2. Dataset Selection and Data Extraction

In [11]:
```
import pandas as pd

data = pd.read_csv('HRDataSets.csv')

print("Dataset Info:")
data.info()

print("\n Dataset shape:", data.shape)

print("\n Value counts of Attrition:")
print(data['Attrition'].value_counts())

print("\n First 5 rows of the dataset:")
data.head()
```

```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11906 entries, 0 to 11905
Data columns (total 23 columns):
 #   Column                    Non-Null Count  Dtype 
---  ------                    --------------  ----- 
 0   Employee ID               11906 non-null  int64 
 1   Age                       11906 non-null  int64 
 2   Gender                    11906 non-null  object
 3   Years at Company          11906 non-null  int64 
 4   Job Role                  11906 non-null  object
 5   Monthly Income            11906 non-null  int64 
 6   Work-Life Balance         11906 non-null  object
 7   Job Satisfaction          11906 non-null  object
 8   Performance Rating        11906 non-null  object
 9   Number of Promotions      11906 non-null  int64 
 10  Overtime                  11906 non-null  object
 11  Distance from Home        11906 non-null  int64 
 12  Education Level           11906 non-null  object
 13  Marital Status            11906 non-null  object
 14  Company Tenure            11906 non-null  int64 
 15  Number of Dependents      11906 non-null  int64 
 16  Job Level                 11906 non-null  object
 17  Remote Work               11906 non-null  object
 18  Leadership Opportunities  11906 non-null  object
 19  Innovation Opportunities  11906 non-null  object
 20  Company Reputation        11906 non-null  object
 21  Employee Recognition      11906 non-null  object
 22  Attrition                 11906 non-null  object
dtypes: int64(8), object(15)
memory usage: 2.1+ MB

 Dataset shape: (11906, 23)

 Value counts of Attrition:
Attrition
Stayed    6278
Left      5628
Name: count, dtype: int64

 First 5 rows of the dataset:
```

Out[11]:

	Employee ID	Age	Gender	Years at Company	Job Role	Monthly Income	Work-Life Balance	Job Satisfaction	Perform Ra
0	30585	35	Male	7	Education	4563	Good	High	Ave
1	54656	50	Male	7	Education	5583	Fair	High	Ave
2	33442	58	Male	44	Media	5525	Fair	Very High	
3	46775	22	Female	5	Healthcare	8700	Good	High	Ave
4	65181	55	Female	16	Media	5939	Poor	High	Ave

5 rows × 23 columns

3. Data Cleaning and Preprocessing

In [13]:

```
print("\nMissing values per column:")
print(data.isnull().sum())
```

```
Missing values per column:
Employee ID                 0
Age                         0
Gender                      0
Years at Company            0
Job Role                    0
Monthly Income              0
Work-Life Balance           0
Job Satisfaction            0
Performance Rating          0
Number of Promotions        0
Overtime                    0
Distance from Home          0
Education Level             0
Marital Status              0
Number of Dependents        0
Job Level                   0
Remote Work                 0
Leadership Opportunities    0
Innovation Opportunities    0
Company Reputation          0
Employee Recognition        0
Attrition                   0
dtype: int64
```

In [15]:

```
data.describe().round(0).astype(int)
```

Out[15]:

	Employee ID	Age	Years at Company	Monthly Income	Number of Promotions	Distance from Home	Number of Dependents
count	11906	11906	11906	11906	11906	11906	11906
mean	37151	38	16	7298	1	50	2
std	21479	12	11	2154	1	29	2
min	5	18	1	1226	0	1	0
25%	18580	28	7	5645	0	25	0
50%	37005	38	13	7346	1	50	1
75%	55732	49	22	8862	2	75	3
max	74465	59	51	15063	4	99	6

In [17]:

```
print("\nData types of each column:")
data.dtypes
```

```
Data types of each column:
```

Out[17]:

```
Employee ID                   int64
Age                           int64
Gender                       object
Years at Company              int64
Job Role                     object
Monthly Income                int64
Work-Life Balance            object
Job Satisfaction             object
Performance Rating           object
Number of Promotions          int64
Overtime                     object
Distance from Home            int64
Education Level              object
Marital Status               object
Number of Dependents          int64
Job Level                    object
Remote Work                  object
Leadership Opportunities     object
Innovation Opportunities     object
Company Reputation           object
Employee Recognition         object
Attrition                    object
dtype: object
```

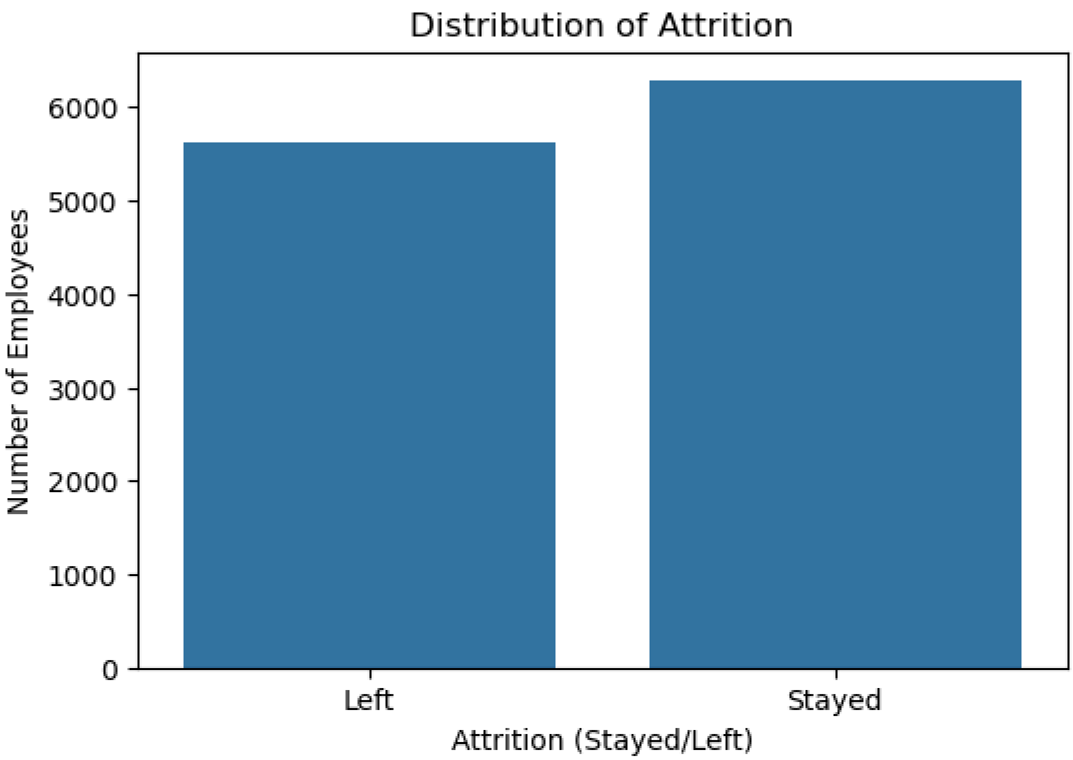
In [12]:

```
if 'Company Tenure' in data.columns:
    data = data.drop('Company Tenure', axis=1)
    print("\n'Company Tenure' column removed.")
else:
    print("\n'Company Tenure' column not found.")
```

```
'Company Tenure' column removed.
```

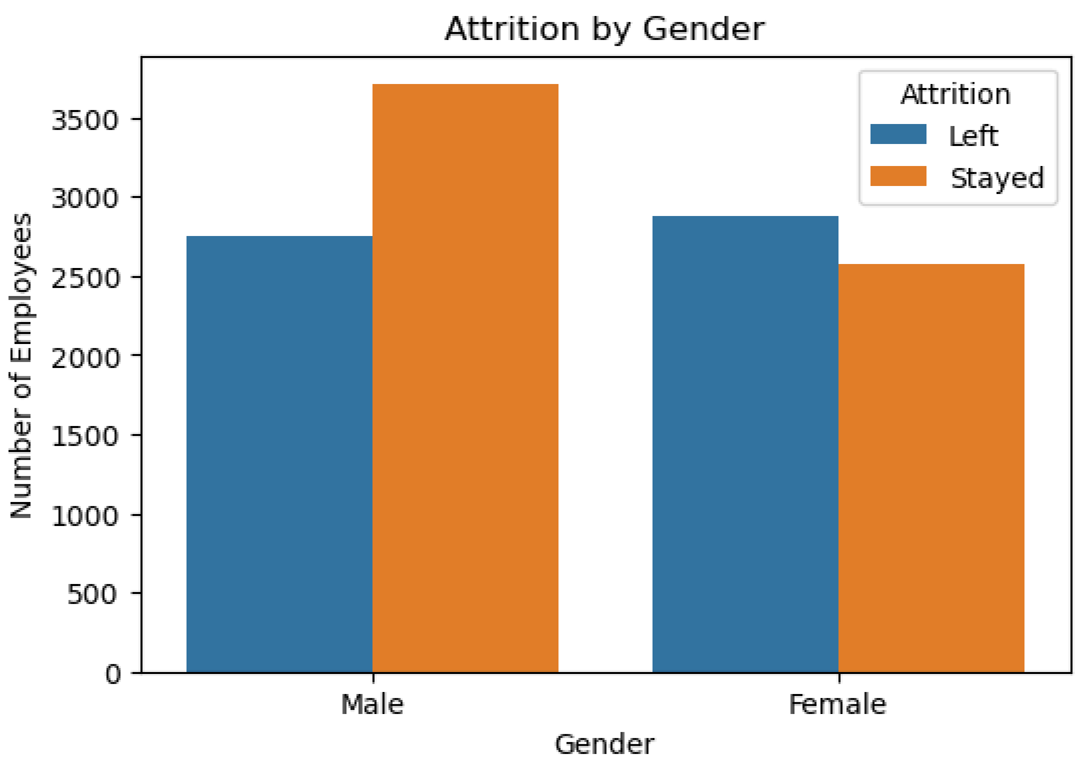
4. Exploratory Data Analytics (EDA)

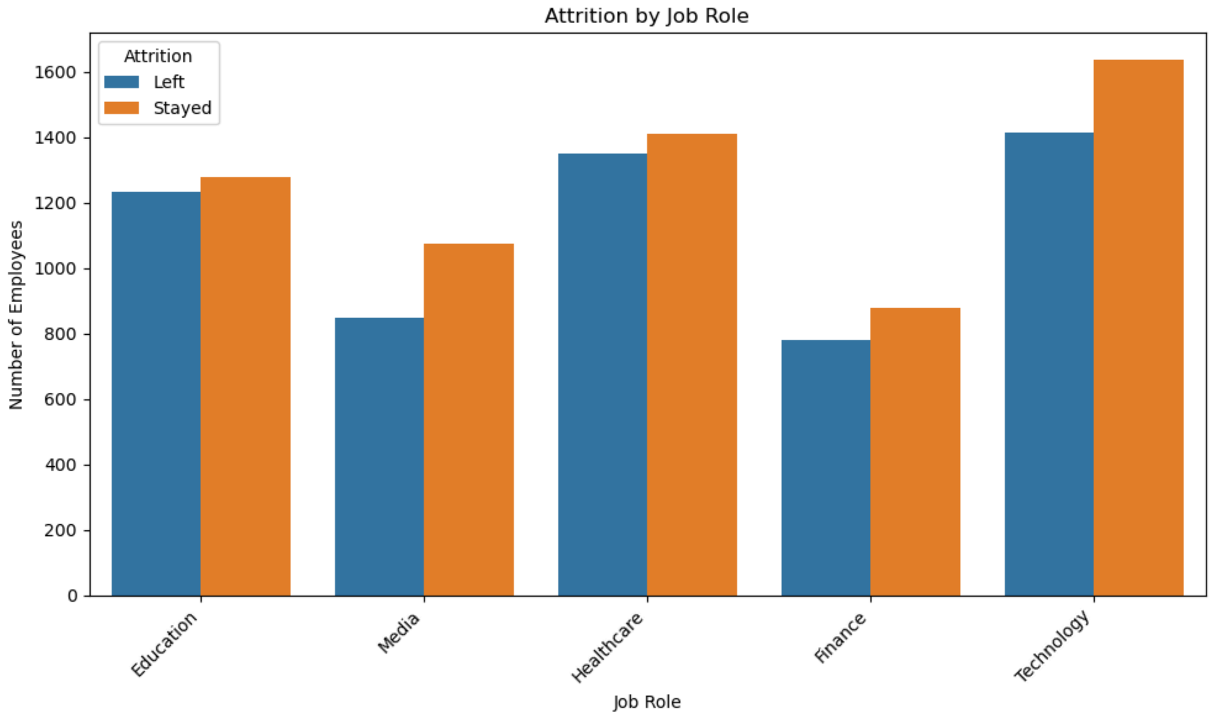
In [19]:
```
import matplotlib.pyplot as mp
import seaborn as sb

mp.figure(figsize=(6, 4))
sb.countplot(data=data, x='Attrition')
mp.title('Distribution of Attrition')
mp.xlabel('Attrition (Stayed/Left)')
mp.ylabel('Number of Employees')
mp.show()
```

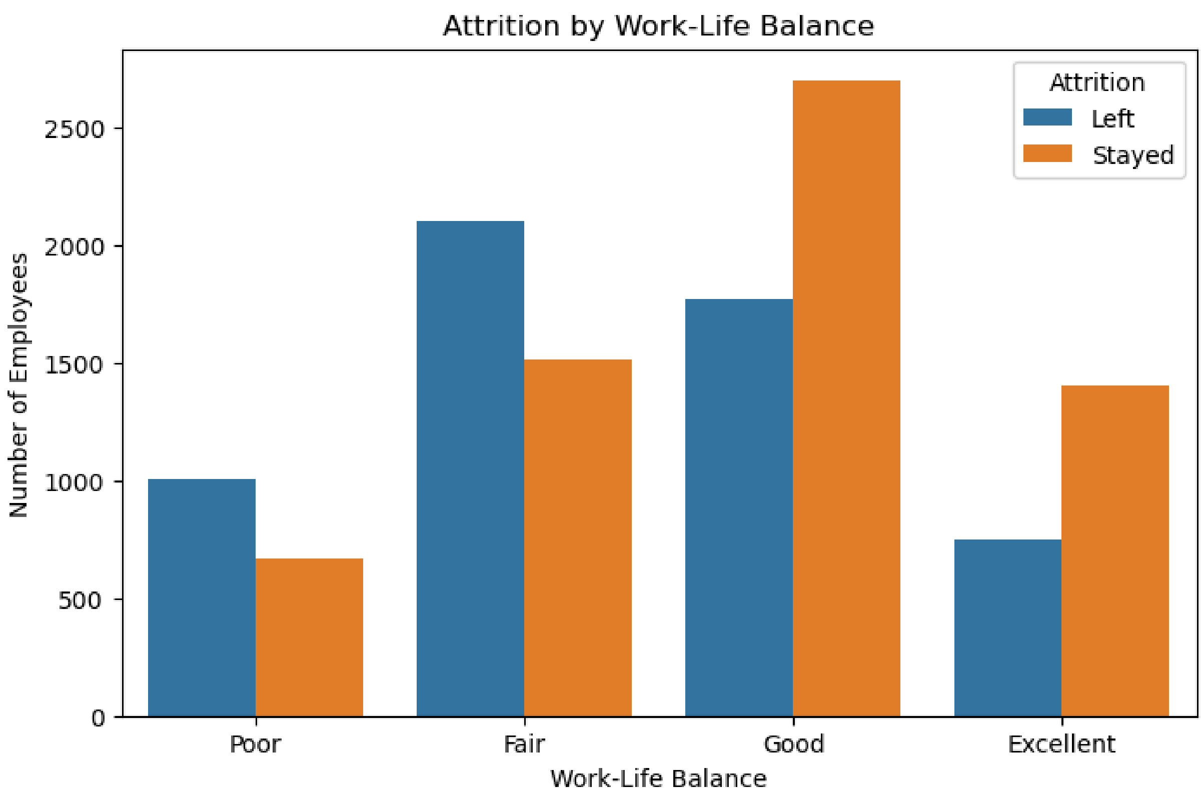


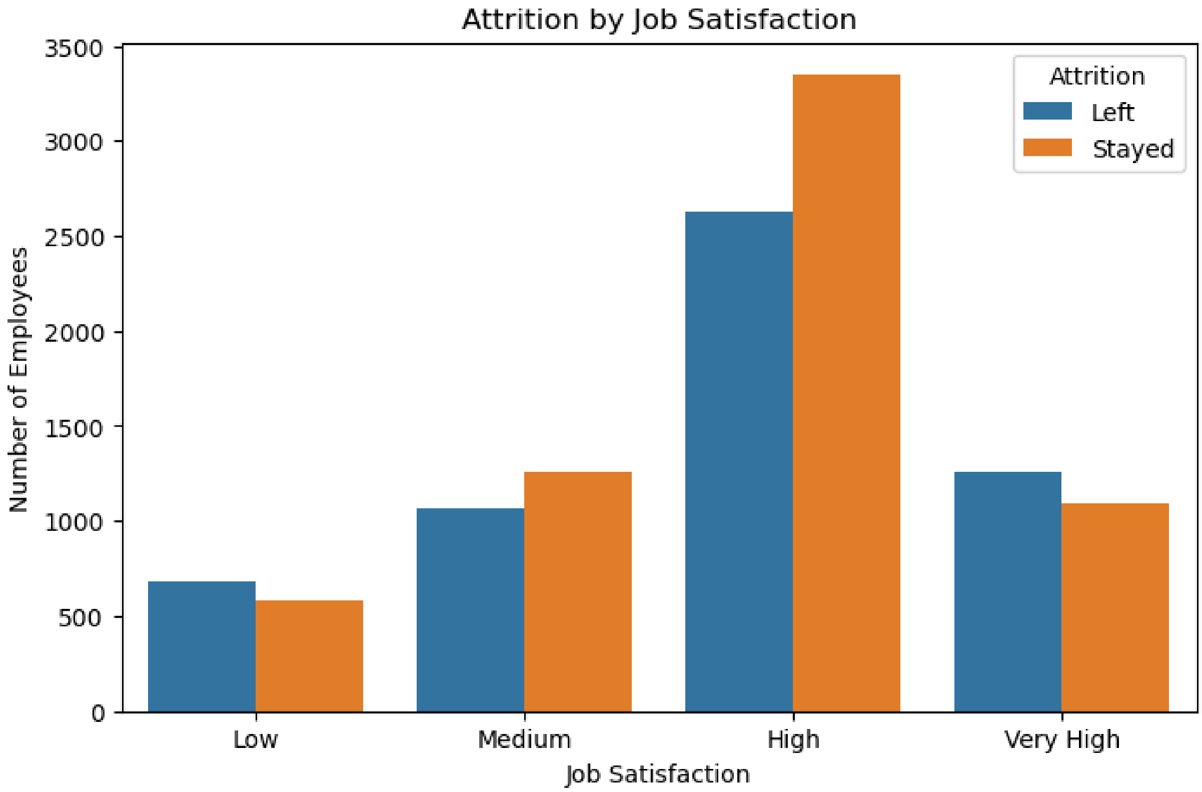
In [20]:
```
# Attrition by Gender
mp.figure(figsize=(6, 4))
sb.countplot(data=data, x='Gender', hue='Attrition')
mp.title('Attrition by Gender')
mp.xlabel('Gender')
mp.ylabel('Number of Employees')
mp.show()

# Attrition by Job Role
mp.figure(figsize=(10, 6))
sb.countplot(data=data, x='Job Role', hue='Attrition')
mp.title('Attrition by Job Role')
mp.xlabel('Job Role')
mp.ylabel('Number of Employees')
mp.xticks(rotation=45, ha='right')
mp.tight_layout()
mp.show()
```

```
# Attrition by Work-Life Balance
mp.figure(figsize=(8, 5))
sb.countplot(data=data, x='Work-Life Balance', hue='Attrition', order=['Poor', 'Fai
mp.title('Attrition by Work-Life Balance')
mp.xlabel('Work-Life Balance')
mp.ylabel('Number of Employees')
mp.show()

# Attrition by Job Satisfaction
mp.figure(figsize=(8, 5))
sb.countplot(data=data, x='Job Satisfaction', hue='Attrition', order=['Low', 'Mediu
mp.title('Attrition by Job Satisfaction')
mp.xlabel('Job Satisfaction')
mp.ylabel('Number of Employees')
mp.show()
```

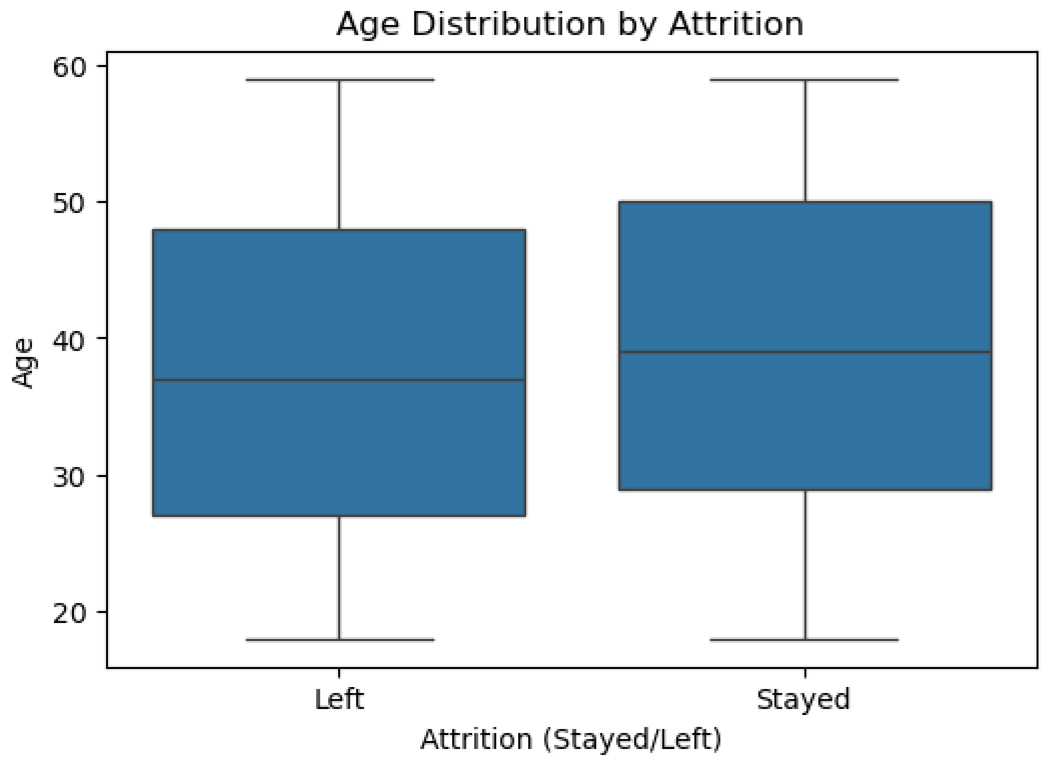


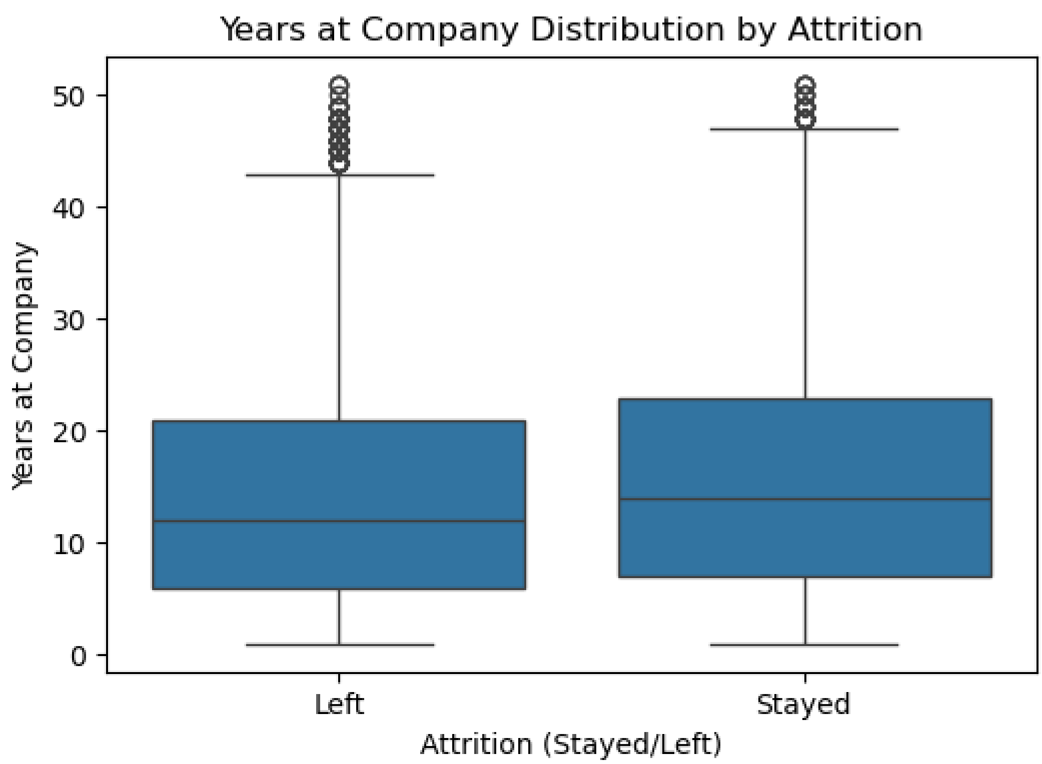

Attrition by Job Role
Attrition
Left
Stayed
Number of Employees
0
200
400
600
800
1000
1200
1400
1600
Education
Media
Healthcare
Finance
Technology
Job Role

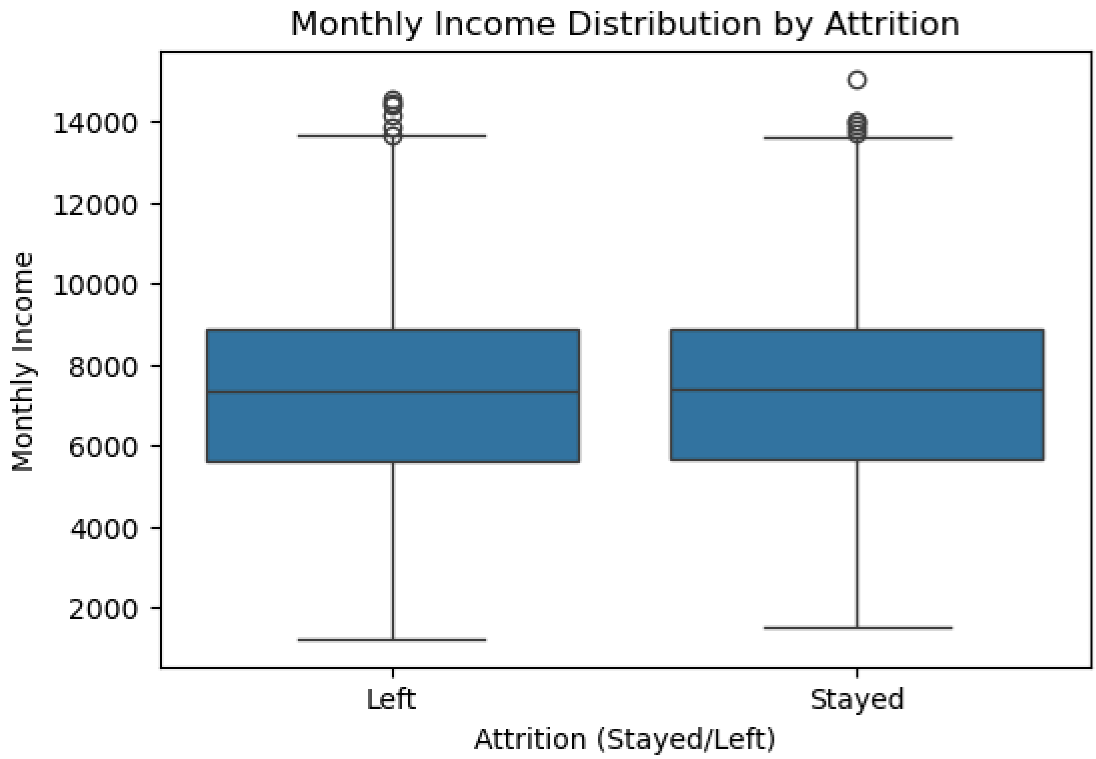

Attrition by Work-Life Balance
Attrition
Left
Stayed
Number of Employees
0
500
1000
1500
2000
2500
Poor
Fair
Good
Excellent
Work-Life Balance

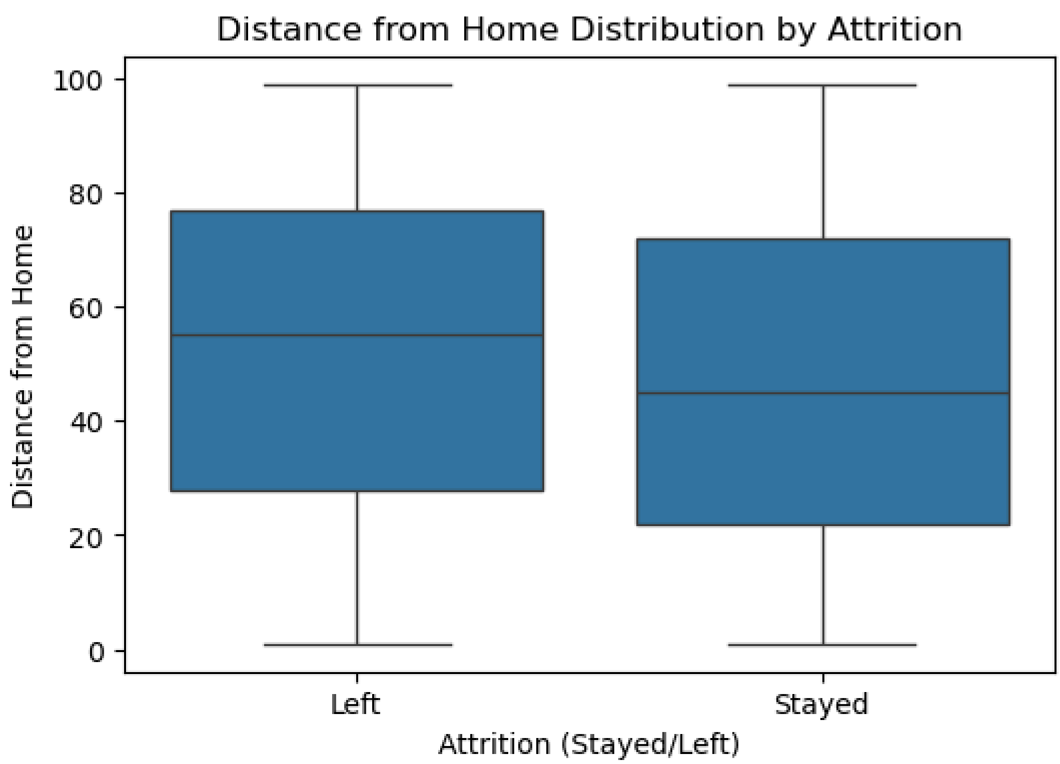


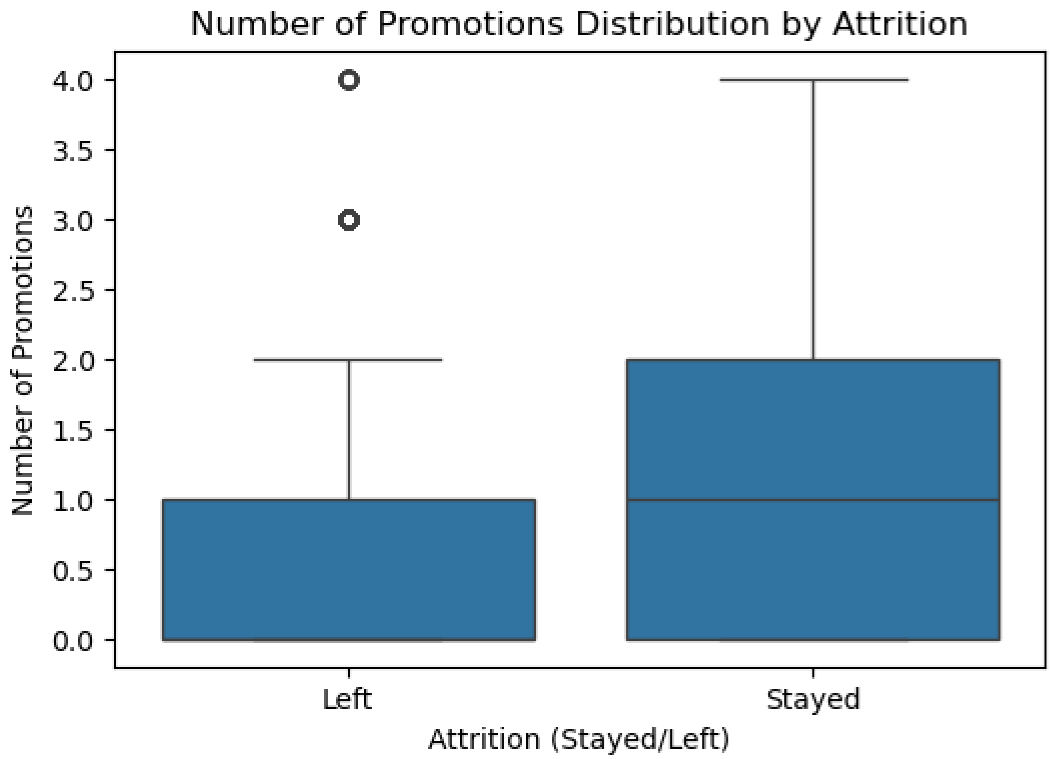
In [42]:
```
numerical_columns = ['Age', 'Years at Company', 'Monthly Income', 'Distance from Ho
for col in numerical_columns:
    mp.figure(figsize=(4, ))
    sb.boxplot(data=data, x='Attrition', y=col)
    mp.title(f'{col} Distribution by Attrition')
    mp.xlabel('Attrition (Stayed/Left)')
    mp.ylabel(col)
    mp.show()
```

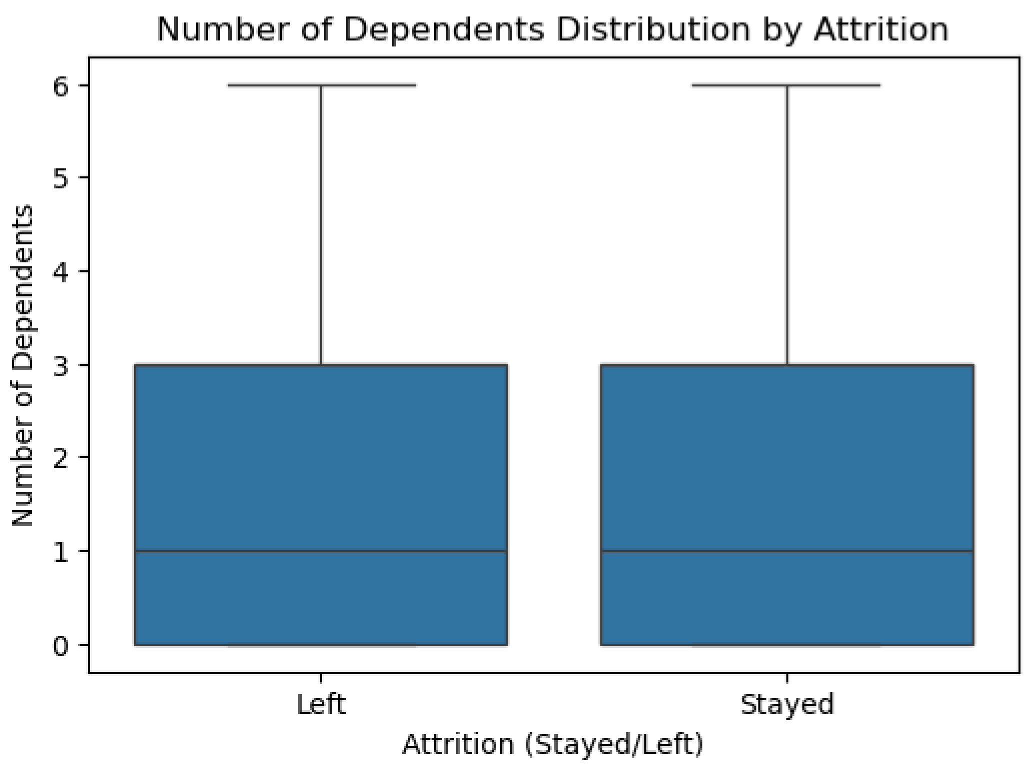

Age Distribution by Attrition
60
50
40
30
20
Age
Left
Stayed
Attrition (Stayed/Left)


Years at Company Distribution by Attrition
50
40
30
20
10
0
Years at Company
Left
Stayed
Attrition (Stayed/Left)


Monthly Income Distribution by Attrition
Monthly Income
14000
12000
10000
8000
6000
4000
2000
Left
Stayed
Attrition (Stayed/Left)

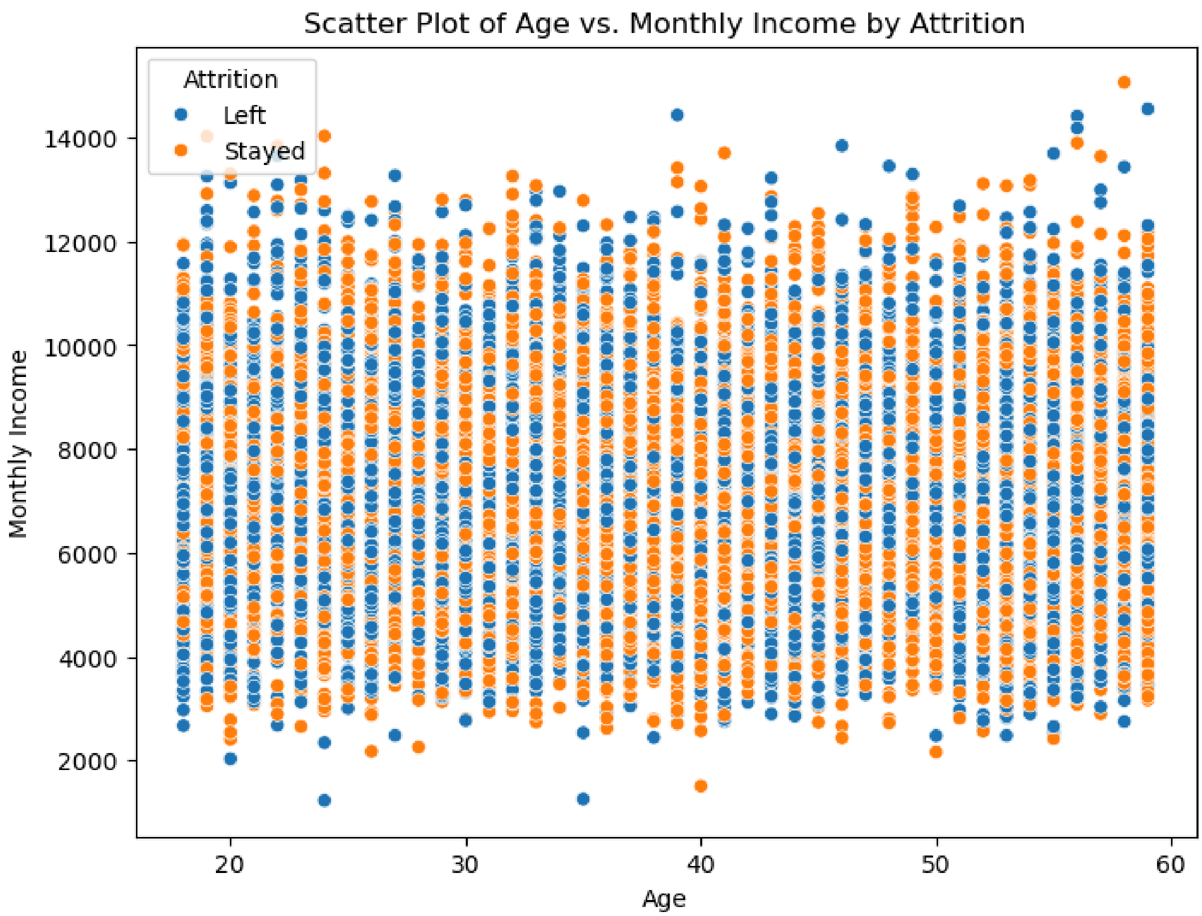

Distance from Home Distribution by Attrition
Distance from Home
100
80
60
40
20
0
Left
Stayed
Attrition (Stayed/Left)





In [51]:
```
numerical_data = data.select_dtypes(include=['number'])
cor_matrix = numerical_data.corr()
mp.figure(figsize=(10, 8))
sb.heatmap(cor_matrix, annot=True, cmap='RdBu', linewidths=0.5)
mp.title('Correlation Matrix of Numerical Variables')
mp.xticks(rotation = 45, ha='right')
mp.show()
```

In [52]:
```
mp.figure(figsize=(8, 6))
sb.scatterplot(data=data, x='Age', y='Monthly Income', hue='Attrition')
mp.title('Scatter Plot of Age vs. Monthly Income by Attrition')
mp.xlabel('Age')
mp.ylabel('Monthly Income')
mp.show()
```



Project Implementation (Analytical Techniques and Methods - Implementation Focus)

Feature Encoding

In [54]:
```
from sklearn.preprocessing import LabelEncoder

X = data.drop(['Employee ID', 'Attrition'], axis=1)
y = data['Attrition']

label_encoder = LabelEncoder()
y = label_encoder.fit_transform(y)

X = pd.get_dummies(X, drop_first=True)
print("\nFeatures (X) after one-hot encoding (first 5 rows):")
X.head()
```

```
Features (X) after one-hot encoding (first 5 rows):
```

Out[54]:

	Age	Years at Company	Monthly Income	Number of Promotions	Distance from Home	Number of Dependents	Gender_Male	Jo Role_Financ
0	35	7	4563	1	55	4	True	Fals
1	50	7	5583	3	14	2	True	Fals
2	58	44	5525	0	43	4	True	Fals
3	22	5	8700	0	2	0	False	Fals
4	55	16	5939	0	31	1	False	Fals

5 rows × 38 columns

Data Splitting

In [55]:

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

print("\nShape of X_train:", X_train.shape)
print("Shape of X_test:", X_test.shape)
print("Shape of y_train:", y_train.shape)
print("Shape of y_test:", y_test.shape)
```

```
Shape of X_train: (9524, 38)
Shape of X_test: (2382, 38)
Shape of y_train: (9524,)
Shape of y_test: (2382,)
```

Logistic Regression Implementation

In [68]:

```
from sklearn.linear_model import LogisticRegression

lm = LogisticRegression(random_state=42, solver='liblinear')
lm.fit(X_train, y_train)
y_pred_logistic = lm.predict(X_test)
print("\nLogistic Regression Model Trained.")
```

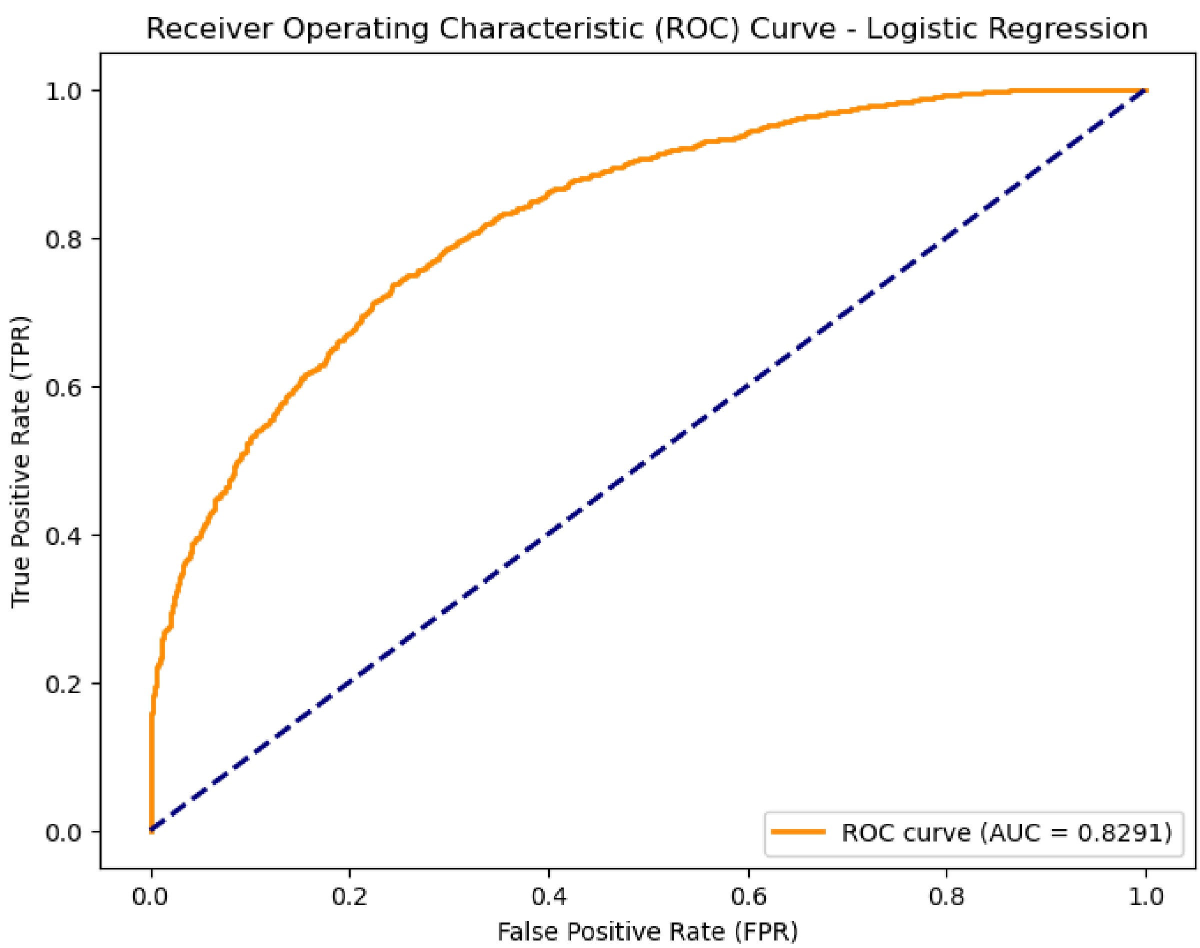
```
Logistic Regression Model Trained.
```

In [71]:

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
import matplotlib.pyplot as plt

accuracy = accuracy_score(y_test, y_pred_logistic)
precision = precision_score(y_test, y_pred_logistic)
recall = recall_score(y_test, y_pred_logistic)
f1 = f1_score(y_test, y_pred_logistic)
roc_auc = roc_auc_score(y_test, lm.predict_proba(X_test)[:, 1])
```

```
print("Logistic Regression Performance:")
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision (Predicting 'Left'): {precision:.4f}")
print(f"Recall (Identifying 'Left'): {recall:.4f}")
print(f"F1-Score: {f1:.4f}")
print(f"AUC-ROC: {roc_auc:.4f}")


fpr, tpr, thresholds = roc_curve(y_test, lm.predict_proba(X_test)[:, 1])
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.4f}
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate (FPR)')
plt.ylabel('True Positive Rate (TPR)')
plt.title('Receiver Operating Characteristic (ROC) Curve - Logistic Regression')
plt.legend(loc='lower right')
plt.show()
```

```
Logistic Regression Performance:
Accuracy: 0.7443
Precision (Predicting 'Left'): 0.7483
Recall (Identifying 'Left'): 0.7763
F1-Score: 0.7620
AUC-ROC: 0.8291
```



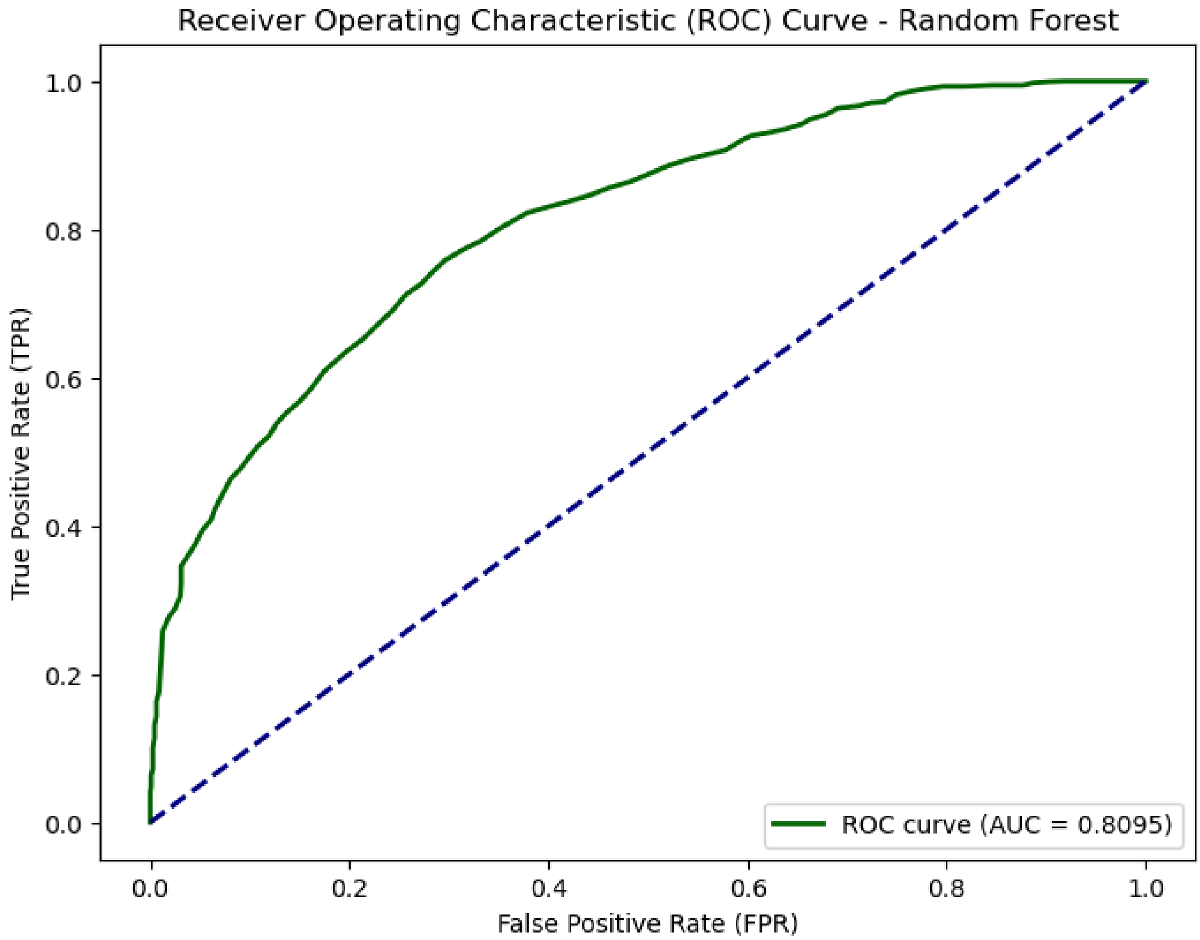
Random Forest Implementation

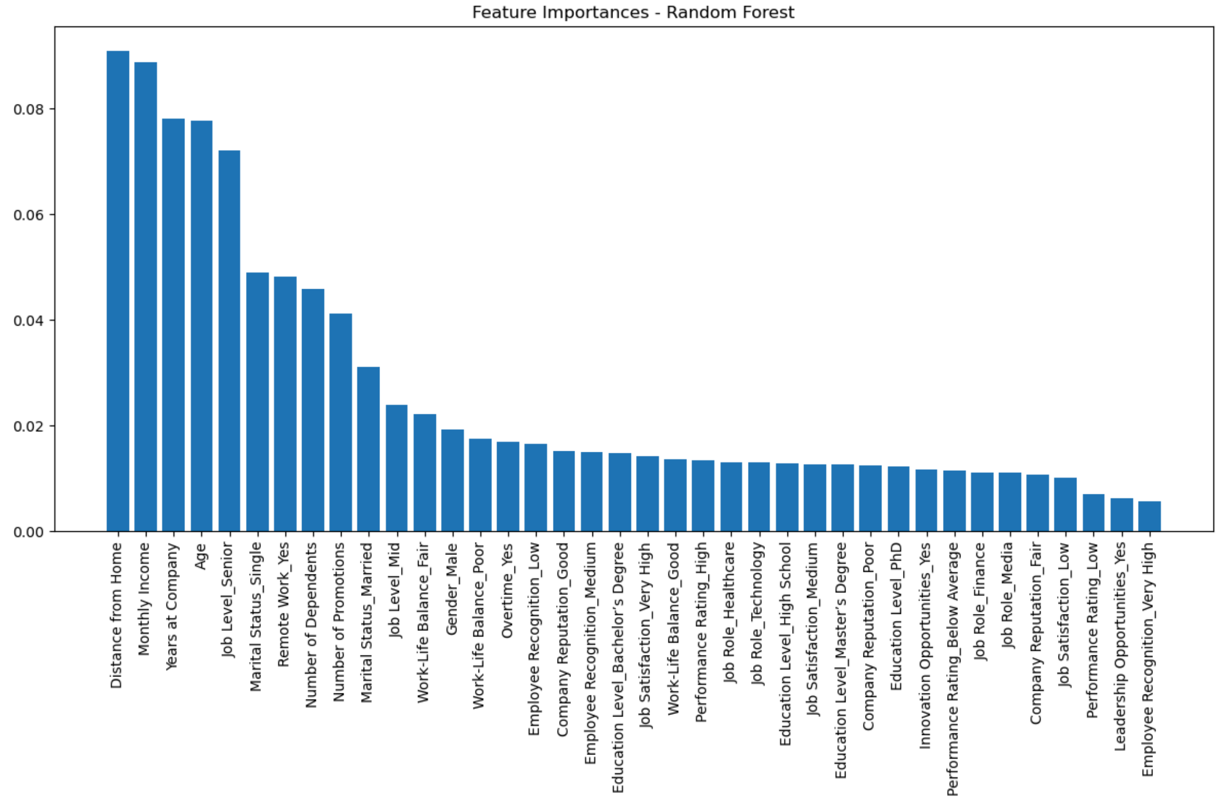
In [74]:
```
from sklearn.ensemble import RandomForestClassifier

rfm = RandomForestClassifier(random_state=42)
rfm.fit(X_train, y_train)
y_pred_rf = rfm.predict(X_test)
print("\nRandom Forest Model Trained.")
```

```
Random Forest Model Trained.
```

In [77]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
import matplotlib.pyplot as plt
import numpy as np


accuracy_rf = accuracy_score(y_test, y_pred_rf)
precision_rf = precision_score(y_test, y_pred_rf)
recall_rf = recall_score(y_test, y_pred_rf)
f1_rf = f1_score(y_test, y_pred_rf)
roc_auc_rf = roc_auc_score(y_test, rfm.predict_proba(X_test)[:, 1])

print("Random Forest Performance:")
print(f"Accuracy: {accuracy_rf:.4f}")
print(f"Precision (Predicting 'Left'): {precision_rf:.4f}")
print(f"Recall (Identifying 'Left'): {recall_rf:.4f}")
print(f"F1-Score: {f1_rf:.4f}")
print(f"AUC-ROC: {roc_auc_rf:.4f}")


fpr_rf, tpr_rf, thresholds_rf = roc_curve(y_test, rfm.predict_proba(X_test)[:, 1])
plt.figure(figsize=(8, 6))
plt.plot(fpr_rf, tpr_rf, color='darkgreen', lw=2, label=f'ROC curve (AUC = {roc_auc
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate (FPR)')
plt.ylabel('True Positive Rate (TPR)')
plt.title('Receiver Operating Characteristic (ROC) Curve - Random Forest')
plt.legend(loc='lower right')
plt.show()


importances =rfm.feature_importances_
feature_names = X_train.columns
sorted_indices = np.argsort(importances)[::-1]

plt.figure(figsize=(12, 8))
plt.title("Feature Importances - Random Forest")
plt.bar(range(X_train.shape[1]), importances[sorted_indices], align="center")
plt.xticks(range(X_train.shape[1]), feature_names[sorted_indices], rotation = 'vert
plt.tight_layout()
plt.show()
```

```
Random Forest Performance:
Accuracy: 0.7326
Precision (Predicting 'Left'): 0.7405
Recall (Identifying 'Left'): 0.7588
F1-Score: 0.7495
AUC-ROC: 0.8095
```





Data Analytics Artefact (Implemented Model)

In [62]:
```
import joblib
joblib.dump(lm, 'attrition_model.pkl')
print("Logistic Regression model is saved to attrition_model.pkl")
```

```
Logistic Regression model is saved to attrition_model.pkl
```

In [64]:
```
joblib.dump(rfm, 'attrition_model_rf.pkl')
print("Random Forest model is saved to attrition_model_rf.pkl")
```

```
Random Forest model is saved to attrition_model_rf.pkl
```

In [ ]: