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In [1]:

```
import pandas as pd
import numpy as np
# import dataset: https://www.kaggle.com/datasets/rishikeshkonapure/hr-analytics
dataset = pd.read_csv("HR Analysis/HR-Employee-Attrition.csv")
dataset.head()
```

Out[1]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	Educat
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life
4	27	No	Travel_Rarely	591	Research & Development	2	1	

5 rows × 35 columns

Prework - Data Cleansing

In [2]:

```
# Identify Unique/Null Values
nulls = pd.DataFrame({
    'Unique':dataset.nunique(),
    'Null':dataset.isna().sum(),
})
print(nulls)
print(len(dataset.columns))
```

```
                          Unique  Null
Age                           43     0
Attrition                      2     0
BusinessTravel                 3     0
DailyRate                    886     0
Department                     3     0
DistanceFromHome              29     0
Education                      5     0
EducationField                 6     0
EmployeeCount                  1     0
EmployeeNumber              1470     0
EnvironmentSatisfaction        4     0
Gender                         2     0
HourlyRate                    71     0
JobInvolvement                 4     0
JobLevel                       5     0
```

```
JobRole                        9      0
JobSatisfaction                4      0
MaritalStatus                  3      0
MonthlyIncome               1349      0
MonthlyRate                 1427      0
NumCompaniesWorked            10      0
Over18                         1      0
OverTime                       2      0
PercentSalaryHike             15      0
PerformanceRating              2      0
RelationshipSatisfaction       4      0
StandardHours                  1      0
StockOptionLevel               4      0
TotalWorkingYears             40      0
TrainingTimesLastYear          7      0
WorkLifeBalance                4      0
YearsAtCompany                37      0
YearsInCurrentRole            19      0
YearsSinceLastPromotion       16      0
YearsWithCurrManager          18      0
35
```

In [3]:

```
# Drop redundant columns that don't differentiate employee data
# No need to check for duplicate employees because the number of unique employee
for col in dataset.columns:
    if len(dataset[col].unique()) == 1:
        print(col)
        dataset.drop(col,inplace=True,axis=1)
print(len(dataset.columns))
```

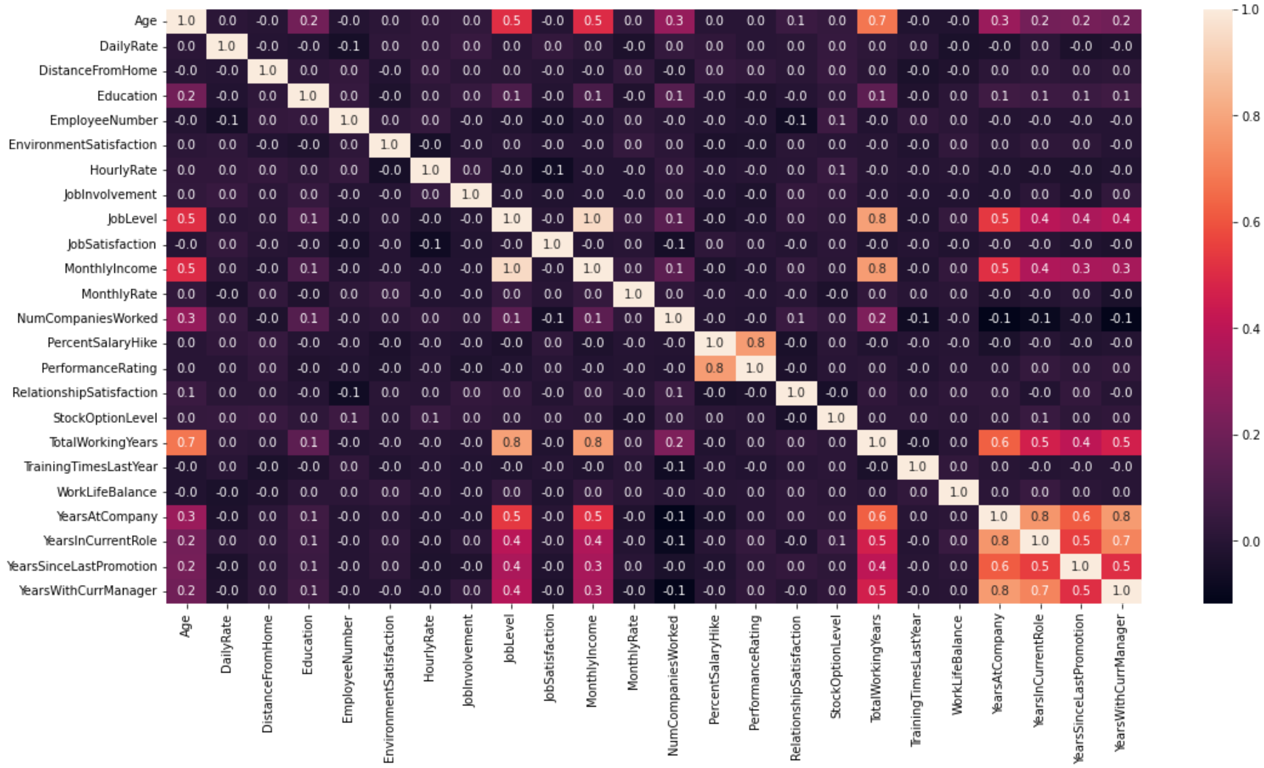
```
EmployeeCount
Over18
StandardHours
32
```

Step 1: Correlation Matrix to determine which variables tend to coincide.

In [4]:

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

plt.figure(figsize=(18,9))
sns.heatmap(dataset.corr(), annot=True, fmt='.1f')
```

Out[4]: <AxesSubplot:>



In [5]:

```python
# Convert categorical data to numerical data
objects = list(dataset.select_dtypes(include='O'))
print(objects)
numerical = pd.get_dummies(data=dataset, columns=objects)
numerical
```

```
['Attrition', 'BusinessTravel', 'Department', 'EducationField', 'Gender', 'JobRole', 'MaritalStatus', 'OverTime']
```

Out[5]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeNumber	EnvironmentSatisfaction
0	41	1102	1	2	1	2
1	49	279	8	1	2	3
2	37	1373	2	2	4	4
3	33	1392	3	4	5	4
4	27	591	2	1	7	1
...	...	...	...	...	...	...
1465	36	884	23	2	2061	3
1466	39	613	6	1	2062	4
1467	27	155	4	3	2064	2
1468	49	1023	2	3	2065	4
1469	34	628	8	3	2068	2

1470 rows × 54 columns

In [6]:
```
plt.figure(figsize=(18,9))
x = numerical.drop(columns = ['EmployeeNumber'])
corrs = x.corr()
np.fill_diagonal(corrs.values, -2)
#corrs
#sns.heatmap(corrs, mask = (np.abs(corrs) >= 0.8))
```

```
<Figure size 1296x648 with 0 Axes>
```

In [7]:
```
def get_redundant_pairs(x):
    pairs_to_drop = set()
    cols = x.columns
    for i in range(0, x.shape[1]):
        for j in range(0, i+1):
            pairs_to_drop.add((cols[i], cols[j]))
    return pairs_to_drop

def get_top_correlations(x, n=10):
    au_corr = x.corr().unstack()
    labels_to_drop = get_redundant_pairs(x)
    au_corr = au_corr.drop(labels=labels_to_drop).sort_values(ascending=False)
    return au_corr[0:n]

print("Top Correlations")
print(get_top_correlations(x))
```

```
Top Correlations
JobLevel                     MonthlyIncome            0.950300
Department_Human Resources   JobRole_Human Resources  0.904983
Department_Sales             JobRole_Sales Executive  0.808869
JobLevel                     TotalWorkingYears        0.782208
PercentSalaryHike            PerformanceRating        0.773550
MonthlyIncome                TotalWorkingYears        0.772893
YearsAtCompany               YearsWithCurrManager     0.769212
                             YearsInCurrentRole       0.758754
YearsInCurrentRole           YearsWithCurrManager     0.714365
Age                          TotalWorkingYears        0.680381
dtype: float64
```

The most highly correlated factors are unsurprising, the highest being Job Level and Income. Years and experience contribute to higher pay. You can also see that this company has a common pay for performance philosophy as salary hikes are more correlated with performance as opposed to job level or experience.

Step 2: Gender

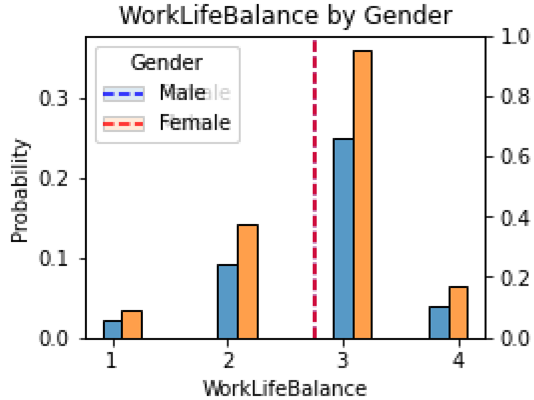
In [8]:
```
avgGender = dataset.groupby(['Gender']).mean()
cols = ['MonthlyIncome','HourlyRate','PercentSalaryHike','StockOptionLevel']

fig, axes = plt.subplots(1, len(cols), figsize=(10, 5))

axes[0].bar(avgGender.index, avgGender['MonthlyIncome'])
axes[0].set_title('Avg Monthly Income')

axes[1].bar(avgGender.index, avgGender['HourlyRate'], color = 'red')
axes[1].set_title('Avg Hourly Rate')
```

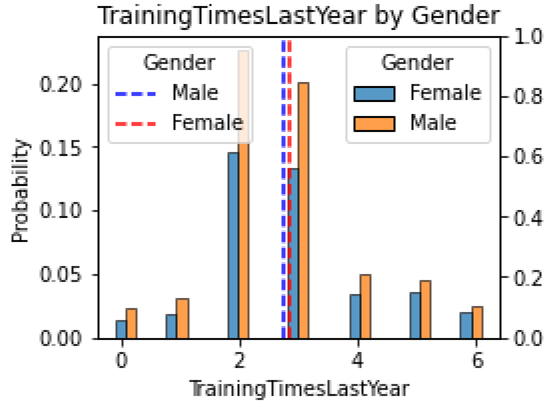
```
axes[2].bar(avgGender.index, avgGender['PercentSalaryHike'], color = 'green')
axes[2].set_title('Avg Percent Salary Increase')

axes[3].bar(avgGender.index, avgGender['StockOptionLevel'], color = 'orange')
axes[3].set_title('Avg Stock Option Level')

plt.tight_layout()
plt.show()
```

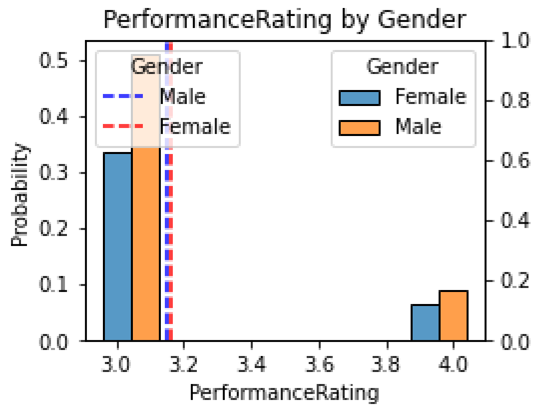
Can conclude that this company doesn't have a pay equity problem to address

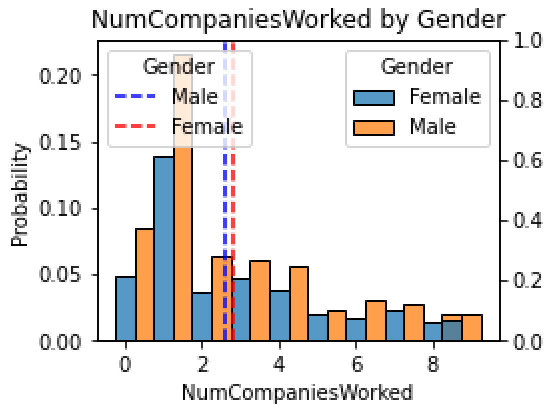
Exploring other data

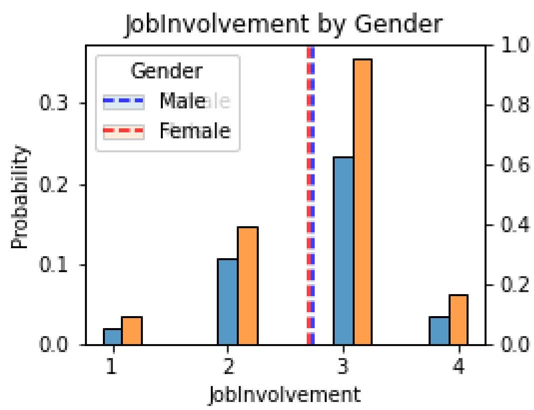
In [9]:
```
cols = ['WorkLifeBalance','TrainingTimesLastYear','PerformanceRating','NumCompar
   'JobInvolvement', 'JobLevel', 'JobSatisfaction',
   'EnvironmentSatisfaction','Education']
plt.figure(figsize=(9, 36))
for i, col in enumerate(cols):
    gender_means = dataset.groupby('Gender').mean()

    axes = plt.subplot(len(cols), 2, i + 1)
    sns.histplot(dataset, x=dataset[col], hue="Gender", stat="probability", mult

    ax = axes.twinx()
    male_line = ax.axvline(gender_means.loc['Male', col], color='blue', linestyl
    female_line = ax.axvline(gender_means.loc['Female', col], color='red', lines

    axes.set_xlabel(col)
    axes.set_title(f'{col} by Gender')

    ax.legend(loc='upper right')
    plt.legend(title='Gender',loc = 'upper left')

plt.subplots_adjust(hspace=.5, wspace = .5)


plt.show()
# ideally figure out how to keep legends from overlapping
```

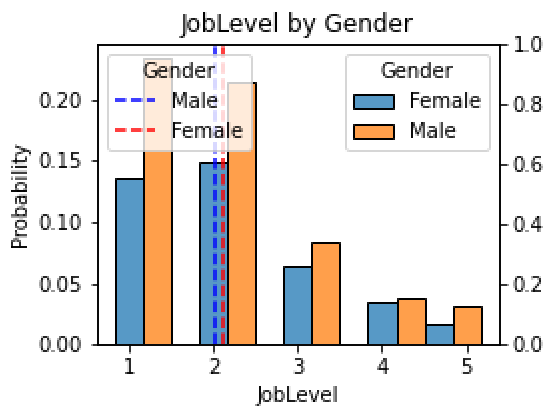

WorkLifeBalance by Gender
Gender
Male
Female
Probability
WorkLifeBalance

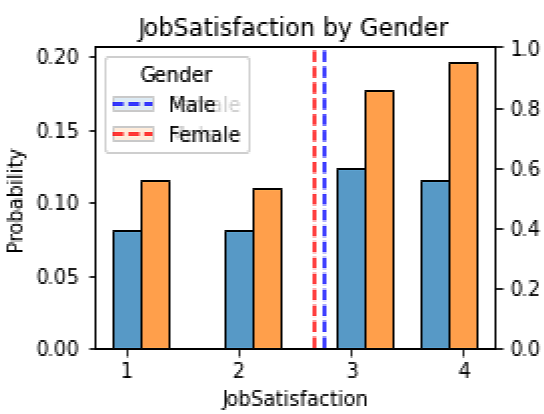

TrainingTimesLastYear by Gender
Gender
Male
Female
Gender
Female
Male
Probability
TrainingTimesLastYear

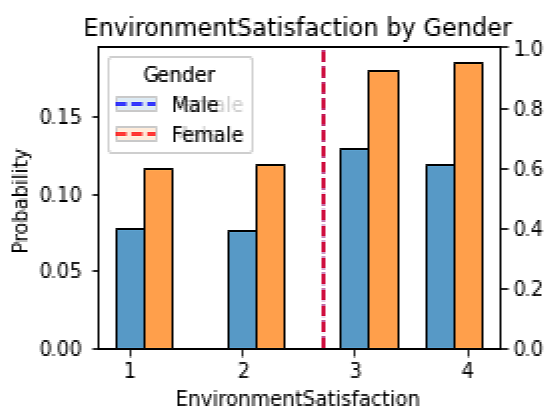

PerformanceRating by Gender
Gender
Male
Female
Gender
Female
Male
Probability
PerformanceRating

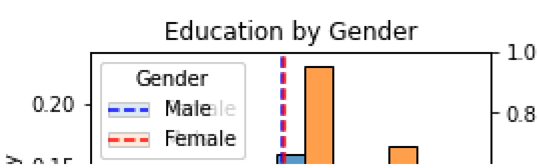

NumCompaniesWorked by Gender
Gender
Male
Female
Gender
Female
Male
Probability
NumCompaniesWorked

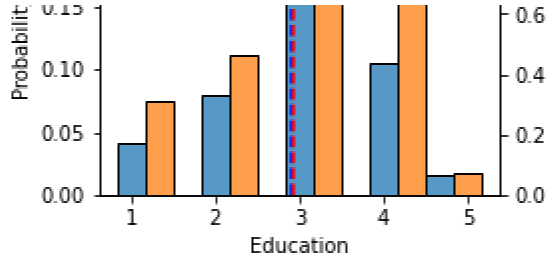

JobInvolvement by Gender
Gender
Male
Female
Probability
JobInvolvement


JobLevel by Gender
Gender
Male
Female
Gender
Female
Male
Probability
JobLevel


JobSatisfaction by Gender
Gender
Male
Female
Probability
JobSatisfaction


EnvironmentSatisfaction by Gender
Gender
Male
Female
Probability
EnvironmentSatisfaction


Education by Gender
Gender
Male
Female

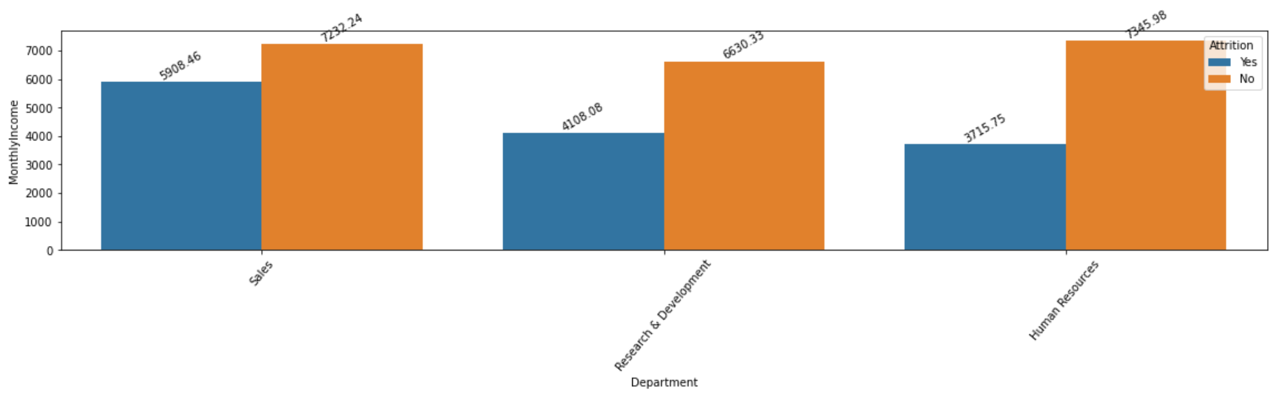


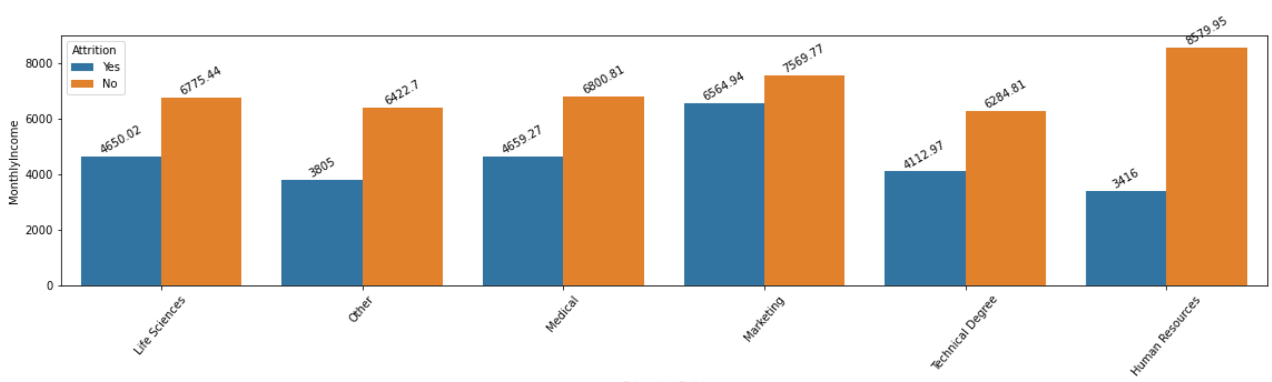
Most factors are equal, on average, amongst males and females. Males **slightly** tend to be more satisfied with their jobs, while women **slightly** tend to have worked at slightly more companies.

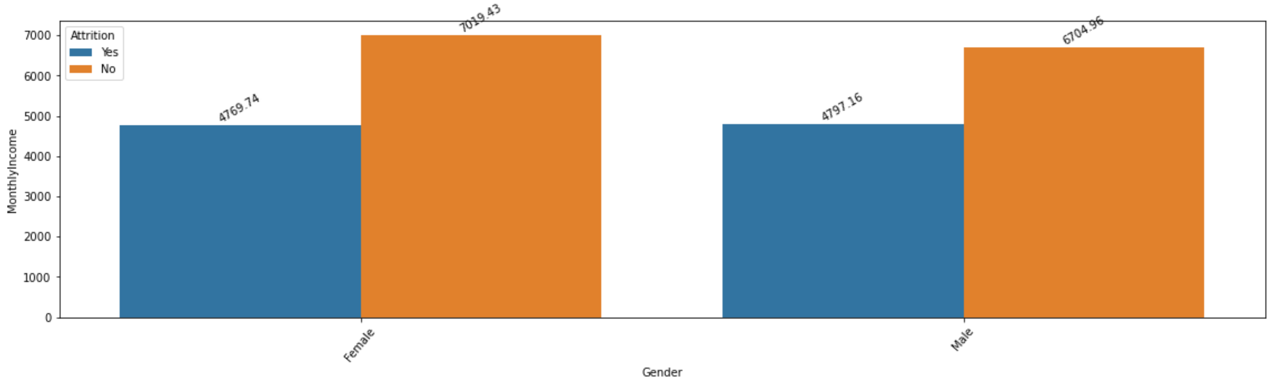
Step 3: Attrition Patterns

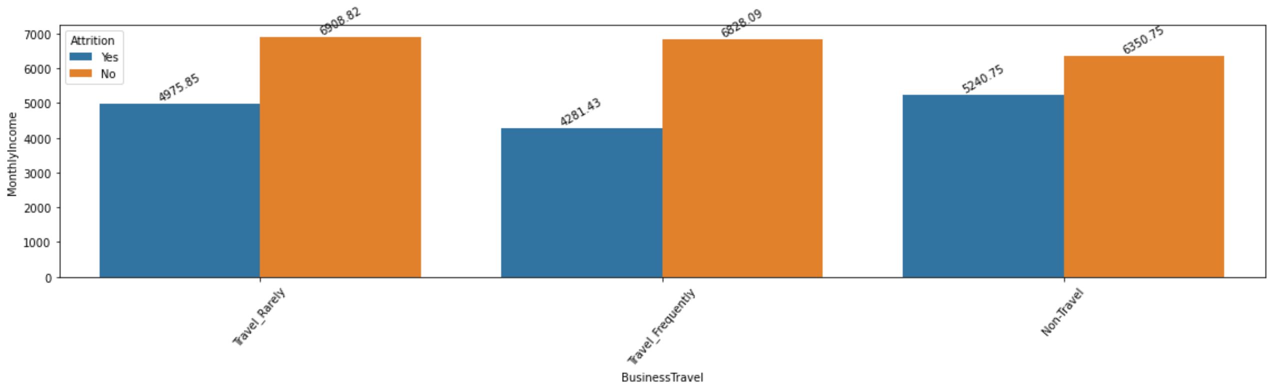
Reminder, when attrition = yes, that means the employee left the company.

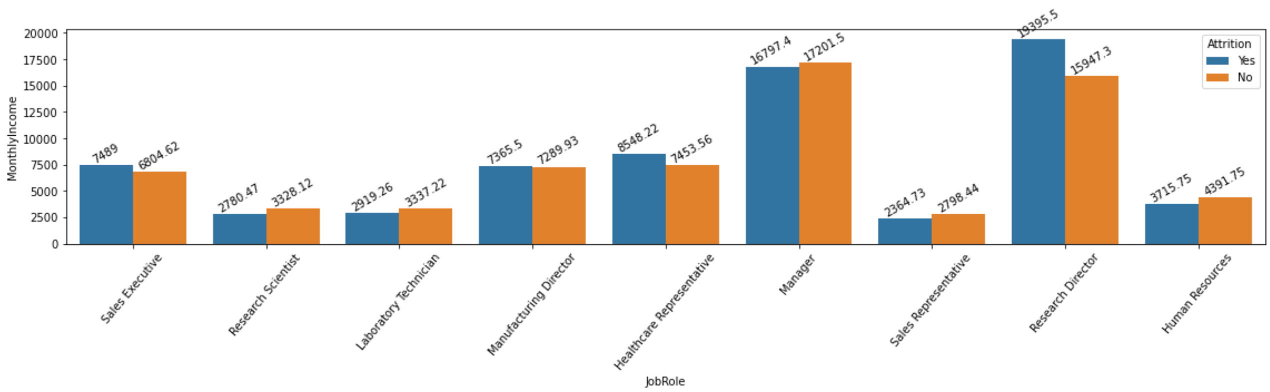
In [10]:
```
cols = ['Department','EducationField','Gender','BusinessTravel','JobRole']

for i in cols:
    fig, axes = plt.subplots(figsize=(16,5))
    sns.barplot(x=dataset[i], y=dataset['MonthlyIncome'], hue=dataset['Attritior
    plt.xticks(rotation=50,fontsize=10)
    for cont in axes.containers:
        axes.bar_label(cont,rotation=30,fontsize=10)
    plt.tight_layout()
    plt.show()
```











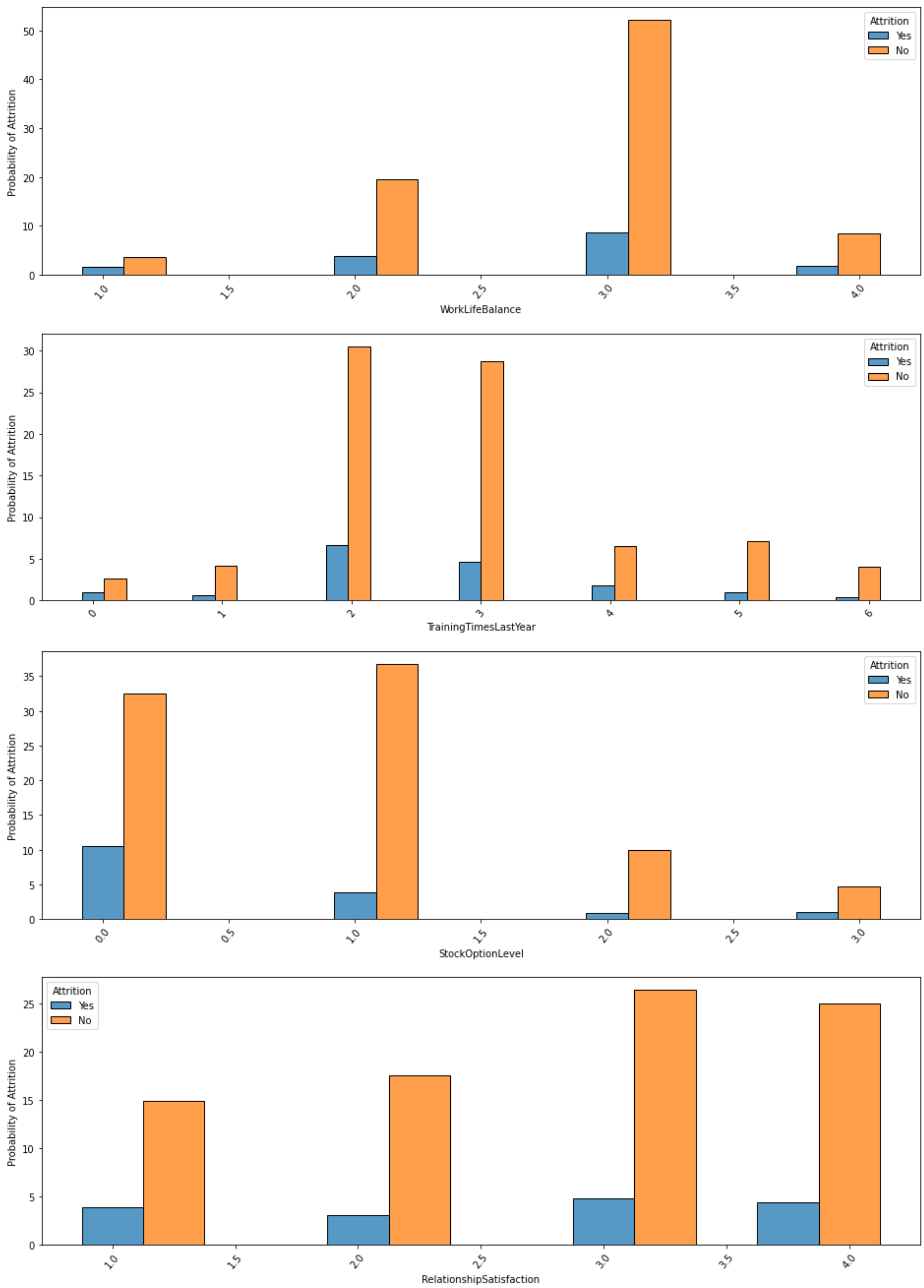
You can see that income isn't always the driving force of attrition. For example, the research directors who left tended to have higher salaries than the research directors who stayed. This is a case where the company may want to explore issues in the research department that may be driving employees out.

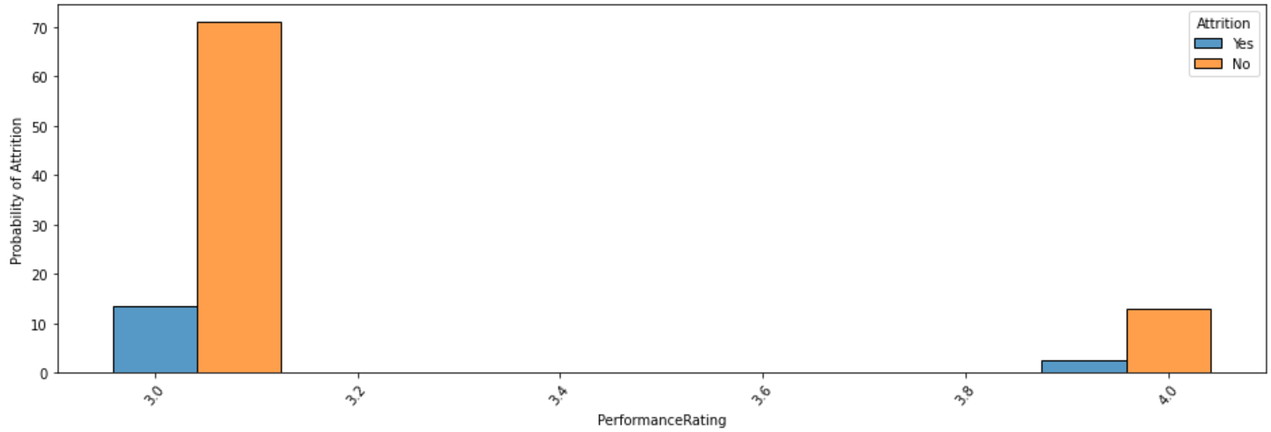
These are some additional factors independent of income. You'll see there's no overwhelming evidence of turnover in any of these cases, even in the case of low environmental/job satisfaction.

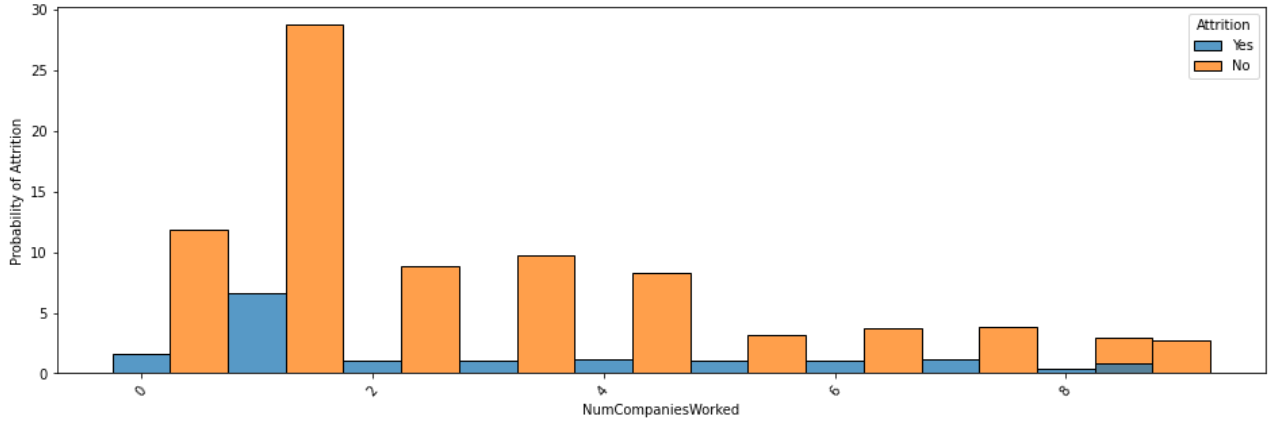
In [11]:

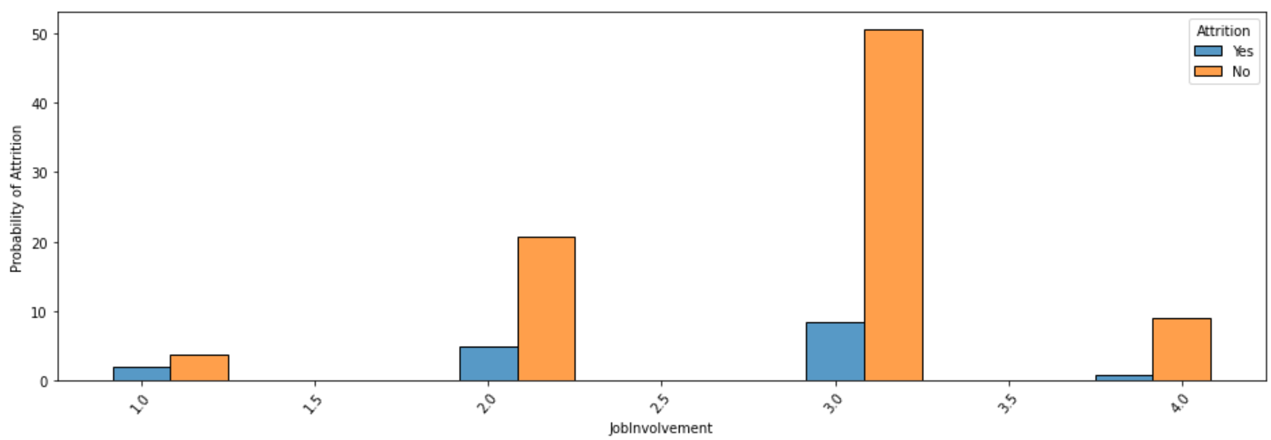
```
cols = ['WorkLifeBalance','TrainingTimesLastYear','StockOptionLevel',
    'RelationshipSatisfaction','PerformanceRating','NumCompaniesWorked',
   'JobInvolvement', 'JobLevel', 'JobSatisfaction',
   'EnvironmentSatisfaction','Education']

for col in cols:
    fig, axes = plt.subplots(figsize=(16,5))
    sns.histplot(dataset, x=dataset[col], hue="Attrition", stat="percent", multi
    axes.set(ylabel="Probability of Attrition")
    plt.xticks(rotation=50,fontsize=10)
for cont in axes.containers:
```

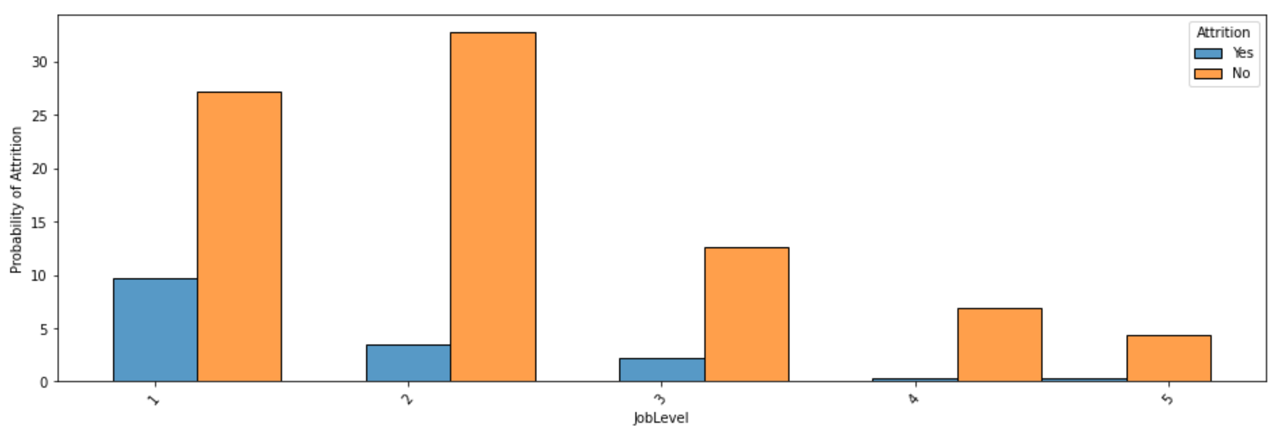
```
    axes.bar_label(cont,rotation=30,fontsize=10)
plt.tight_layout()
plt.show()
```

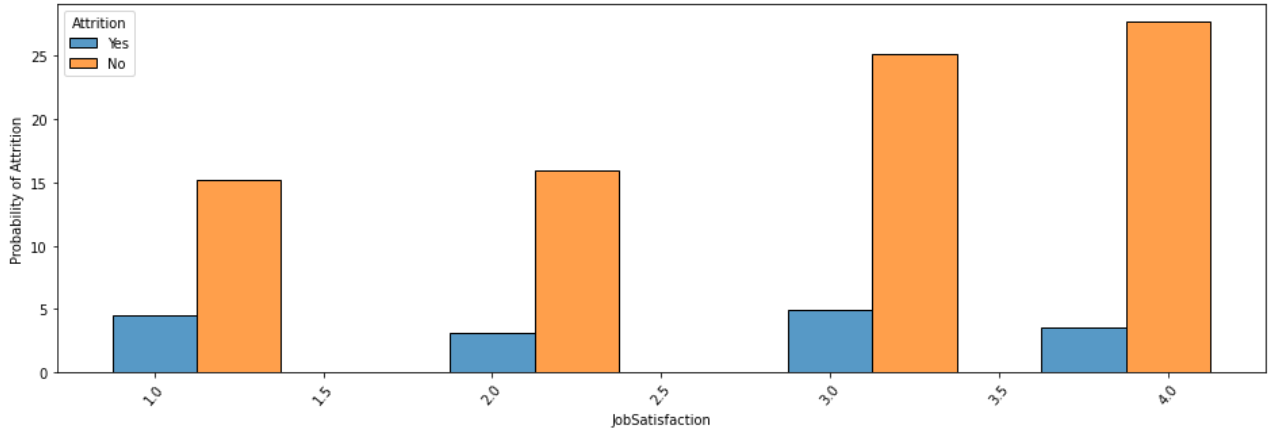


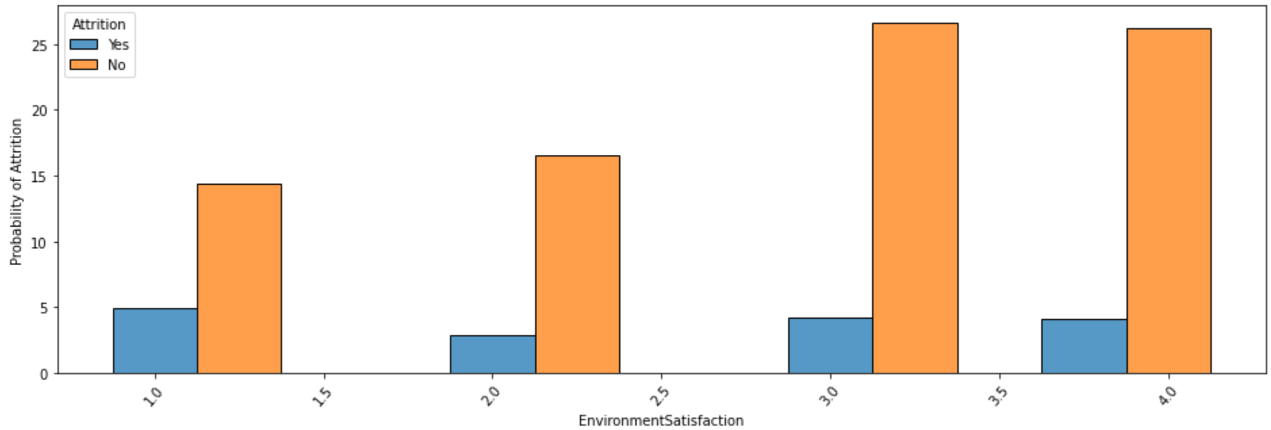

Attrition
Yes
No
Probability of Attrition
PerformanceRating

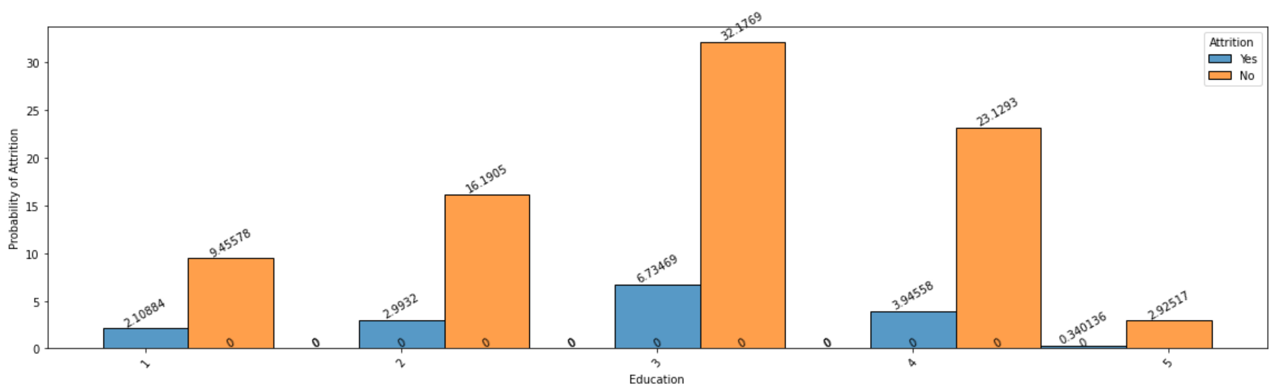

Attrition
Yes
No
Probability of Attrition
NumCompaniesWorked


Attrition
Yes
No
Probability of Attrition
JobInvolvement


Attrition
Yes
No
Probability of Attrition
JobLevel







Step 4: Performance Prediction

In [12]:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error
```

In [13]:

```
x.head()
x.columns
```

Out[13]:

```
Index(['Age', 'DailyRate', 'DistanceFromHome', 'Education',
       'EnvironmentSatisfaction', 'HourlyRate', 'JobInvolvement', 'JobLevel',
       'JobSatisfaction', 'MonthlyIncome', 'MonthlyRate', 'NumCompaniesWorked',
       'PercentSalaryHike', 'PerformanceRating', 'RelationshipSatisfaction',
       'StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear',
       'WorkLifeBalance', 'YearsAtCompany', 'YearsInCurrentRole',
```

```
       'YearsSinceLastPromotion', 'YearsWithCurrManager', 'Attrition_No',
       'Attrition_Yes', 'BusinessTravel_Non-Travel',
       'BusinessTravel_Travel_Frequently', 'BusinessTravel_Travel_Rarely',
       'Department_Human Resources', 'Department_Research & Development',
       'Department_Sales', 'EducationField_Human Resources',
       'EducationField_Life Sciences', 'EducationField_Marketing',
       'EducationField_Medical', 'EducationField_Other',
       'EducationField_Technical Degree', 'Gender_Female', 'Gender_Male',
       'JobRole_Healthcare Representative', 'JobRole_Human Resources',
       'JobRole_Laboratory Technician', 'JobRole_Manager',
       'JobRole_Manufacturing Director', 'JobRole_Research Director',
       'JobRole_Research Scientist', 'JobRole_Sales Executive',
       'JobRole_Sales Representative', 'MaritalStatus_Divorced',
       'MaritalStatus_Married', 'MaritalStatus_Single', 'OverTime_No',
       'OverTime_Yes'],
      dtype='object')
```

I realize in the workplace, companies may not have easy access to this quantity of features, but to improve accuracy I will use them all.

In [25]:

```
# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(x[['Age', 'DailyRate', 'Dist
       'EnvironmentSatisfaction', 'HourlyRate', 'JobInvolvement', 'JobLevel',
       'JobSatisfaction', 'MonthlyIncome', 'MonthlyRate', 'NumCompaniesWorked',
       'PercentSalaryHike', 'RelationshipSatisfaction',
       'StockOptionLevel', 'TotalWorkingYears', 'TrainingTimesLastYear',
       'WorkLifeBalance', 'YearsAtCompany', 'YearsInCurrentRole',
       'YearsSinceLastPromotion', 'YearsWithCurrManager', 'Attrition_No',
       'Attrition_Yes', 'BusinessTravel_Non-Travel',
       'BusinessTravel_Travel_Frequently', 'BusinessTravel_Travel_Rarely',
       'Department_Human Resources', 'Department_Research & Development',
       'Department_Sales', 'EducationField_Human Resources',
       'EducationField_Life Sciences', 'EducationField_Marketing',
       'EducationField_Medical', 'EducationField_Other',
       'EducationField_Technical Degree', 'Gender_Female', 'Gender_Male',
       'JobRole_Healthcare Representative', 'JobRole_Human Resources',
       'JobRole_Laboratory Technician', 'JobRole_Manager',
       'JobRole_Manufacturing Director', 'JobRole_Research Director',
       'JobRole_Research Scientist', 'JobRole_Sales Executive',
       'JobRole_Sales Representative', 'MaritalStatus_Divorced',
       'MaritalStatus_Married', 'MaritalStatus_Single', 'OverTime_No',
       'OverTime_Yes']], x['PerformanceRating'], test_size=0.25, random_state=42

model = LinearRegression()

model.fit(X_train, y_train)

y_pred = model.predict(X_test)

mae = mean_absolute_error(y_test, y_pred)

print('MAE:', mae)
X_test.head()
```

```
MAE: 0.17656749614659223
```

Out[25]:

	Age	DailyRate	DistanceFromHome	Education	EnvironmentSatisfaction	HourlyRate	JobInv
1041	28	866	5	3	4	84	

	Age	DailyRate	DistanceFromHome	Education	EnvironmentSatisfaction	HourlyRate	JobInv
184	53	1084	13	2	4	57	
1222	24	240	22	1	4	58	
67	45	1339	7	3	2	59	
220	36	1396	5	2	4	62	

5 rows × 52 columns

In [15]:
```
params = x.drop('PerformanceRating', axis=1)
```

Test first line in dataset, employee 0, and see how our models predicts their performance rating.

In [16]:
```
x.head()
```

Out[16]:

	Age	DailyRate	DistanceFromHome	Education	EnvironmentSatisfaction	HourlyRate	JobInvolve
0	41	1102	1	2	2	94	
1	49	279	8	1	3	61	
2	37	1373	2	2	4	92	
3	33	1392	3	4	4	56	
4	27	591	2	1	1	40	

5 rows × 53 columns

In [17]:
```
employee_data = params.loc[[0]]
prediction = model.predict(employee_data)
print(f'This employee is predicted to receive a performance rating of {predictio
```

```
This employee is predicted to receive a performance rating of 2.8223723789723687
```

In [18]:
```
actual = x.loc[0]['PerformanceRating']
```

The model predicted that this employee would receive a performance score of 2.82, and the employee actually received a score of 3. Lets see if other models could be more accurate.

In [19]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [20]:
```
# Create a decision tree classifier
dtc = DecisionTreeClassifier()

# Fit the classifier to the training data
dtc.fit(X_train, y_train)

y_pred = dtc.predict(X_test)
```

```
prediction = dtc.predict(employee_data)

# Print the prediction
print(f'This employee is predicted to receive a performance rating of {predictic
```

```
This employee is predicted to receive a performance rating of [3]
```

In [21]:
```
from sklearn.metrics import accuracy_score
```

In [22]:
```
accuracy = accuracy_score(y_test, y_pred)
accuracy
```

Out[22]:
```
1.0
```

Decision Tree Classifier has a perfect score. In reality, I would train this model on a smaller, more feasible list of features, so other HR members could easily enter data. See below for an example.

In [23]:
```
X_train, X_test, y_train, y_test = train_test_split(x[['Age', 'JobLevel',
       'MonthlyIncome', 'TotalWorkingYears', 'TrainingTimesLastYear',
       'WorkLifeBalance', 'YearsAtCompany', 'YearsInCurrentRole',
       'YearsSinceLastPromotion', 'Gender_Female', 'Gender_Male',
       ]], x['PerformanceRating'], test_size=0.25, random_state=42)
```

In [24]:
```
# Create a decision tree classifier
dtc = DecisionTreeClassifier()

# Fit the classifier to the training data
dtc.fit(X_train, y_train)

y_pred = dtc.predict(X_test)


employee_data = pd.DataFrame({'Age': 40, 'JobLevel':3,
       'MonthlyIncome':5000, 'TotalWorkingYears':5, 'TrainingTimesLastYear':0,
       'WorkLifeBalance':1, 'YearsAtCompany':5, 'YearsInCurrentRole':2,
       'YearsSinceLastPromotion':2, 'Gender_Female':1, 'Gender_Male':0},index=[0

prediction = dtc.predict(employee_data.loc[[0]])

# Print the prediction
print(f'This employee is predicted to receive a performance rating of {predictic
```

```
This employee is predicted to receive a performance rating of [4]
```

In [ ]:
```
```