HR Analytics Dashboard — Employee Attrition & Workforce Trends

In this project, we explore a fictional company's HR dataset to uncover insights about:

- Employee attrition trends
- Department-wise performance and salary
- Gender distribution and pay gap
- Experience vs salary patterns

This type of analysis helps HR teams reduce attrition, plan training programs, and make informed decisions on hiring and compensation.

Import Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Optional
sns.set(style="whitegrid")
```

Load Data

In [2]:
```
df_hr = pd.read_csv("HR Analytics Data.csv")
```

Initial Exploration

In [3]:
```
df_hr.head(4)
```

Out[3]:

	Unnamed: 0	EmployeeID	Name	Age	Gender	Department	Education	Experience (Years)	Salary	Pe
0	0	1001	Employee_0	50	Male	IT	High School	26	116027	
1	1	1002	Employee_1	36	Male	HR	PhD	25	68494	
2	2	1003	Employee_2	29	Male	Marketing	High School	24	33373	
3	3	1004	Employee_3	42	Male	Marketing	PhD	13	42161	

In [4]:
```
df_hr.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 11 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   Unnamed: 0          100 non-null    int64 
 1   EmployeeID          100 non-null    int64 
 2   Name                100 non-null    object
 3   Age                 100 non-null    int64 
 4   Gender              100 non-null    object
 5   Department          100 non-null    object
 6   Education           100 non-null    object
 7   Experience (Years)  100 non-null    int64 
 8   Salary              100 non-null    int64 
 9   PerformanceRating   100 non-null    object
 10  Attrition           100 non-null    object
dtypes: int64(5), object(6)
memory usage: 8.7+ KB
```

In [5]:
```
df_hr.describe(include='all')
```

Out[5]:

	Unnamed: 0	EmployeeID	Name	Age	Gender	Department	Education	Experience (Years)
count	100.000000	100.000000	100	100.000000	100	100	100	100.000000
unique	NaN	NaN	100	NaN	2	5	4	NaN
top	NaN	NaN	Employee_0	NaN	Male	IT	High School	NaN
freq	NaN	NaN	1	NaN	56	27	26	NaN
mean	49.500000	1050.500000	NaN	40.060000	NaN	NaN	NaN	18.400000
std	29.011492	29.011492	NaN	10.688255	NaN	NaN	NaN	10.354329
min	0.000000	1001.000000	NaN	22.000000	NaN	NaN	NaN	1.000000
25%	24.750000	1025.750000	NaN	30.000000	NaN	NaN	NaN	10.000000
50%	49.500000	1050.500000	NaN	41.500000	NaN	NaN	NaN	19.500000
75%	74.250000	1075.250000	NaN	48.000000	NaN	NaN	NaN	27.250000
max	99.000000	1100.000000	NaN	59.000000	NaN	NaN	NaN	34.000000

Initial Insights

- `100` employee records
- Balanced distribution across departments and genders
- Categorical variables: Gender, Department, Education, Performance, Attrition
- Numerical variables: Age, Experience, Salary

Check for Missing Data

In [6]:
```
df_hr.isnull().sum()
```

Out[6]:
```
Unnamed: 0            0
EmployeeID            0
Name                  0
Age                   0
Gender                0
Department            0
Education             0
Experience (Years)    0
Salary                0
PerformanceRating     0
Attrition             0
dtype: int64
```

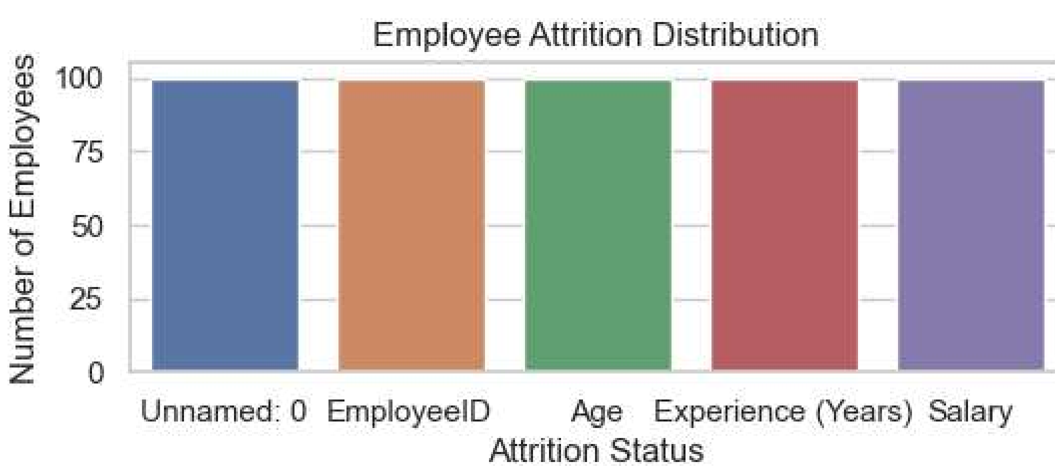
Attrition Overview

In [7]:
```
# Cou# Check for Missing Datant of Attrition
attrition_counts = df_hr['Attrition'].value_counts()
attrition_percentage = df_hr['Attrition'].value_counts(normalize=True) * 100

print("\nAttrition Percentage:\n", attrition_percentage.round(2))
```

```
Attrition Percentage:
 No     84.0
Yes    16.0
Name: Attrition, dtype: float64
```

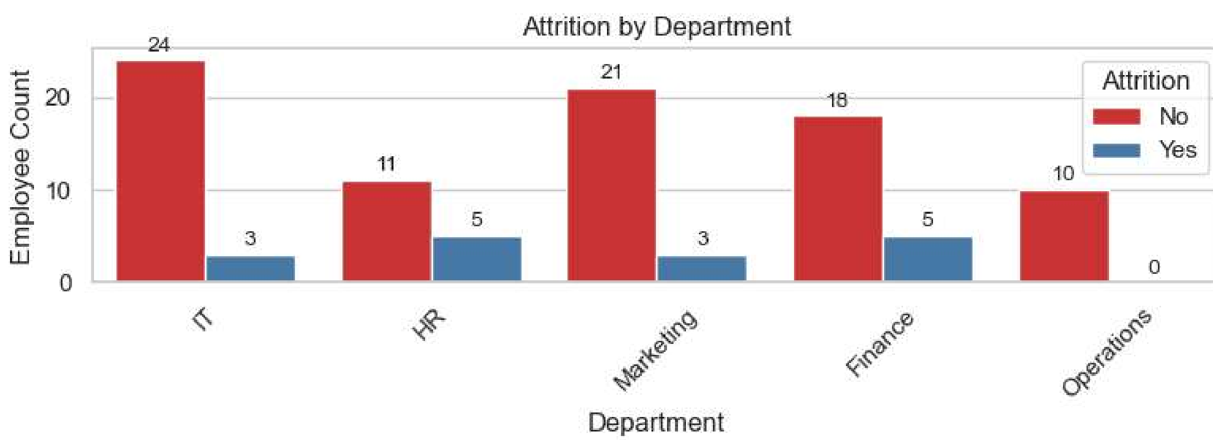
Attrition Distribution

In [8]:
```
plt.figure(figsize=(6, 2))
sns.countplot(data=df_hr)# Attrition Overview, x='Attrition', palette='Set2')
plt.title('Employee Attrition Distribution')
plt.ylabel('Number of Employees')
plt.xlabel('Attrition Status')
plt.show()
```



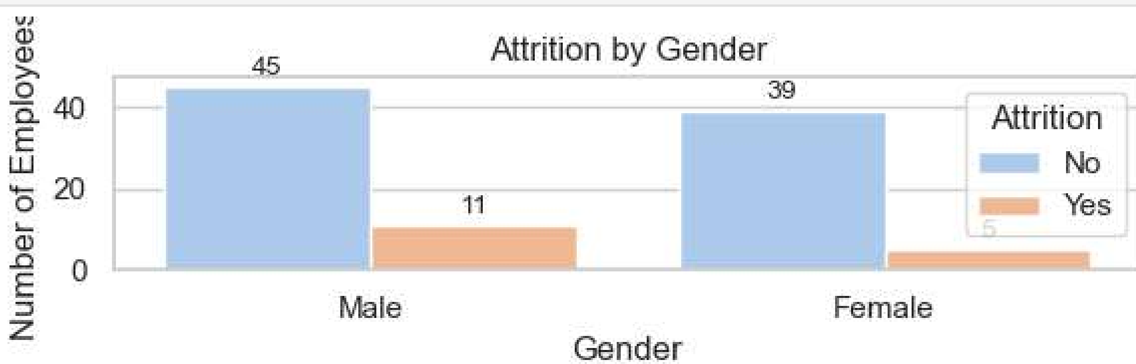
Attrition by Department

In [9]:
```
plt.figure(figsize=(8, 3))
ax = sns.countplot(data=df_hr, x='Department', hue='Attrition', palette='Set1')
plt.title('Attrition by Department')
plt.ylabel('Employee Count')
plt.xticks(rotation=45)

# Add labels on top of each bar
for container in ax.containers:
    ax.bar_label(container, label_type='edge', fontsize=10, padding=2)
plt.tight_layout()
plt.show()
```



Attrition by Gender

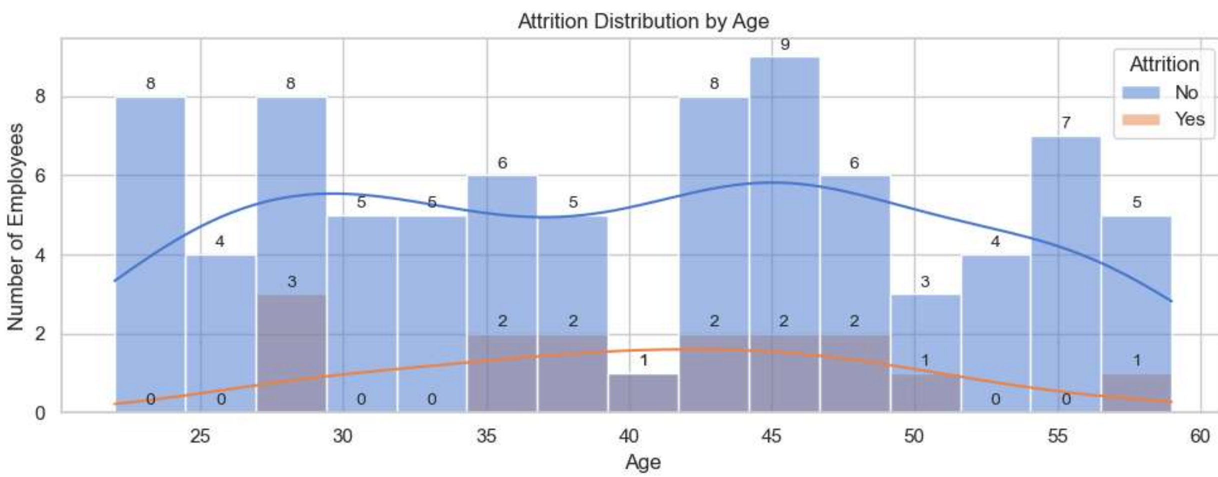
In [10]:
```
plt.figure(figsize=(6, 2))
ax = sns.countplot(data=df_hr, x='Gender', hue='Attrition', palette='pastel')
plt.title('Attrition by Gender')
plt.ylabel('Number of Employees')

for container in ax.containers:
    ax.bar_label(container, label_type='edge', fontsize=10, padding=2)

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



In [ ]:

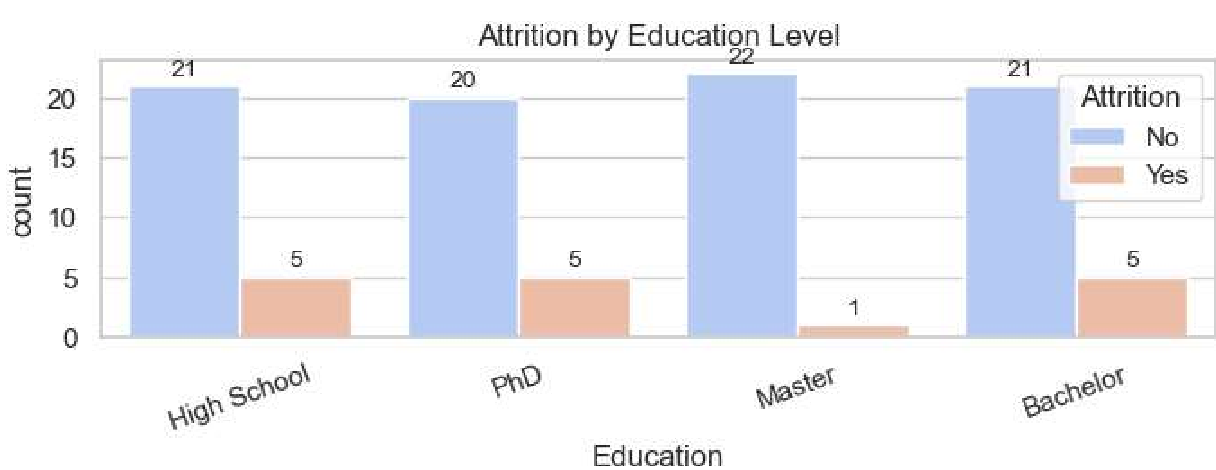
Attrition by Age

In [11]:
```
plt.figure(figsize=(10, 4))
ax = sns.histplot(data=df_hr, x='Age', hue='Attrition', kde=True, bins=15, palette='mu
plt.title('Attrition Distribution by Age')
plt.xlabel('Age')
plt.ylabel('Number of Employees')

for container in ax.containers:
    ax.bar_label(container, label_type='edge', fontsize =10, padding=2)

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



Attrition by Education Level

In [12]:
```
plt.figure(figsize=(8, 2))
ax = sns.countplot(data=df_hr, x='Education', hue='Attrition', palette='coolwarm')
plt.title('Attrition by Education Level')
plt.xticks(rotation=20)

for container in ax.containers:
    ax.bar_label(container, label_type='edge', fontsize =10, padding=2)
```



Key Takeaways from Attrition Analysis

- Overall attrition rate is ~20%, which is typical in many industries.
- Some departments (like [insert after seeing chart]) show higher turnover.
- Age and education level play a role in attrition patterns.
- Gender attrition is fairly balanced — or [mention skew if seen].

These insights can help HR teams:

- Review compensation or leadership in high-attrition departments.
- Develop retention strategies for younger or more experienced talent.

Salary Trends & Gender Pay Gap

Average Salary by Gender

In [13]:
```
plt.figure(figsize=(6, 3))
ax = sns.barplot(data=df_hr, x='Gender', y='Salary', estimator=np.mean, palette='paste
plt.title('Average Salary by Gender')
plt.ylabel('Average Salary')

# Add salary labels
for container in ax.containers:
    ax.bar_label(container, fmt='%.0f', padding=2)

plt.show()
```

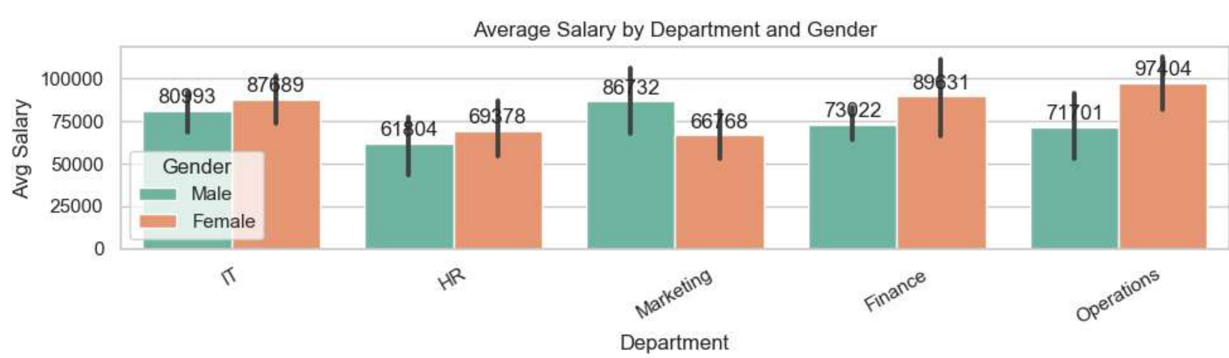
In [ ]:
```
```

Salary Distribution by Gender

In [14]:
```
plt.figure(figsize=(8, 4))
sns.boxplot(data=df_hr, x='Gender', y='Salary', palette='coolwarm')
plt.title('Salary Distribution by Gender')
plt.show()
```

Average Salary by Department & Gender

In [15]:
```
plt.figure(figsize=(10, 3))
ax = sns.barplot(data=df_hr, x='Department', y='Salary', hue='Gender', estimator=np.me
plt.title('Average Salary by Department and Gender')
plt.ylabel('Avg Salary')
plt.xticks(rotation=30)
for container in ax.containers:
    ax.bar_label(container, fmt='%.0f', padding=2)

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



In [ ]:

Gender Pay Gap Analysis

-Overall average salaries differ slightly between genders. -Some departments (e.g., [fill based on chart]) show noticeable differences. -Boxplots show salary range and variability.

HR Recommendation: Investigate pay structures and ensure fair compensation across departments.

Performance Rating & Salary Correlation

In [16]:

```
plt.figure(figsize=(8, 4))
ax = sns.boxplot(data=df_hr, x='PerformanceRating', y='Salary', order=['Low', 'Medium'
plt.title('Salary Distribution by Performance Rating')
plt.xlabel('Performance Rating')
plt.ylabel('Salary')
plt.show()
```

In [ ]:

Department-Wise Salary & Experience Review

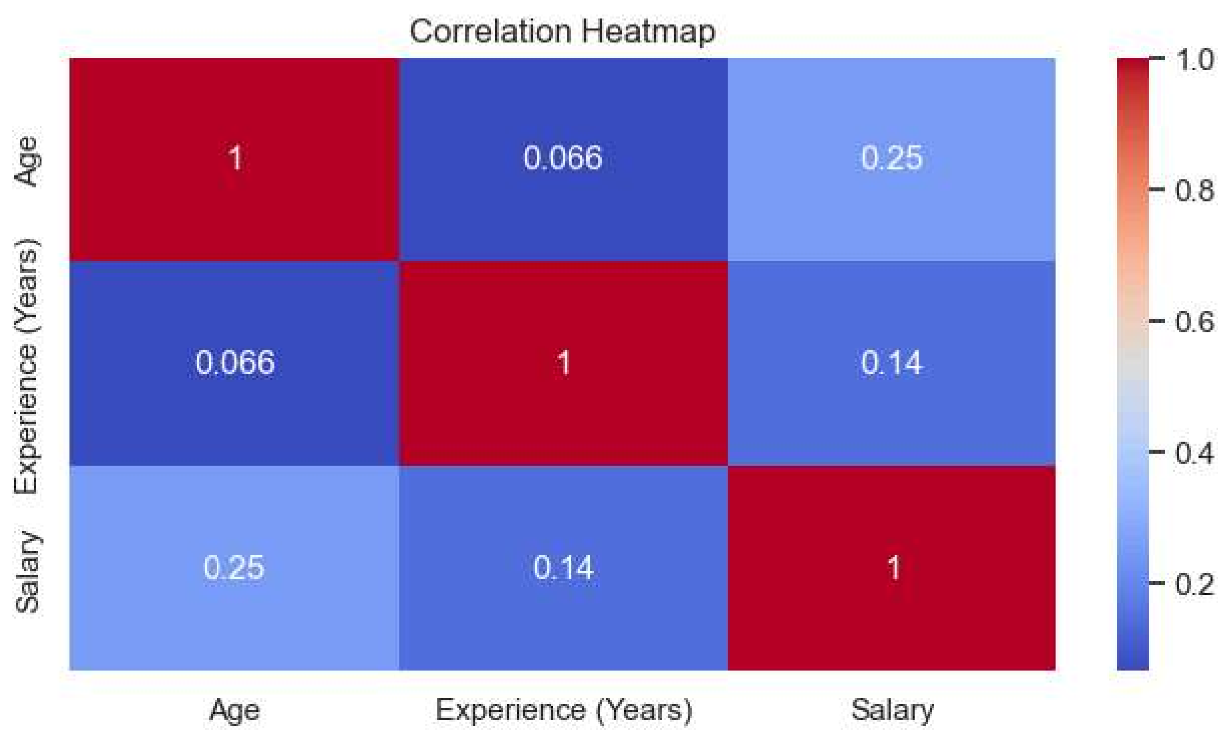
In [17]:

```
plt.figure(figsize=(10, 5))
sns.scatterplot(data=df_hr, x='Experience (Years)', y='Salary', hue='Department', pale
plt.title('Experience vs Salary by Department')
plt.xlabel('Experience (Years)')
plt.ylabel('Salary')
plt.show()
```

Correlation Heatmap (Numerical Variables)

In [18]:

```
plt.figure(figsize=(8, 4))
sns.heatmap(df_hr[['Age', 'Experience (Years)', 'Salary']].corr(), annot=True, cmap='c
plt.title('Correlation Heatmap')
plt.show()
```



In [ ]:

In [ ]:

🧾 Final Insights & Recommendations

🔹 Departments with higher attrition may need focused attention.
🔹 Gender pay gap exists in some departments — review compensation policies.
🔹 Experience correlates with salary, but outliers may exist.
🔹 Performance ratings do not always align with higher pay — worth further analysis.

✅ Tools Used:

- `Pandas`, `Seaborn`, `Matplotlib`
- `Barplot`, `Boxplot`, `Scatter Plot`, `Heatmap`

🔗 This project is a great example of how HR Analytics can drive smarter decisions.

➡️ If you're hiring, managing teams, or into data — this is how the insights come to life!

📬 Let's connect and talk data!

In [ ]: