000000
mean	5.399000	7.547000
std	2.868454	4.035849
min	1.000000	1.000000
25%	3.000000	4.000000
50%	5.000000	8.000000
75%	8.000000	11.000000
max	10.000000	14.000000

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KeyError                                Traceback (most recent call last)
Cell In[1], line 26
    24 # Define features and target (replace 'target_column' with actual column
name)
    25 target_column = "your_target_column_name_here"
--> 26 X = df.drop(columns=[target_column])
    27 y = df[target_column]
    29 # Train-test split

File ~\anaconda3\Lib\site-packages\pandas\core\frame.py:5581, in DataFrame.drop(s
elf, labels, axis, index, columns, level, inplace, errors)
    5433 def drop(
    5434     self,
    5435     labels: IndexLabel | None = None,
    (...)
    5442     errors: IgnoreRaise = "raise",
    5443 ) -> DataFrame | None:
    5444     """
    5445     Drop specified labels from rows or columns.
    5446
    (...)
    5579         weight  1.0      0.8
    5580     """
-> 5581     return super().drop(
    5582         labels=labels,
    5583         axis=axis,
    5584         index=index,
    5585         columns=columns,
    5586         level=level,
    5587         inplace=inplace,
    5588         errors=errors,
    5589     )

File ~\anaconda3\Lib\site-packages\pandas\core\generic.py:4788, in NDFrame.drop(s
elf, labels, axis, index, columns, level, inplace, errors)
    4786 for axis, labels in axes.items():
    4787     if labels is not None:
-> 4788         obj = obj._drop_axis(labels, axis, level=level, errors=errors)
    4790 if inplace:
    4791     self._update_inplace(obj)

File ~\anaconda3\Lib\site-packages\pandas\core\generic.py:4830, in NDFrame._drop_
axis(self, labels, axis, level, errors, only_slice)
    4828     new_axis = axis.drop(labels, level=level, errors=errors)
    4829     else:
-> 4830     new_axis = axis.drop(labels, errors=errors)
    4831     indexer = axis.get_indexer(new_axis)
    4833 # Case for non-unique axis
    4834 else:

File ~\anaconda3\Lib\site-packages\pandas\core\indexes\base.py:7070, in Index.dro
p(self, labels, errors)
    7068 if mask.any():
    7069     if errors != "ignore":
-> 7070         raise KeyError(f"{labels[mask].tolist()} not found in axis")
    7071     indexer = indexer[~mask]
    7072     return self.delete(indexer)

KeyError: "[ 'your_target_column_name_here' ] not found in axis"

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In [ ]: print(f"Dataset contains {df.shape[0]} rows and {df.shape[1]} columns.")
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In [ ]:
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