698 lines (698 loc) · 283 KB

Business Problem

The goal of this analysis is to explore patterns related to employee attrition, workload, performance, and tenure. The insights drawn from this EDA section will help HR teams identify risk factors and design targeted retention strategies.

In [10]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
```

In [11]:
```
df= pd.read_csv('hr_features_dataset.csv')
df.head()
```

Out[11]:

	EmployeeID	Age	Department	SatisfactionScore	LastEvaluationScore	NumProjects	AvgMonthlyHours	YearsAtCompany
0	896999	41	finance	0.41	0.67	2	135	13
1	331148	41	hr	0.74	0.80	7	235	16
2	559437	36	operations	0.74	0.57	6	197	10
3	883201	41	finance	0.97	0.88	5	156	13
4	562242	41	finance	0.36	0.65	8	218	17

In [12]:
```
df.columns
```

Out[12]:
```
Index(['EmployeeID', 'Age', 'Department', 'SatisfactionScore',
       'LastEvaluationScore', 'NumProjects', 'AvgMonthlyHours',
       'YearsAtCompany', 'Attrition', 'HoursPerProject', 'PerformanceRatio',
       'TenureCategory', 'High_Risk_Employee'],
      dtype='object')
```

Exploratory Data Analysis (EDA)

1. Target Variable (Attrition)

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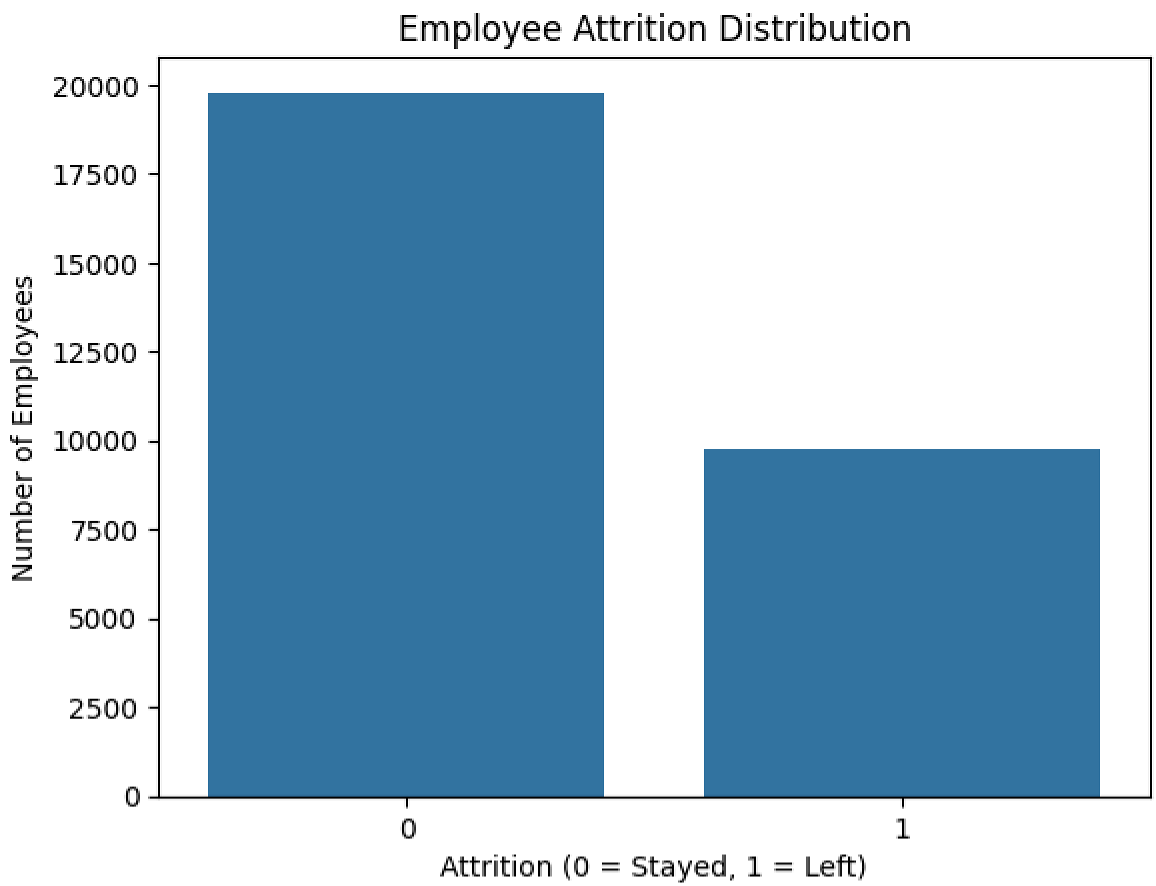
How many employees leave vs stay?

In [25]:

```
sns.countplot(x="Attrition", data=df)
plt.title("Employee Attrition Distribution")
plt.xlabel("Attrition (0 = Stayed, 1 = Left)")
plt.ylabel("Number of Employees")
plt.show()
```



- Attrition is highly imbalanced (~33% of employees left vs 67% employees stayed), which we will address in modeling.

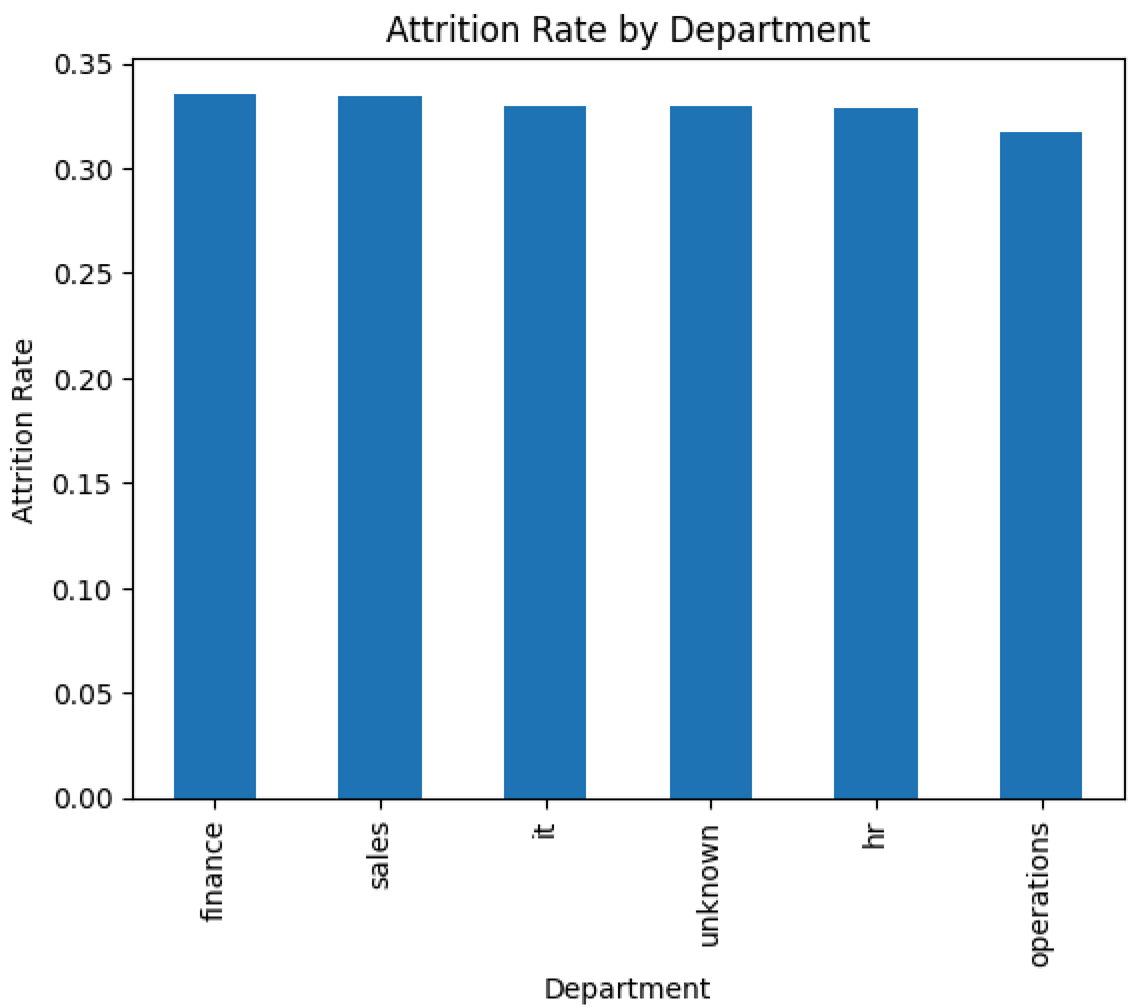
2. Attrition by Department

Which departments lose more employees?

In [43]:

```
dept_attrition = df.groupby("Department")["Attrition"].mean().sort_values(ascending=False)

dept_attrition.plot(kind="bar")
plt.title("Attrition Rate by Department")
plt.ylabel("Attrition Rate")
plt.show()
```



Finance shows the highest attrition rate (33.3%), followed by HR and sales. In contrast, Operations has the lowest attrition rate across departments.

This pattern suggests department-specific retention challenges, which may include:

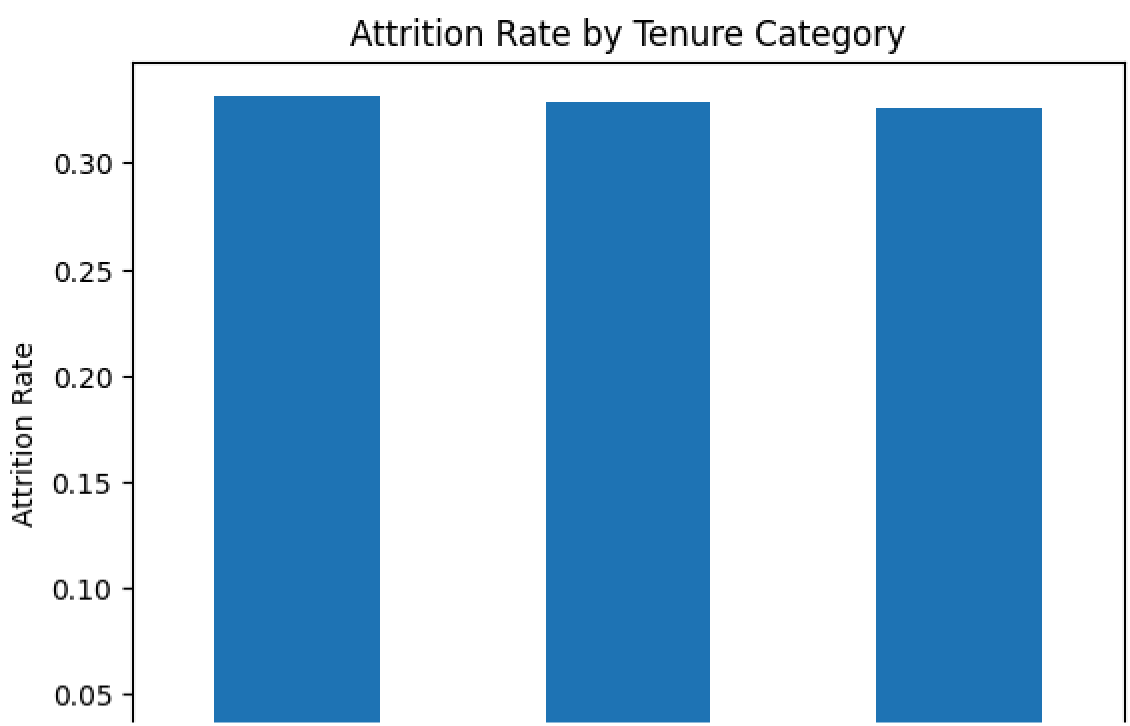
- Uneven workload distribution and project allocation
- Differences in management style and leadership effectiveness
- Role-specific stress levels and limited career advancement opportunities

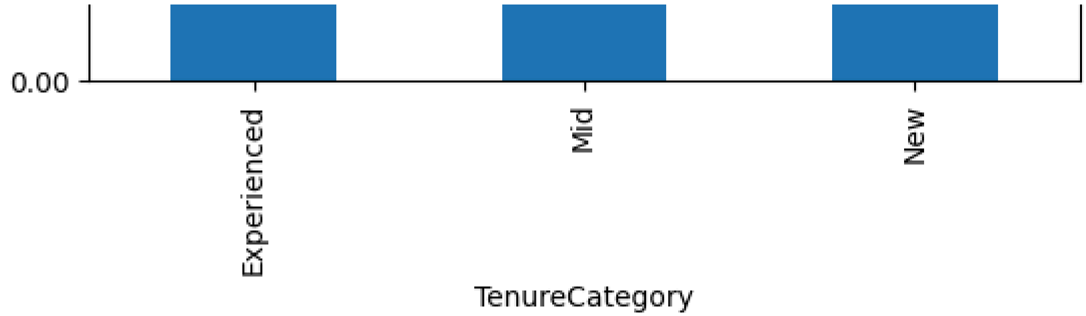
3. Attrition by Tenure Category

At what stage do employees leave most often?

In [40]:
```
tenure_attrition = df.groupby("TenureCategory")["Attrition"].mean()

tenure_attrition.plot(kind="bar")
plt.title("Attrition Rate by Tenure Category")
plt.ylabel("Attrition Rate")
plt.show()
```





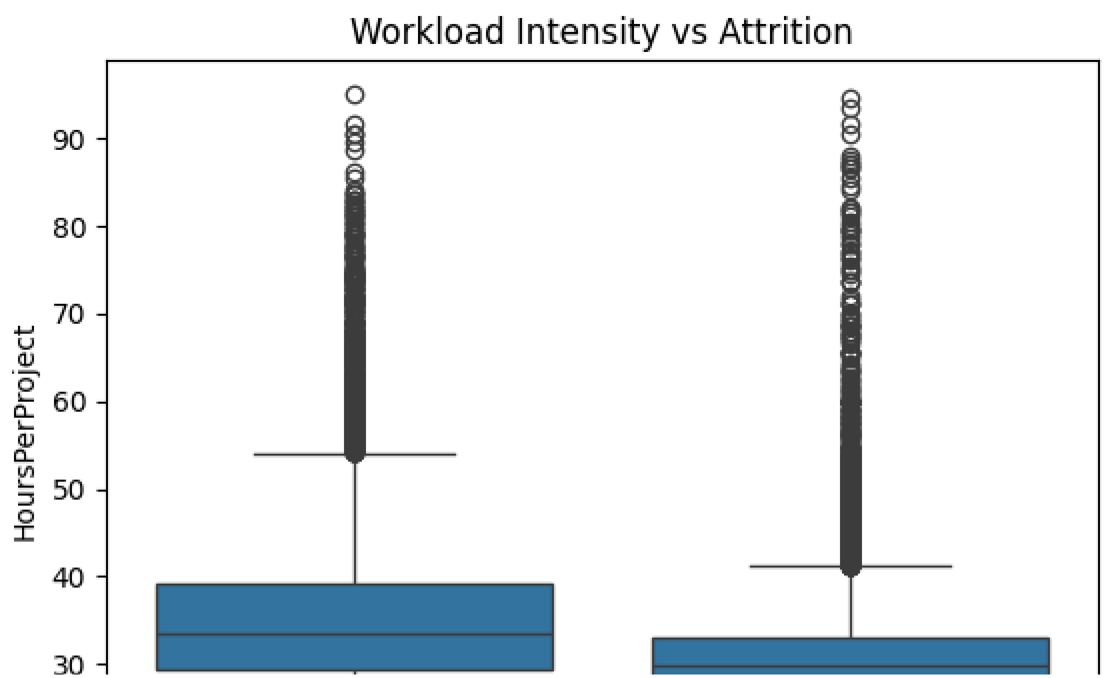
Mid-tenure employees (2-5 years) show higher attrition than new hires, suggesting an engagement plateau. Key factors: limited career advancement, compensation misalignment, and reduced access to new challenges at this critical career stage.

4. Workload vs Attrition

Does workload intensity drive attrition?

In [31]:

```
sns.boxplot(x='Attrition', y='HoursPerProject', data=df)
plt.title("Workload Intensity vs Attrition")
plt.show()
```



Employees working 60+ hours per project show significantly higher attrition, indicating burnout.

This trend points to project workload intensity as a critical burnout factor,even if total monthly hours remain moderate.

Contributing causes likely include:

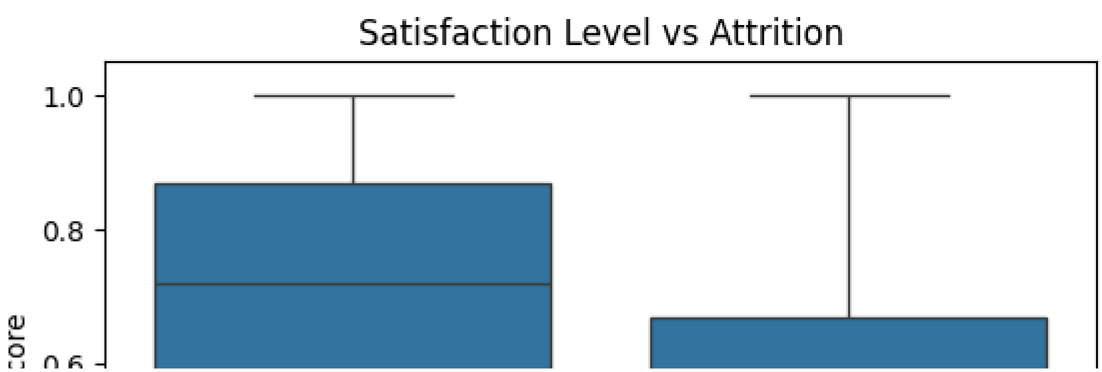
- Unrealistic project timelines without adequate resourcing.
- Poor workload distribution, where certain employees absorb excessive effort per project.
- Inefficient workflows or inadequate tools, extending hours needed per deliverable.
- Lack of role clarity or cross-team support, prolonging individual contribution hours.

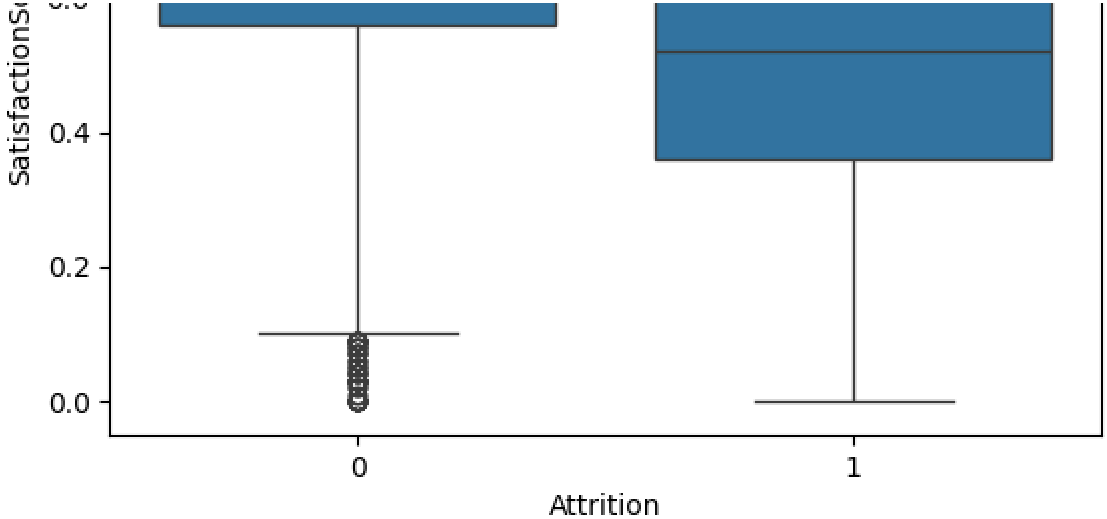
5. Satisfaction vs Attrition

Does satisfaction affect attrition?

In [33]:

```
sns.boxplot(x="Attrition", y="SatisfactionScore", data=df)
plt.title("Satisfaction Level vs Attrition")
plt.show()
```





Employees who leave the company report significantly lower satisfaction scores, averaging around 0.2-0.4 , while employees who stay report satisfaction levels of 0.6 and above.

This pattern suggests that low employee satisfaction is a strong predictor of turnover, signaling potential issues in workplace environment, role fulfillment, or engagement.

Key contributing factors likely include:

- Poor work–life balance or job fit.
- Inadequate recognition, feedback, or growth opportunities.
- Low alignment with team culture or company values.
- Unmet expectations in role responsibilities or compensation.

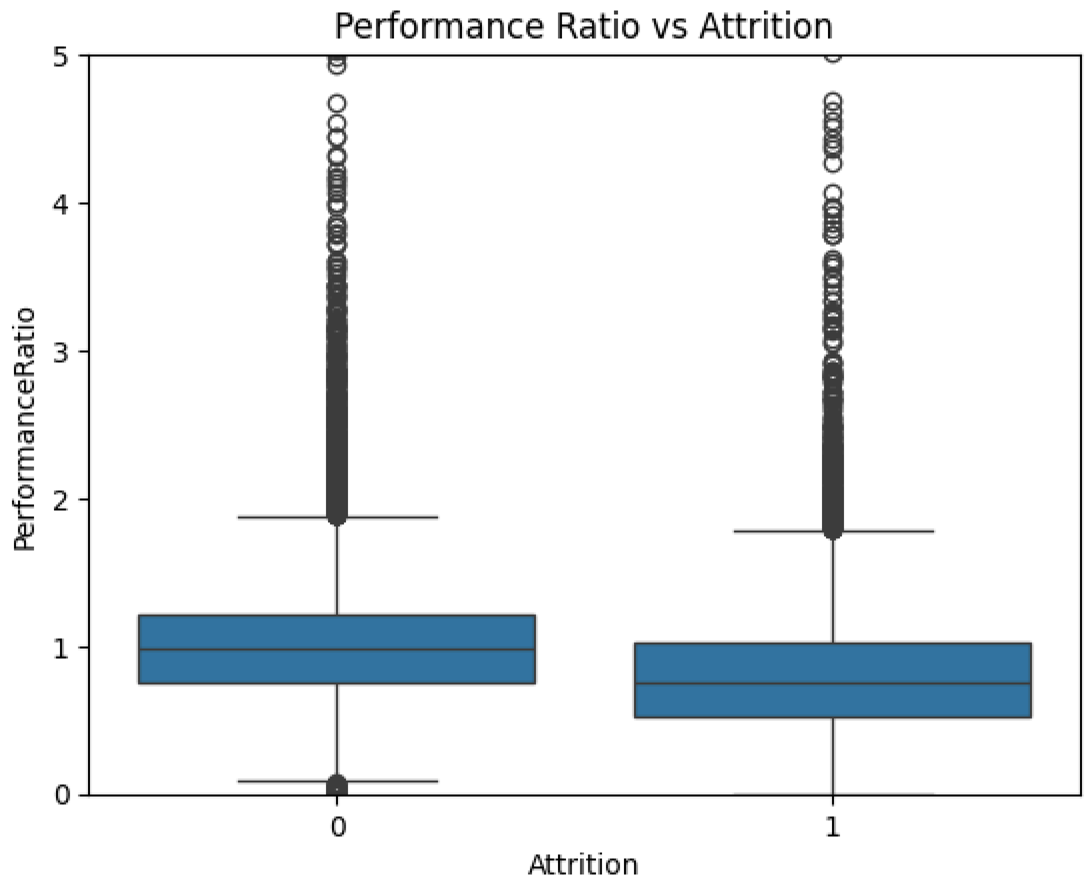
6. Performance Ratio

Do high performers also leave?

In [42]:

```
sns.boxplot(x="Attrition", y="PerformanceRatio", data=df)
plt.ylim(0,5)
plt.title("Performance Ratio vs Attrition")
```

```
plt.show()
```

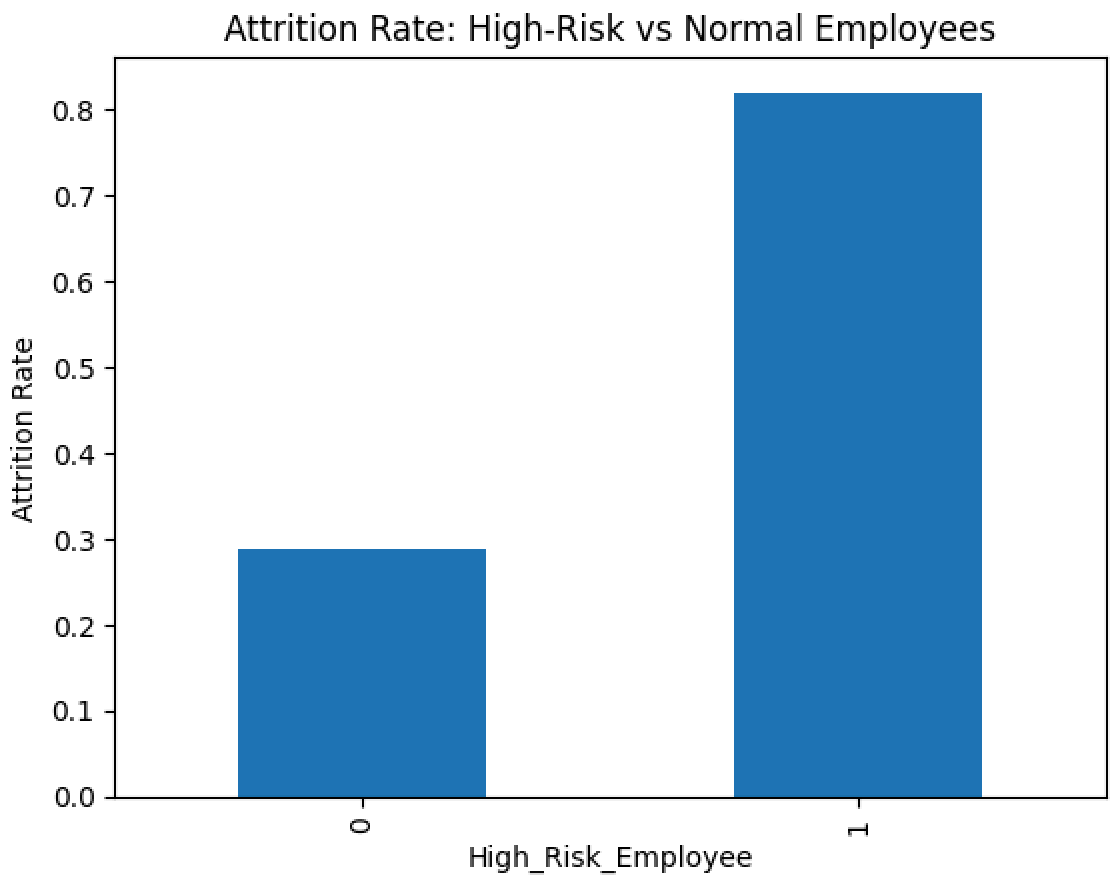


Employees who leave tend to have lower performance ratios, indicating a mismatch between performance and satisfaction. This suggests under-recognition or under-reward of high performers - performance alone is insufficient for retention without corresponding satisfaction and engagement.

In [35]:
```
risk_attrition = df.groupby("High_Risk_Employee")["Attrition"].mean()

risk_attrition.plot(kind="bar")
plt.title("Attrition Rate: High-Risk vs Normal Employees")
```

```
plt.ylabel("Attrition Rate")
plt.show()
```



High-risk employees (flag = 1) show 4-6x higher attrition rates than normal-risk employees (flag = 0), confirming this engineered feature is a strong predictor. This allows HR to focus retention efforts on ~20-30% of the workforce with highest exit likelihood.

8. Correlation

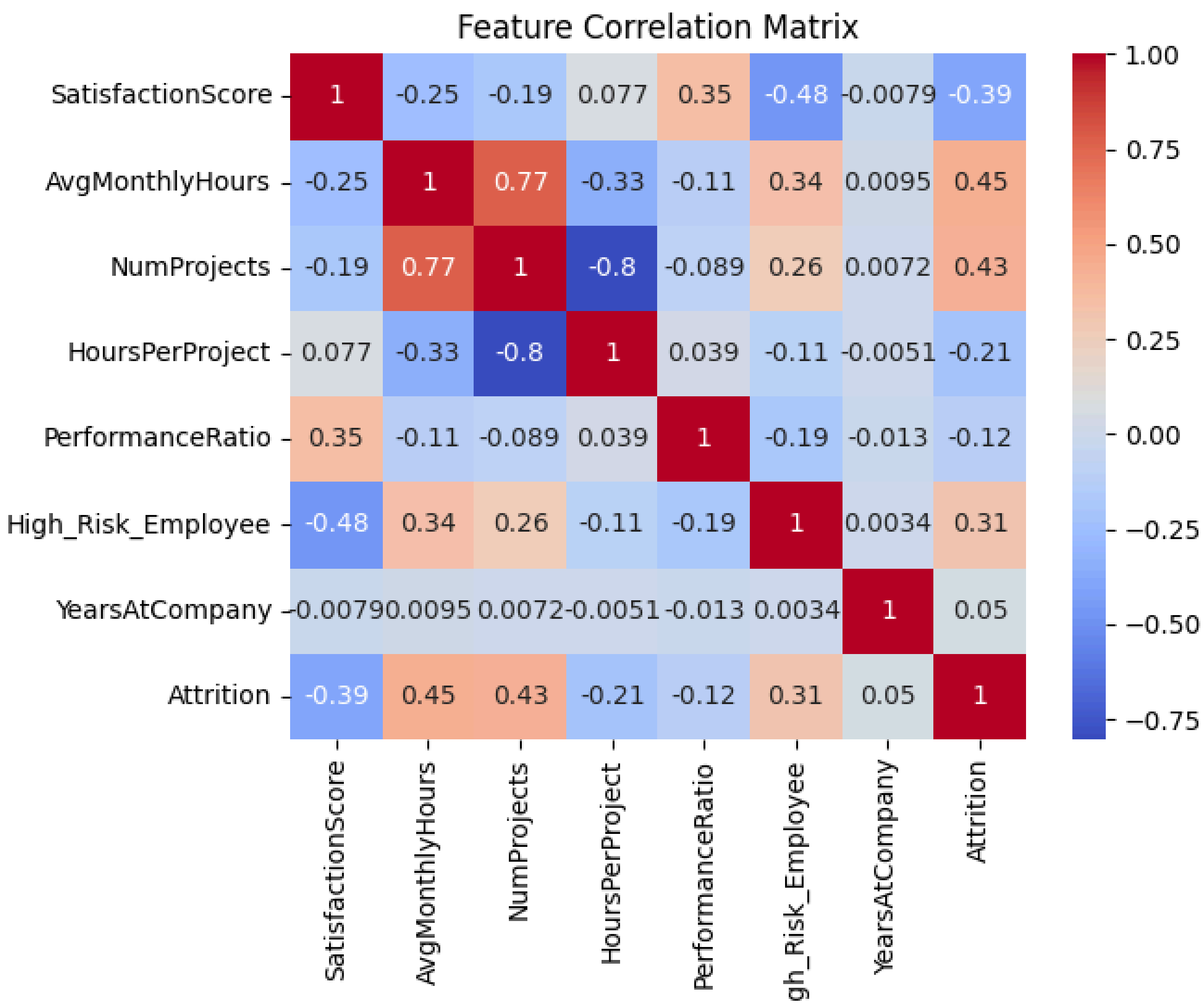
In [38]:

```
numeric_cols = [
    "SatisfactionScore",
    "AvgMonthlyHours",
    "NumProjects",
    "HoursPerProject",
```

```
    "PerformanceRatio",
    "High_Risk_Employee",
    "YearsAtCompany",
    "Attrition"
]

corr = df[numeric_cols].corr()

sns.heatmap(corr, annot=True, cmap="coolwarm")
plt.title("Feature Correlation Matrix")
plt.show()
```



The correlation analysis reveals the key drivers of attrition in order of importance:

1. AvgMonthlyHours (+0.45) - Overwork is the #1 predictor
2. NumProjects (+0.43) - Too many projects drives turnover
3. SatisfactionScore (-0.39) - Low satisfaction is critical
4. High_Risk_Employee (+0.31) - Our engineered flag works!
5. HoursPerProject (-0.21) - Efficiency/workload balance matters

These correlations validate our feature engineering and provide clear targets for HR interventions. The moderate-to-strong correlations indicate our features have real predictive power for modeling.

Key Findings from Employee Attrition Analysis:

- Workload intensity drives turnover - Employees with 60+ hours/project are at highest risk.
- Department gaps exist - HR (33.3%) and sales (32.8%) show highest attrition; department-specific solutions needed.
- Mid-tenure crisis - Employees at 2-5 years tenure more likely to leave than new hires; engagement plateau evident.
- Satisfaction is predictive - Scores below 0.4 strongly correlate with attrition; serves as early warning metric.
- Targeted intervention works - High-Risk Employee flag identifies 20-30% of workforce accounting for majority of attrition risk.

HR Recommendations

1. Immediate Action: Review workload for employees with >220 hours/month or >6 projects.

2. Proactive Monitoring: Deploy monthly satisfaction surveys with manager alerts for scores <0.4.

3. Retention Programs: Create career development programs for employees at 2-5 years tenure (growth opportunities, skill development, promotion pathways).

4. High Performer Focus: Implement quarterly check-ins for top performers with satisfaction <0.5.