HR Analytics - Employee Attrition Prediction

This notebook performs EDA, builds classification models, and uses SHAP analysis to understand employee attrition.

In [39]:
```
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 LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_rep
import shap

# Load dataset
df = pd.read_csv("HR_Analytics.csv")
df.head()
```

Out[39]:

	EmpID	Age	AgeGroup	Attrition	BusinessTravel	DailyRate	Department	Distanc
0	RM297	18	18-25	Yes	Travel_Rarely	230	Research & Development	
1	RM302	18	18-25	No	Travel_Rarely	812	Sales	
2	RM458	18	18-25	Yes	Travel_Frequently	1306	Sales	
3	RM728	18	18-25	No	Non-Travel	287	Research & Development	
4	RM829	18	18-25	Yes	Non-Travel	247	Research & Development	

5 rows × 38 columns

In [40]:
```
df.info()
df.isnull().sum()
```

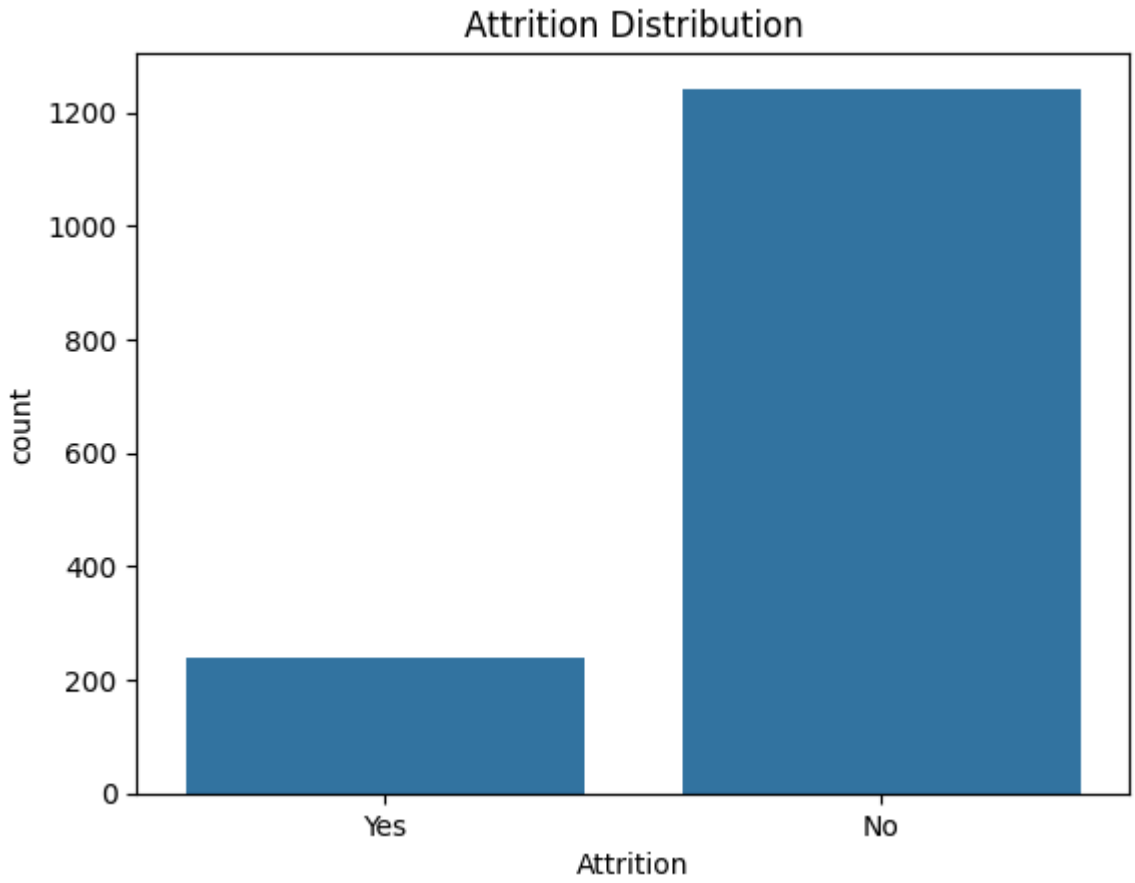
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1480 entries, 0 to 1479
Data columns (total 38 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   EmpID                     1480 non-null   object 
 1   Age                       1480 non-null   int64  
 2   AgeGroup                  1480 non-null   object 
 3   Attrition                 1480 non-null   object 
 4   BusinessTravel            1480 non-null   object 
 5   DailyRate                 1480 non-null   int64  
 6   Department                1480 non-null   object 
 7   DistanceFromHome          1480 non-null   int64  
 8   Education                 1480 non-null   int64  
 9   EducationField            1480 non-null   object 
 10  EmployeeCount             1480 non-null   int64  
 11  EmployeeNumber            1480 non-null   int64  
 12  EnvironmentSatisfaction   1480 non-null   int64  
 13  Gender                    1480 non-null   object 
 14  HourlyRate                1480 non-null   int64  
 15  JobInvolvement            1480 non-null   int64  
 16  JobLevel                  1480 non-null   int64  
 17  JobRole                   1480 non-null   object 
 18  JobSatisfaction           1480 non-null   int64  
 19  MaritalStatus             1480 non-null   object 
 20  MonthlyIncome             1480 non-null   int64  
 21  SalarySlab                1480 non-null   object 
 22  MonthlyRate               1480 non-null   int64  
 23  NumCompaniesWorked        1480 non-null   int64  
 24  Over18                    1480 non-null   object 
 25  OverTime                  1480 non-null   object 
 26  PercentSalaryHike         1480 non-null   int64  
 27  PerformanceRating         1480 non-null   int64  
 28  RelationshipSatisfaction  1480 non-null   int64  
 29  StandardHours             1480 non-null   int64  
 30  StockOptionLevel          1480 non-null   int64  
 31  TotalWorkingYears         1480 non-null   int64  
 32  TrainingTimesLastYear     1480 non-null   int64  
 33  WorkLifeBalance           1480 non-null   int64  
 34  YearsAtCompany            1480 non-null   int64  
 35  YearsInCurrentRole        1480 non-null   int64  
 36  YearsSinceLastPromotion   1480 non-null   int64  
 37  YearsWithCurrManager      1423 non-null   float64
dtypes: float64(1), int64(25), object(12)
memory usage: 439.5+ KB
```

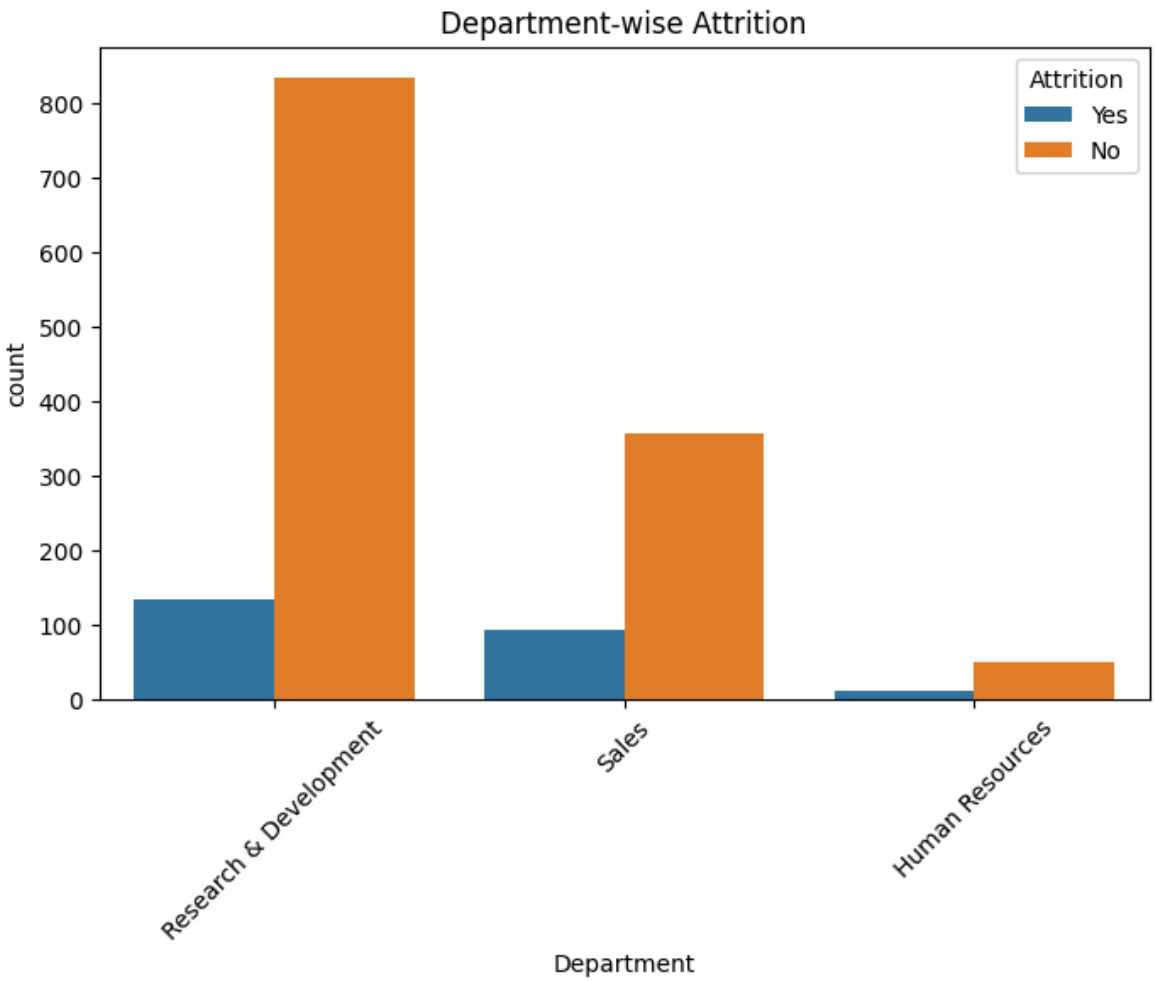
Out[40]:
```
EmpID                       0
Age                         0
AgeGroup                    0
Attrition                   0
BusinessTravel              0
DailyRate                   0
Department                  0
DistanceFromHome            0
Education                   0
EducationField              0
EmployeeCount               0
EmployeeNumber              0
EnvironmentSatisfaction     0
Gender                      0
HourlyRate                  0
JobInvolvement              0
JobLevel                    0
JobRole                     0
JobSatisfaction             0
MaritalStatus               0
MonthlyIncome               0
SalarySlab                  0
MonthlyRate                 0
NumCompaniesWorked          0
Over18                      0
OverTime                    0
PercentSalaryHike           0
PerformanceRating           0
RelationshipSatisfaction    0
StandardHours               0
StockOptionLevel            0
TotalWorkingYears           0
TrainingTimesLastYear       0
WorkLifeBalance             0
YearsAtCompany              0
YearsInCurrentRole          0
YearsSinceLastPromotion     0
YearsWithCurrManager       57
dtype: int64
```

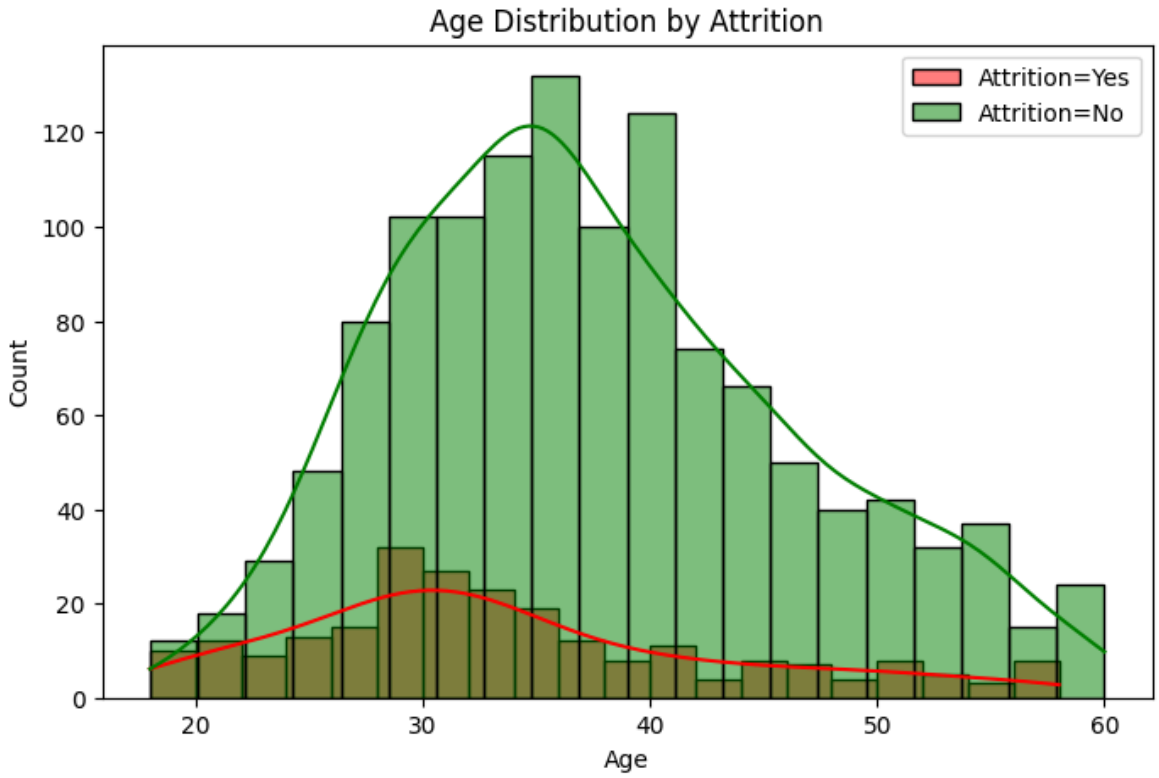
In [41]:
```
# Attrition distribution
sns.countplot(x='Attrition', data=df)
plt.title("Attrition Distribution")
plt.show()

# Department vs Attrition
plt.figure(figsize=(8,5))
sns.countplot(x='Department', hue='Attrition', data=df)
plt.title("Department-wise Attrition")
plt.xticks(rotation=45)
plt.show()

# Age distribution
plt.figure(figsize=(8,5))
sns.histplot(df[df['Attrition']=='Yes']['Age'], bins=20, color='red', kde=True,
sns.histplot(df[df['Attrition']=='No']['Age'], bins=20, color='green', kde=True,
plt.legend()
plt.title("Age Distribution by Attrition")
plt.show()
```


Attrition Distribution
count
1200
1000
800
600
400
200
0
Yes
No
Attrition


Department-wise Attrition
Attrition
Yes
No
count
800
700
600
500
400
300
200
100
0
Research & Development
Sales
Human Resources
Department



In [42]:
```
# Encode categorical variables
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split

df_encoded = df.copy()
le = LabelEncoder()
for col in df_encoded.select_dtypes(include='object').columns:
    df_encoded[col] = le.fit_transform(df_encoded[col])

X = df_encoded.drop(['Attrition','EmpID'], axis=1)
y = df_encoded['Attrition']

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

In [44]:
```
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix, classification_rep
import pandas as pd

# 1. Impute missing values
imputer = SimpleImputer(strategy='median')
X_imputed = pd.DataFrame(imputer.fit_transform(X), columns=X.columns)

# 2. Scale features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_imputed)

# 3. Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.3, random_state=42, stratify=y
)
```

```
# 4. Logistic Regression
log_reg = LogisticRegression(max_iter=5000, solver='lbfgs', class_weight='balanc
log_reg.fit(X_train, y_train)

# 5. Predictions & Evaluation
y_pred_log = log_reg.predict(X_test)

print("Logistic Regression Accuracy:", accuracy_score(y_test, y_pred_log))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_log))
print("Classification Report:\n", classification_report(y_test, y_pred_log))
```

```
Logistic Regression Accuracy: 0.7432432432432432
Confusion Matrix:
 [[277  96]
 [ 18  53]]
Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.74      0.83       373
           1       0.36      0.75      0.48        71

    accuracy                           0.74       444
   macro avg       0.65      0.74      0.66       444
weighted avg       0.85      0.74      0.77       444
```

In [46]:
```
dt = DecisionTreeClassifier(max_depth=5, random_state=42)
dt.fit(X_train, y_train)
y_pred_dt = dt.predict(X_test)

print("Decision Tree Accuracy:", accuracy_score(y_test, y_pred_dt))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_dt))
print("Classification Report:\n", classification_report(y_test, y_pred_dt))
```

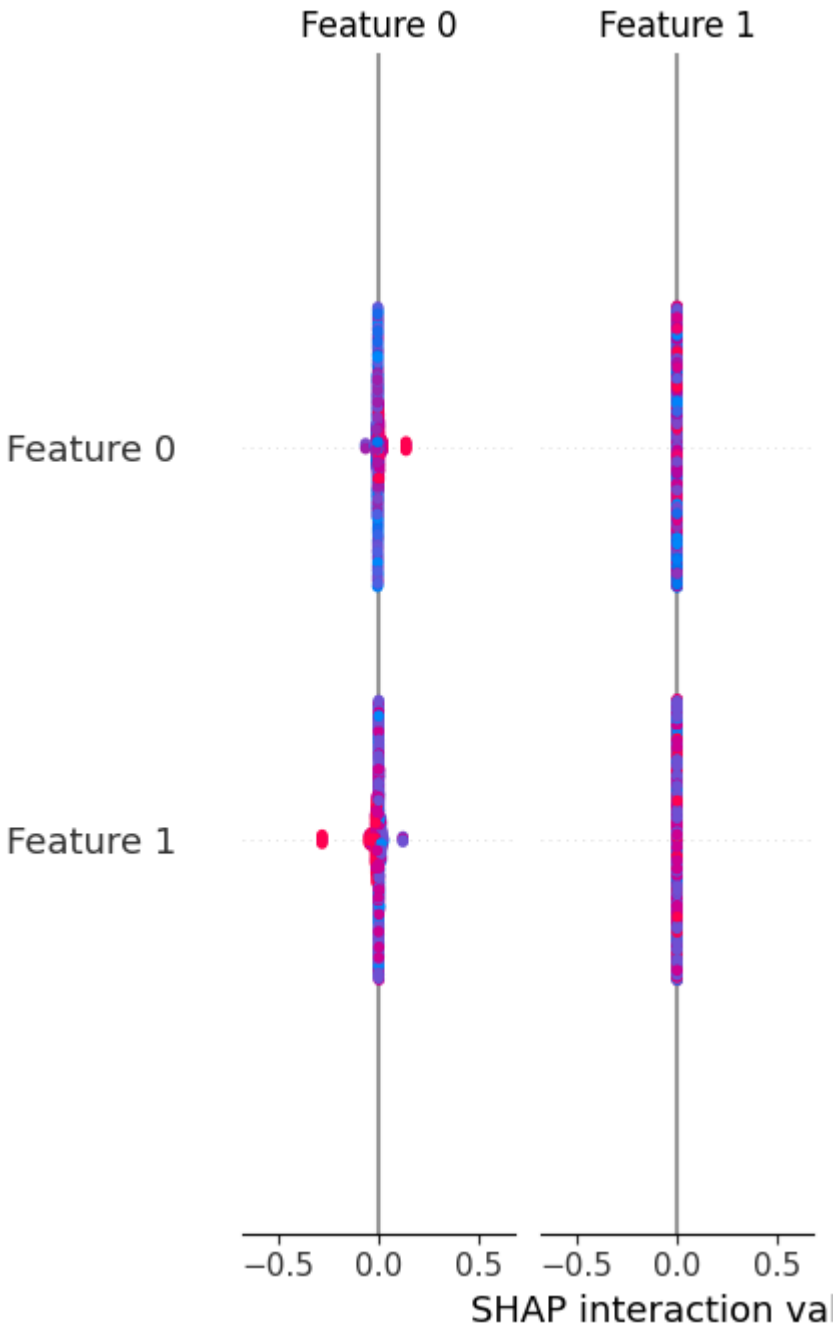
```
Decision Tree Accuracy: 0.8175675675675675
Confusion Matrix:
 [[343  30]
 [ 51  20]]
Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.92      0.89       373
           1       0.40      0.28      0.33        71

    accuracy                           0.82       444
   macro avg       0.64      0.60      0.61       444
weighted avg       0.80      0.82      0.80       444
```

In [47]:
```
# SHAP for Decision Tree
explainer = shap.TreeExplainer(dt)
shap_values = explainer.shap_values(X_test)

# Feature importance
shap.summary_plot(shap_values, X_test, plot_type="bar")
```


Feature 0
Feature 1
Feature 0
Feature 1
−0.5
0.0
0.5
−0.5
0.0
0.5
SHAP interaction va