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priscillanzula update e81ea10 · 2 hours ago

706 lines (706 loc) · 295 KB

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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
0	896999	41	finance	0.41	0.67	2	135
1	331148	41	hr	0.74	0.80	7	235
2	559437	36	operations	0.74	0.57	6	197
3	883201	41	finance	0.97	0.88	5	156
4	562242	41	finance	0.36	0.65	8	218

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

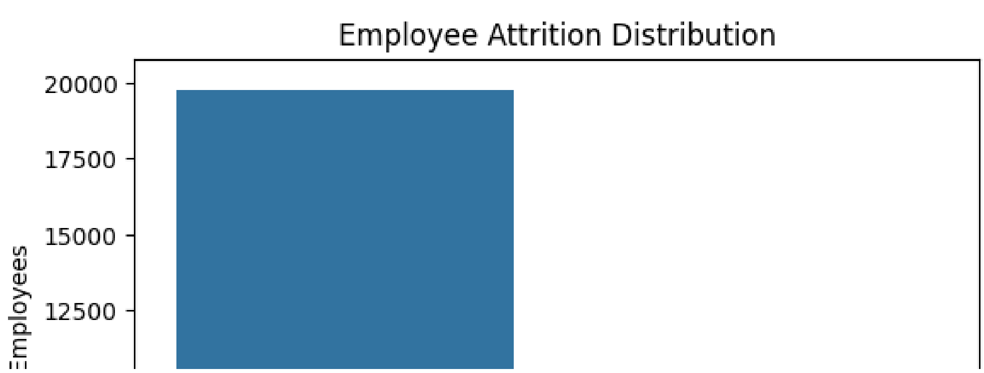
Out[12]:
```
Index(['EmployeeID', 'Age', 'Department', 'SatisfactionScore',
       'LastEvaluationScore', 'NumProjects', 'AvgMonthlyHours',
       'YearsAtCompany', 'Attrition', 'HoursPerProject', 'PerformanceRatio',
       'TenureCategory', 'High_Risk_Employee'],
      dtype='object')
```

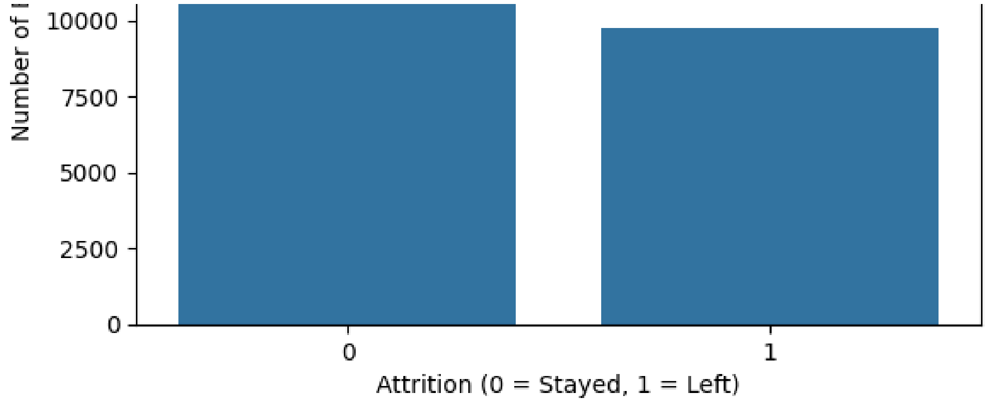
Exploratory Data Analysis (EDA)

1. Target Variable (Attrition)

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, with far more employees staying than leaving.

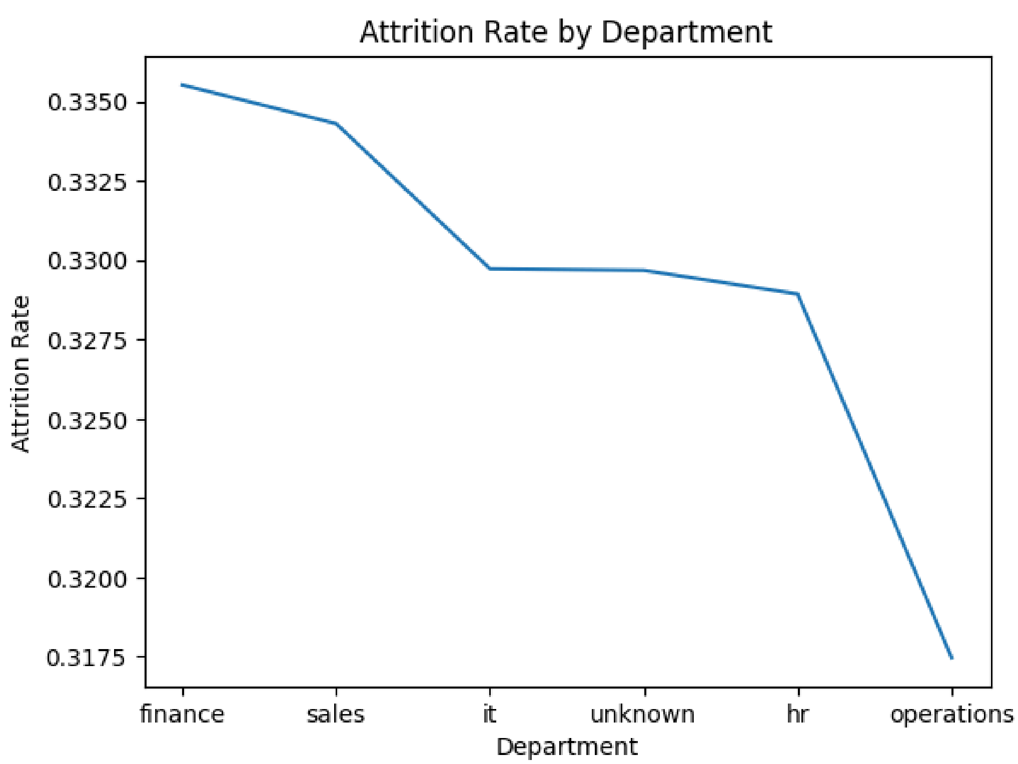
2. Attrition by Department

Which departments lose more employees?

In [39]:

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

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



Finance shows the highest attrition rate, followed closely by 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

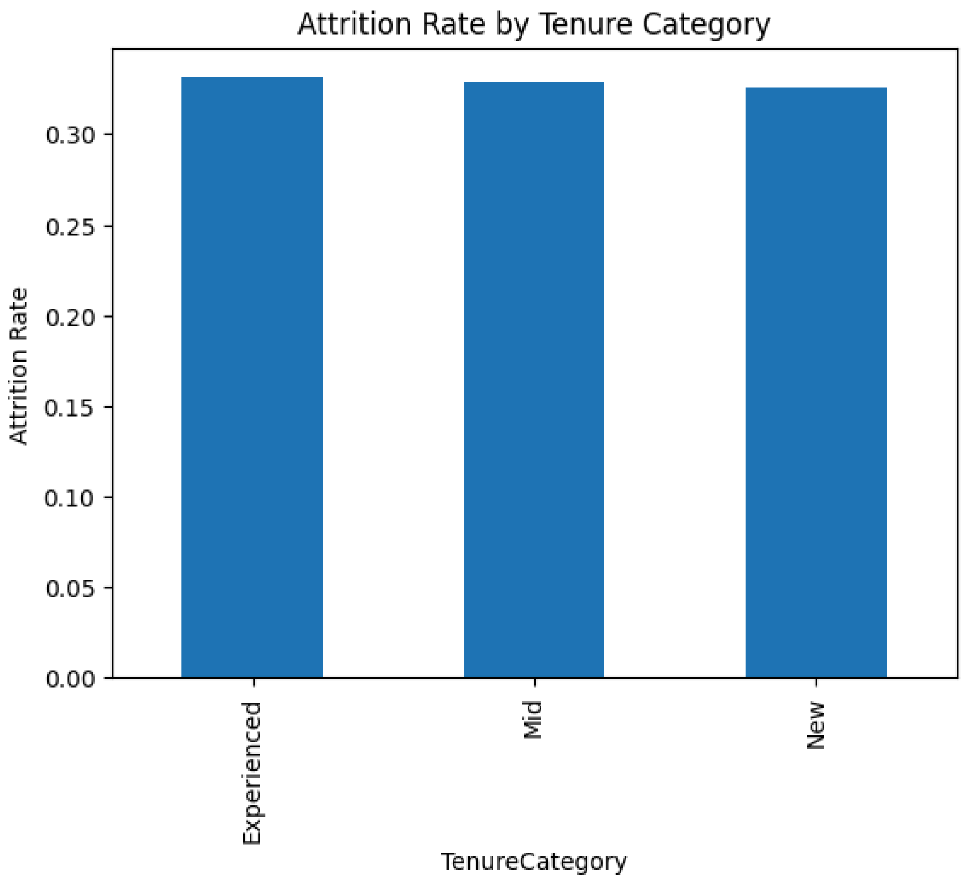
- Role-specific stress levels and limited career advancement opportunities

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()
```



Employees with 5+ years of tenure exhibit the highest attrition rate, while new hires show the lowest attrition rate.

This pattern suggests a potential engagement or growth plateau, where longer-tenured employees begin to reassess their long-term future with the organization. Likely contributing factors include:

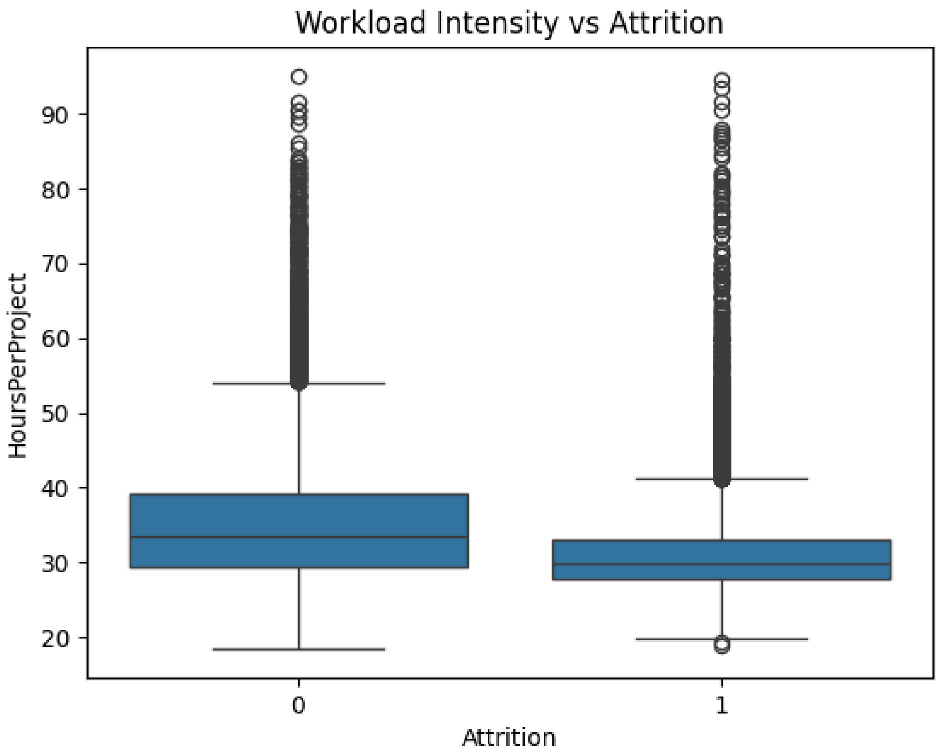
- Limited career advancement opportunities.
- Compensation not keeping pace with market benchmarks.
- Reduced access to new challenges or skill development.
- Attractive external opportunities that value their accumulated experience.

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 with 60+ hours per project show a sharp rise in attrition, while those with 20–50 hours per project see significantly lower turnover.

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

Contributing causes likely include:

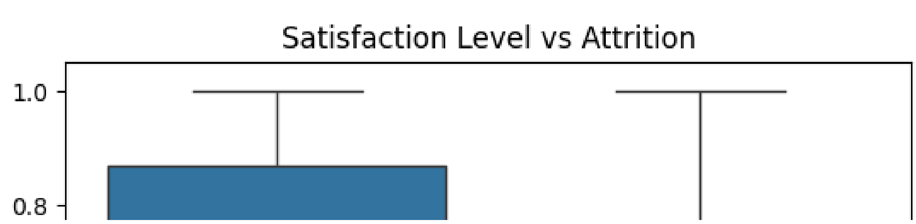
- Unrealistic project timelines without adequate resourcing.
- Poor workload distribution, where certain employees absorb excessive effort per project.
- Inefficient workflows or inadequate tools, extending hours needed per deliverable.
- Lack of role clarity or cross-team support, prolonging individual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

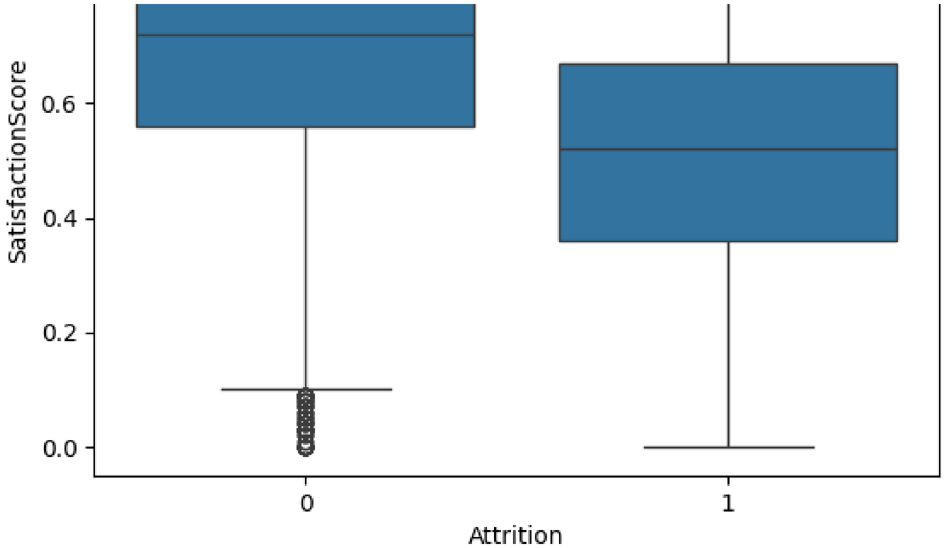
5. Satisfaction vs Attrition

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:

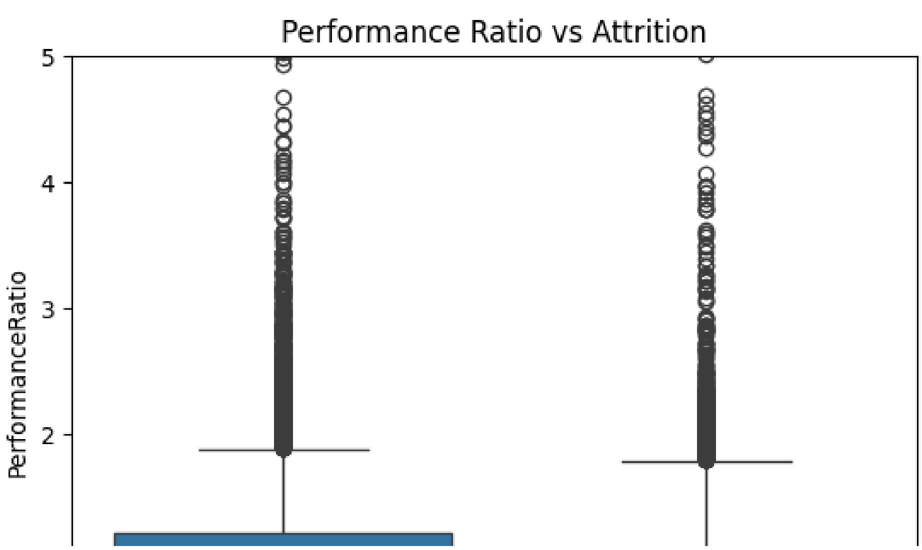
- Poor work–life balance or job fit.
- Inadequate recognition, feedback, or growth opportunities.
- Low alignment with team culture or company values.
- Unmet expectations in role responsibilities or compensation.

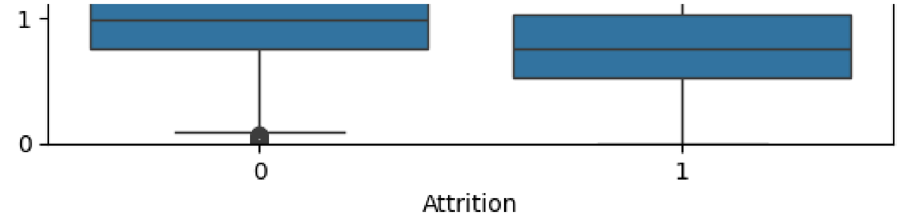
6. Performance Ratio: Hidden Risk

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()
```





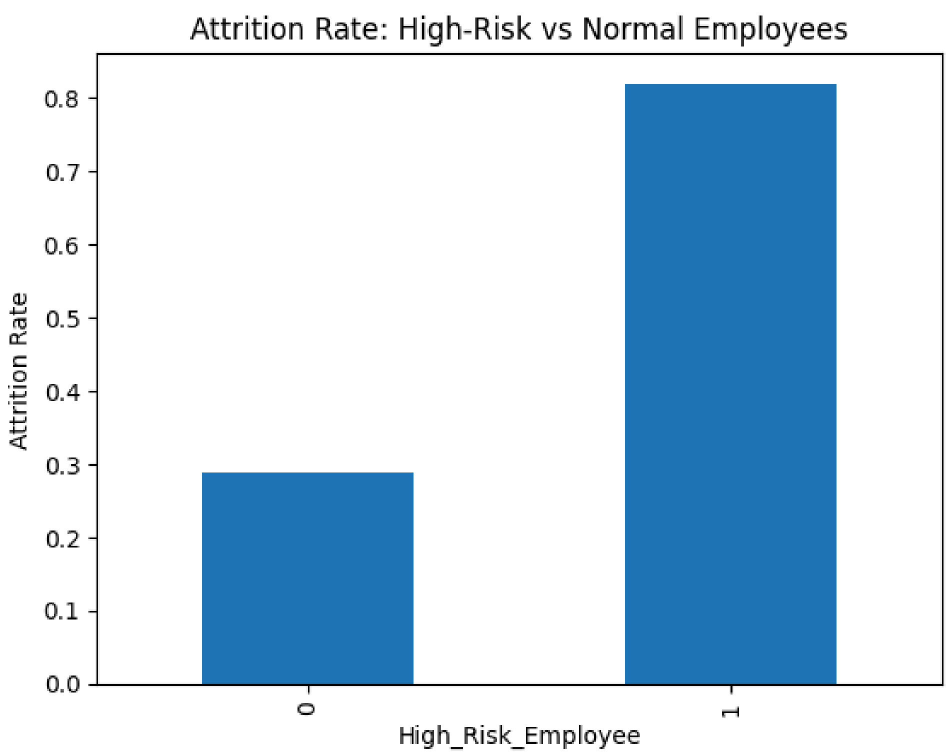
- Employees who leave the company tend to have a lower performance ratio, indicating a mismatch between their performance level and their satisfaction. While these employees may perform well, their perceived value, fulfillment, or engagement does not scale with their contribution.
- This finding suggests that the performance ratio is a meaningful attrition signal. A low ratio reflects under-recognition or under-reward of performance, which increases the likelihood of exit even among strong contributors.
- This means performance alone is not sufficient for retention. Attrition risk increases when employee output exceeds perceived satisfaction, making the performance ratio a more informative indicator than raw performance scores alone.

7. High-Risk Employee Flag

Does the High_Risk_Employee feature actually work?

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 a higher attrition rates compared to normal-risk employees (flag = 0).

This confirms the high-risk employee flag is a strong predictor of turnover, with a 4–6times increase in attrition likelihood for flagged employees.

Why this matters:

- Focusing on the ~20–30% of employees flagged as high-risk allows HR and managers to target retention efforts with 4–6 times greater efficiency than addressing the entire workforce.

Key contributing factors include:

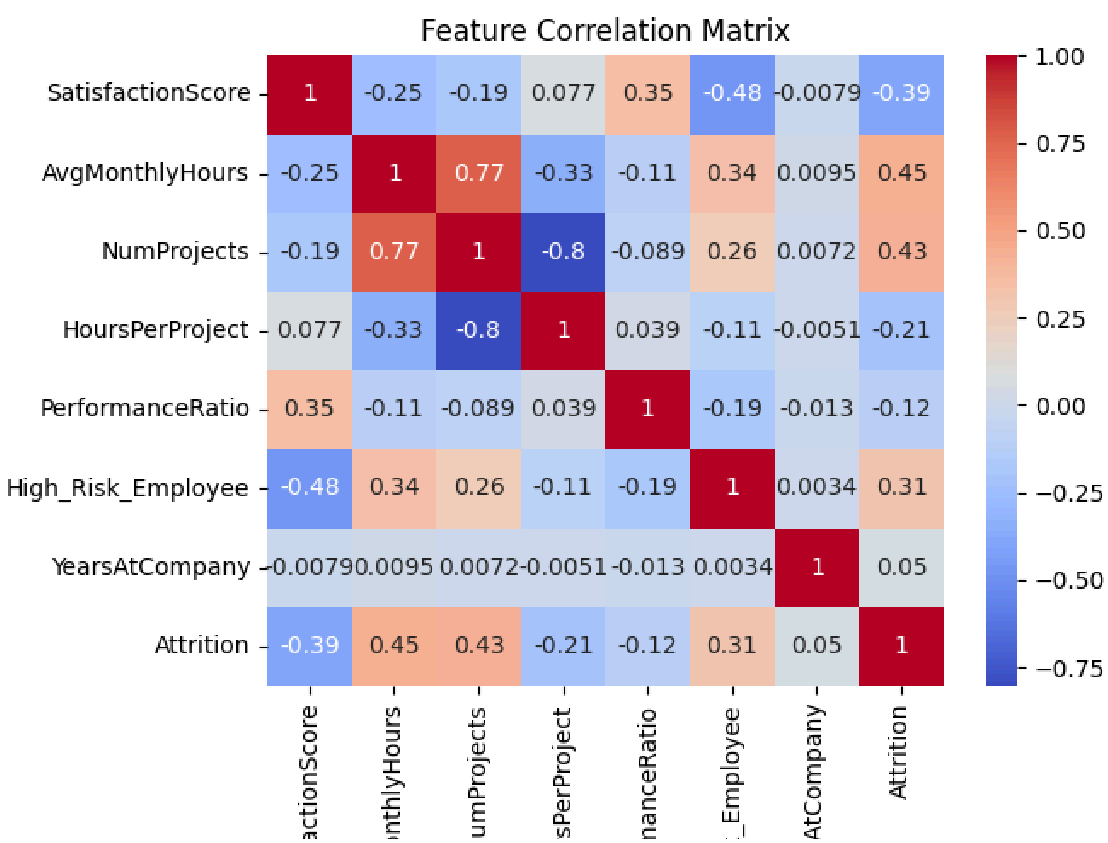
- Unsustainable workloads without adequate support or recognition.
- Chronic low satisfaction due to misalignment, poor feedback, or limited growth.
- Compensation or role-fit mismatches that are not addressed over time.
- Burnout accumulation from prolonged high-demand, low-reward cycles.

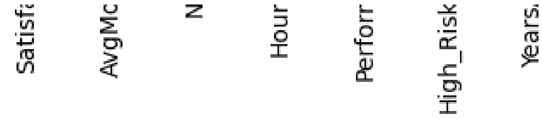
8. Correlation

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.

HR RECOMMENDATIONS