jupyter Depi_HR_Project Last Checkpoint: 19 hours ago

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Trusted

Code

JupyterLab Python 3 (ipykernel)

[1]:
```
#Final Project
```

[6]:
```
import pandas as pd
import numpy as np
```

[8]:
```
# Define file paths (Update these if filenames change)
Employee= pd.read_csv("/Users/rahmasaadawy/Downloads/Final_Project/HR/Employee.csv")
PerformanceRating= pd.read_csv("/Users/rahmasaadawy/Downloads/Final_Project/HR/PerformanceRating.csv")
RatingLevel= pd.read_csv("/Users/rahmasaadawy/Downloads/Final_Project/HR/RatingLevel.csv")
SatisfiedLevel= pd.read_csv("/Users/rahmasaadawy/Downloads/Final_Project/HR/SatisfiedLevel.csv")
EducationLevel= pd.read_csv("/Users/rahmasaadawy/Downloads/Final_Project/HR/EducationLevel.csv")
```

[10…
```
#Searching for Null values
print(Employee.isnull().sum())
print(PerformanceRating.isnull().sum())
print(RatingLevel.isnull().sum())
print(SatisfiedLevel.isnull().sum())
print(EducationLevel.isnull().sum())
```

```
EmployeeID                0
FirstName                 0
LastName                  0
Gender                    0
Age                       0
BusinessTravel            0
Department                0
DistanceFromHome (KM)     0
State                     0
Ethnicity                 0
Education                 0
EducationField            0
JobRole                   0
MaritalStatus             0
Salary                    0
StockOptionLevel          0
OverTime                  0
HireDate                  0
Attrition                 0
YearsAtCompany            0
YearsInMostRecentRole     0
YearsSinceLastPromotion   0
YearsWithCurrManager      0
dtype: int64
PerformanceID                     0
EmployeeID                        0
ReviewDate                        0
EnvironmentSatisfaction           0
JobSatisfaction                   0
RelationshipSatisfaction          0
TrainingOpportunitiesWithinYear   0
TrainingOpportunitiesTaken        0
WorkLifeBalance                   0
SelfRating                        0
ManagerRating                     0
dtype: int64
RatingID       0
RatingLevel    0
dtype: int64
SatisfactionID       0
SatisfactionLevel    0
dtype: int64
EducationLevelID    0
EducationLevel      0
dtype: int64
```

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Code JupyterLab Python 3 (ipykernel)

[12…]
```
#Searching for duplicated values
print(Employee.duplicated().sum())
print(PerformanceRating.duplicated().sum())
print(RatingLevel.duplicated().sum())
print(SatisfiedLevel.duplicated().sum())
print(EducationLevel.duplicated().sum())
```

```
0
0
0
0
0
```

[14…]
```
# Convert reviewdate to datetime
PerformanceRating['ReviewDate'] = pd.to_datetime(PerformanceRating['ReviewDate'], errors='coerce')

# Confirm the change
print(PerformanceRating.dtypes)
```

```
PerformanceID                        object
EmployeeID                           object
ReviewDate                   datetime64[ns]
EnvironmentSatisfaction              int64
JobSatisfaction                      int64
RelationshipSatisfaction             int64
TrainingOpportunitiesWithinYear      int64
TrainingOpportunitiesTaken           int64
WorkLifeBalance                      int64
SelfRating                           int64
ManagerRating                        int64
dtype: object
```

[16…]
```
#Merging Primary tables
merged_df = pd.merge(Employee, PerformanceRating, on="EmployeeID")

#Merging secondary tables
education_level = pd.DataFrame({
    "EducationLevelID": [1, 2, 3, 4, 5],
    "EducationLevel": ["No Formal Qualifications", "High School", "Bachelors", "Masters", "Doctorate"]
})
merged_df = pd.merge(merged_df, education_level, left_on="Education", right_on="EducationLevelID", how
```

[18…]
```python
# Merge Employee with PerformanceRating (Primary tables)
merged_df = pd.merge(Employee, PerformanceRating, on='EmployeeID', how='left')

# Merge with Satisfaction Levels (EnvironmentSatisfaction)
merged_df = pd.merge(merged_df, SatisfiedLevel, left_on='EnvironmentSatisfaction', right_on='Satisfact

# Merge with Rating Levels (ManagerRating)
merged_df = pd.merge( merged_df, RatingLevel, left_on='ManagerRating', right_on='RatingID', how='left'

# Merge with Education Levels (Education)
merged_df = pd.merge( merged_df, EducationLevel, left_on='Education', right_on='EducationLevelID', how

# Drop duplicate key columns
merged_df.drop(columns=['SatisfactionID', 'RatingID', 'EducationLevelID'], inplace=True)

# Check merged dataset structure
print(merged_df.info())

# Save the cleaned and merged dataset
merged_df.to_csv("Cleaned_Data.csv", index=False)

#Download the cleansed Data
merged_df.to_csv ("/Users/rahmasaadawy/Downloads/Cleaned_HR_Data.csv")
merged_df.to_excel("/Users/rahmasaadawy/Downloads/Cleaned_HR_Data.xlsx", index=False)

print(f"✅ Cleaned dataset saved successfully to: {"/Users/rahmasaadawy/Downloads/Cleaned_HR_Data.csv"
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6899 entries, 0 to 6898
Data columns (total 36 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   EmployeeID                      6899 non-null   object
 1   FirstName                       6899 non-null   object
 2   LastName                        6899 non-null   object
 3   Gender                          6899 non-null   object
 4   Age                             6899 non-null   int64
 5   BusinessTravel                  6899 non-null   object
 6   Department                      6899 non-null   object
 7   DistanceFromHome (KM)           6899 non-null   int64
 8   State                           6899 non-null   object
 9   Ethnicity                       6899 non-null   object
 10  Education                       6899 non-null   int64
 11  EducationField                  6899 non-null   object
 12  JobRole                         6899 non-null   object
 13  MaritalStatus                   6899 non-null   object
 14  Salary                          6899 non-null   int64
 15  StockOptionLevel                6899 non-null   int64
 16  OverTime                        6899 non-null   object
 17  HireDate                        6899 non-null   object
 18  Attrition                       6899 non-null   object
 19  YearsAtCompany                  6899 non-null   int64
 20  YearsInMostRecentRole           6899 non-null   int64
 21  YearsSinceLastPromotion         6899 non-null   int64
 22  YearsWithCurrManager            6899 non-null   int64
 23  PerformanceID                   6709 non-null   object
 24  ReviewDate                      6709 non-null   datetime64[ns]
 25  EnvironmentSatisfaction         6709 non-null   float64
 26  JobSatisfaction                 6709 non-null   float64
 27  RelationshipSatisfaction        6709 non-null   float64
 28  TrainingOpportunitiesWithinYear 6709 non-null   float64
 29  TrainingOpportunitiesTaken      6709 non-null   float64
 30  WorkLifeBalance                 6709 non-null   float64
 31  SelfRating                      6709 non-null   float64
 32  ManagerRating                   6709 non-null   float64
 33  SatisfactionLevel               6709 non-null   object
 34  RatingLevel                     6709 non-null   object
 35  EducationLevel                  6899 non-null   object
dtypes: datetime64[ns](1), float64(8), int64(9), object(18)
memory usage: 1.9+ MB
None
✅ Cleaned dataset saved successfully to: /Users/rahmasaadawy/Downloads/Cleaned_HR_Data.csv
```

[20…]
```
# Check the structure of the dataset
print(merged_df.info())
print(merged_df.head())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6899 entries, 0 to 6898
Data columns (total 36 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   EmployeeID                      6899 non-null   object
 1   FirstName                       6899 non-null   object
 2   LastName                        6899 non-null   object
 3   Gender                          6899 non-null   object
 4   Age                             6899 non-null   int64
 5   BusinessTravel                  6899 non-null   object
 6   Department                      6899 non-null   object
 7   DistanceFromHome (KM)           6899 non-null   int64
 8   State                           6899 non-null   object
 9   Ethnicity                       6899 non-null   object
 10  Education                       6899 non-null   int64
 11  EducationField                  6899 non-null   object
 12  JobRole                         6899 non-null   object
 13  MaritalStatus                   6899 non-null   object
 14  Salary                          6899 non-null   int64
 15  StockOptionLevel                6899 non-null   int64
 16  OverTime                        6899 non-null   object
 17  HireDate                        6899 non-null   object
 18  Attrition                       6899 non-null   object
 19  YearsAtCompany                  6899 non-null   int64
 20  YearsInMostRecentRole           6899 non-null   int64
 21  YearsSinceLastPromotion         6899 non-null   int64
 22  YearsWithCurrManager            6899 non-null   int64
 23  PerformanceID                   6709 non-null   object
 24  ReviewDate                      6709 non-null   datetime64[ns]
 25  EnvironmentSatisfaction         6709 non-null   float64
 26  JobSatisfaction                 6709 non-null   float64
 27  RelationshipSatisfaction        6709 non-null   float64
 28  TrainingOpportunitiesWithinYear 6709 non-null   float64
 29  TrainingOpportunitiesTaken      6709 non-null   float64
 30  WorkLifeBalance                 6709 non-null   float64
 31  SelfRating                      6709 non-null   float64
 32  ManagerRating                   6709 non-null   float64
 33  SatisfactionLevel               6709 non-null   object
 34  RatingLevel                     6709 non-null   object
 35  EducationLevel                  6899 non-null   object
dtypes: datetime64[ns](1), float64(8), int64(9), object(18)
memory usage: 1.9+ MB
None
  EmployeeID FirstName LastName  Gender  Age BusinessTravel Department  \
0  3012-1A41  Leonelle    Simco  Female   30    Some Travel      Sales
1  3012-1A41  Leonelle    Simco  Female   30    Some Travel      Sales
2  3012-1A41  Leonelle    Simco  Female   30    Some Travel      Sales
3  3012-1A41  Leonelle    Simco  Female   30    Some Travel      Sales
4  3012-1A41  Leonelle    Simco  Female   30    Some Travel      Sales

   DistanceFromHome (KM) State Ethnicity  ...  JobSatisfaction  \
0                     27    IL     White  ...              3.0
1                     27    IL     White  ...              4.0
2                     27    IL     White  ...              5.0
3                     27    IL     White  ...              3.0
4                     27    IL     White  ...              4.0

  RelationshipSatisfaction TrainingOpportunitiesWithinYear  \
0                      2.0                             3.0
1                      5.0                             3.0
2                      4.0                             3.0
3                      2.0                             3.0
4                      2.0                             1.0

  TrainingOpportunitiesTaken  WorkLifeBalance  SelfRating ManagerRating  \
0                        0.0              4.0         3.0           3.0
1                        1.0              2.0         3.0           2.0
2                        0.0              4.0         5.0           5.0
3                        1.0              3.0         5.0           4.0
4                        0.0              3.0         4.0           3.0

   SatisfactionLevel           RatingLevel  EducationLevel
0            Neutral     Meets Expectation       Doctorate
1          Satisfied      Needs Improvement       Doctorate
2     Very Satisfied       Above and Beyond       Doctorate
3  Very Dissatisfied  Exceeds Expectation        Doctorate
4            Neutral     Meets Expectation       Doctorate

[5 rows x 36 columns]
```

[23…]
```
############################## Ending of Week 1: Build Data Model, Data Cleaning and Preprocessing
```

[25…]
```
############################## Week 2: Analysis Questions Phase
```

[22…]
```
import matplotlib.pyplot as plt
import seaborn as sns
```

[23…]
```
# Load the cleaned dataset
cleaned_data_path = "/Users/rahmasaadawy/Downloads/Cleaned_HR_Data.csv"
merged_df = pd.read_csv("/Users/rahmasaadawy/Downloads/Cleaned_HR_Data.csv", index_col=0)
merged_df
```

[23…]

	EmployeeID	FirstName	LastName	Gender	Age	BusinessTravel	Department	DistanceFromHome (KM)	Sta
0	3012-1A41	Leonelle	Simco	Female	30	Some Travel	Sales	27	
1	3012-1A41	Leonelle	Simco	Female	30	Some Travel	Sales	27	
2	3012-1A41	Leonelle	Simco	Female	30	Some Travel	Sales	27	
3	3012-1A41	Leonelle	Simco	Female	30	Some Travel	Sales	27	
4	3012-1A41	Leonelle	Simco	Female	30	Some Travel	Sales	27	
...	...	...	...	...	...	...	...	...	
6894	467E-977A	Jud	Melanaphy	Male	20	Some Travel	Technology	28	
6895	6FB9-A624	Marc	Calver	Non-Binary	27	Some Travel	Technology	8	
6896	EBF4-5928	Rudolph	MacDearmont	Male	21	Some Travel	Sales	4	
6897	60E6-B1D9	Merill	Agg	Male	21	Some Travel	Technology	7	
6898	84D4-D4C3	Naoma	Hebbard	Female	20	No Travel	Technology	28	

6899 rows × 36 columns

[26…]
```
# First Categoty
# Employee Demographics & Salary Analysis
```

[33…]
```
#1.1 Calculate and display the total number of employees
total_employees = merged_df["EmployeeID"].nunique()
print(f"Total Number of Employees: {total_employees}")
```

```
Total Number of Employees: 1470
```

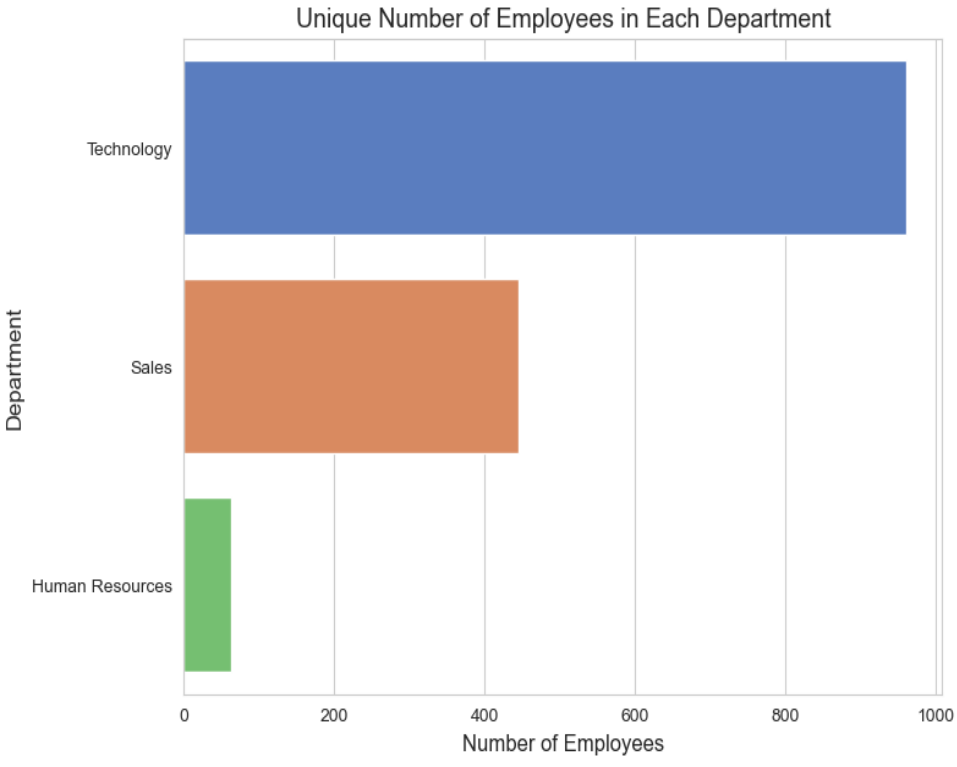
[35…]
```
#1.2 Count unique employees by gender
unique_gender_counts = merged_df.groupby("EmployeeID")["Gender"].first().value_counts()

print("Unique Number of Male and Female Employees:")
print(unique_gender_counts)
```

```
Unique Number of Male and Female Employees:
Gender
Female              675
Male                651
Non-Binary          124
Prefer Not To Say    20
Name: count, dtype: int64
```

[37…

```
#1.3 Count unique employees by department
unique_department_counts = merged_df.groupby("EmployeeID")["Department"].first().value_counts()

print("Unique Number of Employees in Each Department:")
print(unique_department_counts)

# Visualize the unique number of employees in each department
# Set the plot style
sns.set_style("whitegrid")

# Create a bar plot for the unique employee count by department
plt.figure(figsize=(8, 6))
sns.barplot(x=unique_department_counts.values, y=unique_department_counts.index, palette="muted")

# Add labels and title
plt.title("Unique Number of Employees in Each Department", fontsize=14)
plt.xlabel("Number of Employees", fontsize=12)
plt.ylabel("Department", fontsize=12)

# Display the plot
plt.show()
```

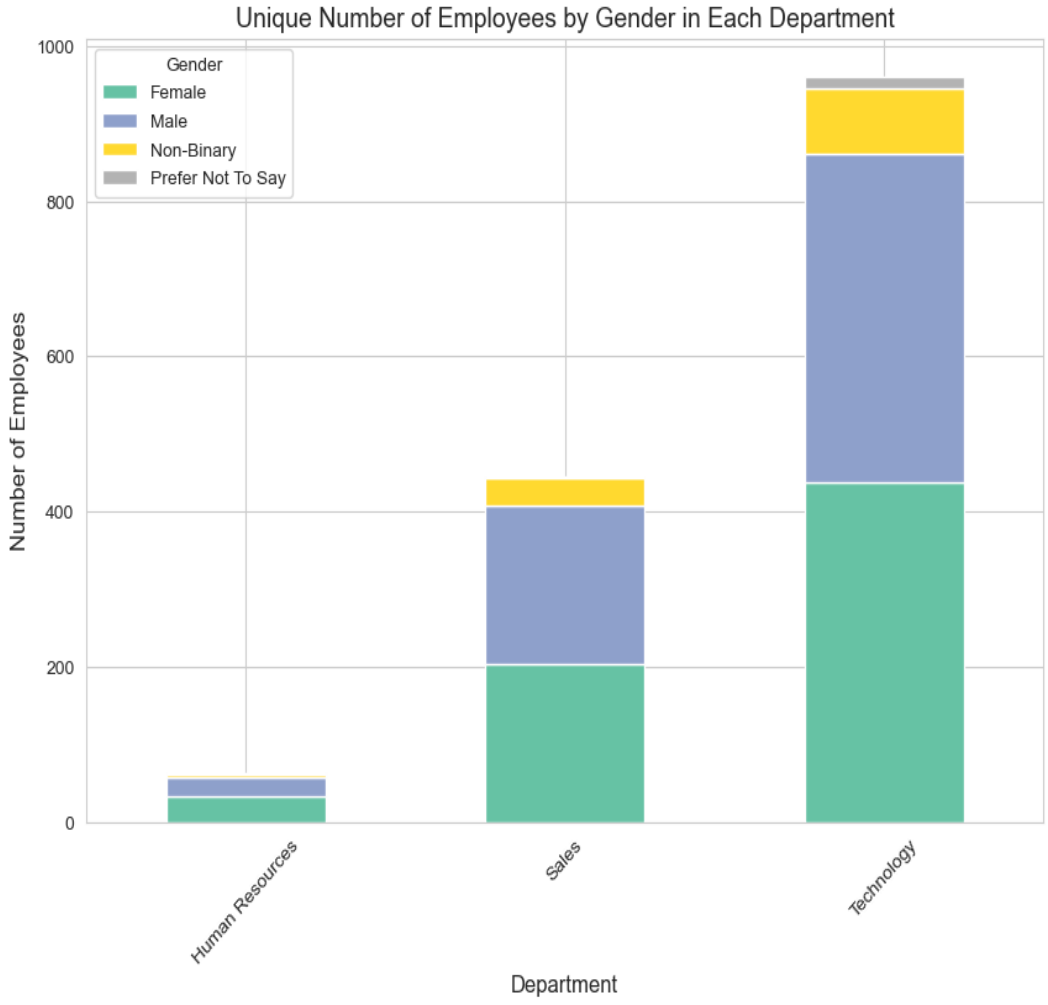
```
Unique Number of Employees in Each Department:
Department
Technology         961
Sales              446
Human Resources     63
Name: count, dtype: int64
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/254342271.py:13: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=unique_department_counts.values, y=unique_department_counts.index, palette="muted")
```



[39…

```python
#1.4 Count unique employees by gender within each department
unique_gender_department_counts = merged_df.groupby(["Department", "EmployeeID"])["Gender"].first().re
gender_by_department = unique_gender_department_counts.groupby(["Department", "Gender"]).size().unstac

print("Unique Number of Employees by Gender in Each Department:")
print(gender_by_department)

# Visualize gender distribution within each department
plt.figure(figsize=(10, 7))
gender_by_department.plot(kind="bar", stacked=True, colormap="Set2", figsize=(10, 7))

plt.title("Unique Number of Employees by Gender in Each Department", fontsize=14)
plt.xlabel("Department", fontsize=12)
plt.ylabel("Number of Employees", fontsize=12)
plt.xticks(rotation=45)
plt.legend(title="Gender")

plt.show()
```

```
Unique Number of Employees by Gender in Each Department:
Gender           Female  Male  Non-Binary  Prefer Not To Say
Department
Human Resources      33    24           5                  1
Sales               204   204          35                  3
Technology          438   423          84                 16
<Figure size 1000x700 with 0 Axes>
```

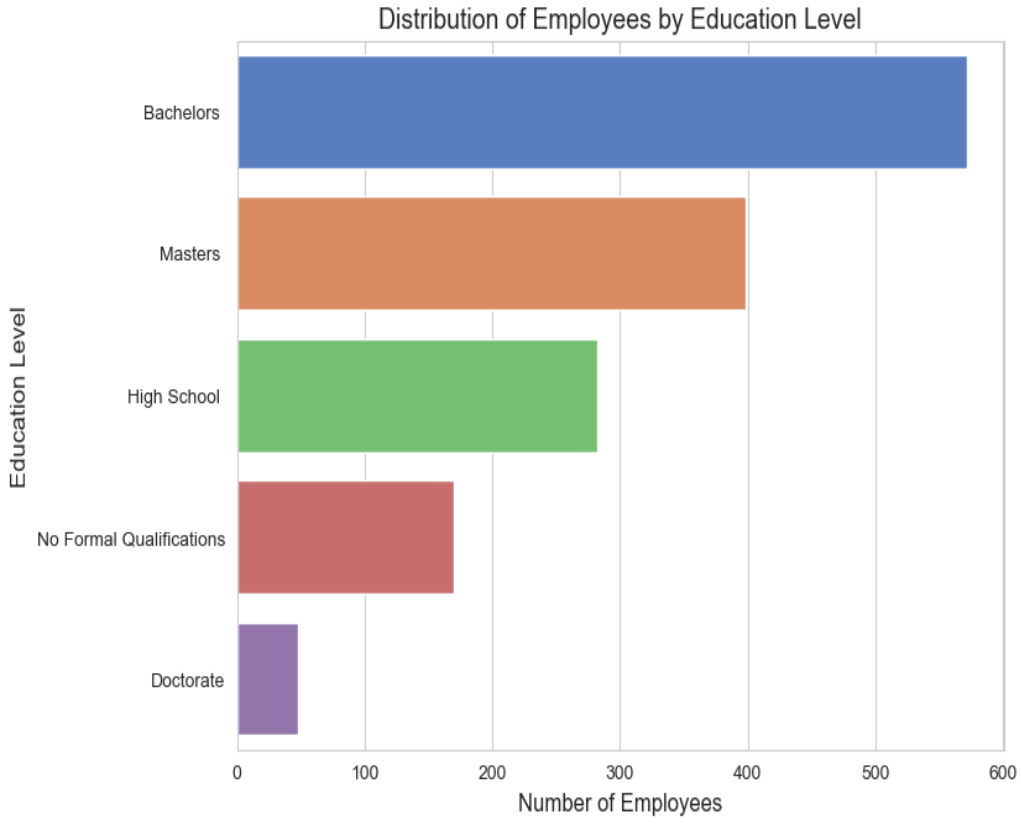


[41…

```
#1.5 Count unique employees by education level
unique_education_counts = merged_df.groupby("EmployeeID")["EducationLevel"].first().value_counts()

print("Unique Number of Employees by Education Level:")
print(unique_education_counts)

# Visualize the distribution of employees by education level
plt.figure(figsize=(8, 6))
sns.barplot(x=unique_education_counts.values, y=unique_education_counts.index, palette="muted")

plt.title("Distribution of Employees by Education Level", fontsize=14)
plt.xlabel("Number of Employees", fontsize=12)
plt.ylabel("Education Level", fontsize=12)

plt.show()
```

```
Unique Number of Employees by Education Level:
EducationLevel
Bachelors                  572
Masters                    398
High School                282
No Formal Qualifications   170
Doctorate                   48
Name: count, dtype: int64
```

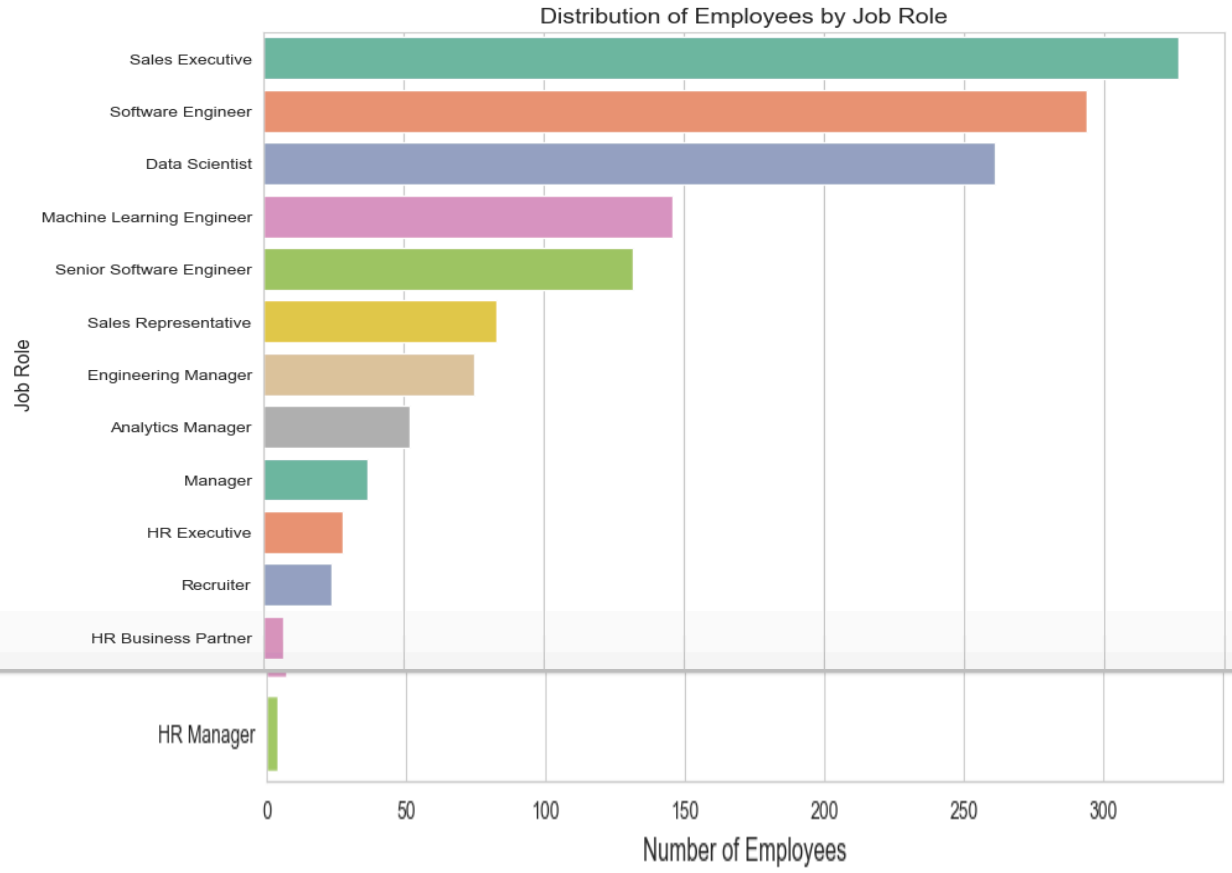
```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/433170451.py:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=unique_education_counts.values, y=unique_education_counts.index, palette="muted")
```



[43…]
```python
#1.6 Count unique employees by job role
unique_jobrole_counts = merged_df.groupby("EmployeeID")["JobRole"].first().value_counts()

print("Unique Number of Employees by Job Role:")
print(unique_jobrole_counts)

# Visualize the distribution of employees by job role
plt.figure(figsize=(10, 8))
sns.barplot(x=unique_jobrole_counts.values, y=unique_jobrole_counts.index, palette="Set2")

plt.title("Distribution of Employees by Job Role", fontsize=14)
plt.xlabel("Number of Employees", fontsize=12)
plt.ylabel("Job Role", fontsize=12)

plt.show()
```

```
Unique Number of Employees by Job Role:
JobRole
Sales Executive              327
Software Engineer            294
Data Scientist               261
Machine Learning Engineer    146
Senior Software Engineer     132
Sales Representative          83
Engineering Manager           75
Analytics Manager             52
Manager                       37
HR Executive                  28
Recruiter                     24
HR Business Partner            7
HR Manager                     4
Name: count, dtype: int64
```

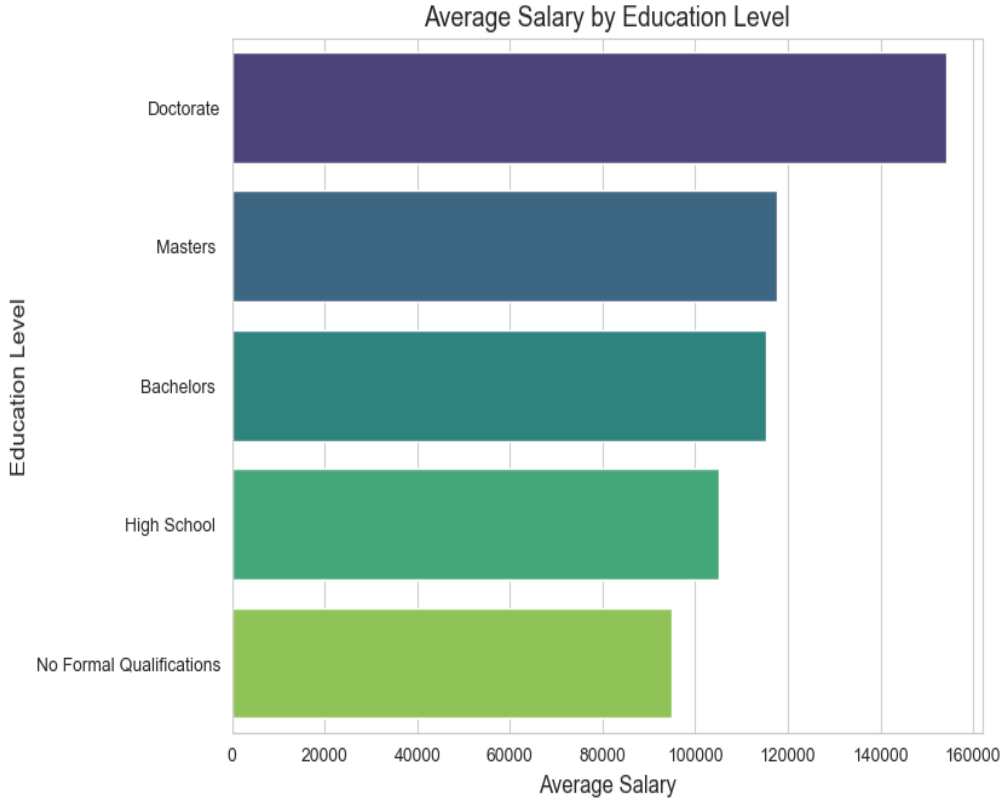
```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/4202081888.py:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=unique_jobrole_counts.values, y=unique_jobrole_counts.index, palette="Set2")
```



[45…]
```
# 2. How does the average salary vary by education level?
avg_salary_by_education = merged_df.groupby("EmployeeID")[["EducationLevel", "Salary"]].first().groupby
print("Average Salary by Education Level:")
print(avg_salary_by_education)

# Convert the series to DataFrame
avg_salary_by_education = avg_salary_by_education.reset_index()

# Visualize the average salary by education level
plt.figure(figsize=(8, 6))
sns.barplot(x='Salary', y='EducationLevel', data=avg_salary_by_education, palette="viridis")

plt.title("Average Salary by Education Level", fontsize=14)
plt.xlabel("Average Salary", fontsize=12)
plt.ylabel("Education Level", fontsize=12)

plt.show()
```

```
Average Salary by Education Level:
EducationLevel
Doctorate                  154268.791667
Masters                    117641.057789
Bachelors                  115405.430070
High School                105180.535461
No Formal Qualifications    94983.482353
Name: Salary, dtype: float64
```

```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/106904704.py:11: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x='Salary', y='EducationLevel', data=avg_salary_by_education, palette="viridis")
```

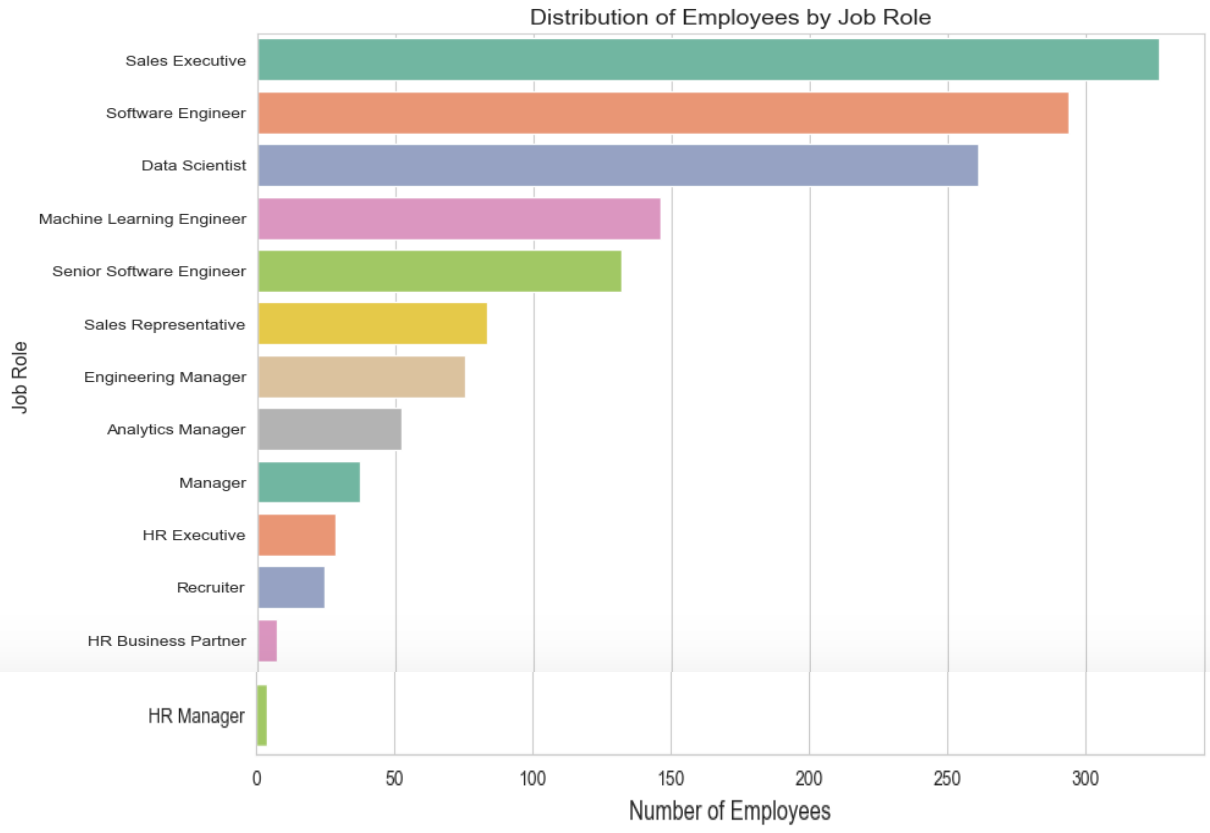


[49…]

```python
# 3. Count unique employees by job role
unique_jobrole_counts = merged_df.groupby("EmployeeID")["JobRole"].first().value_counts()

print("Unique Number of Employees by Job Role:")
print(unique_jobrole_counts)

# Visualize the distribution of employees by job role
plt.figure(figsize=(10, 8))
sns.barplot(x=unique_jobrole_counts.values, y=unique_jobrole_counts.index, palette="Set2")

plt.title("Distribution of Employees by Job Role", fontsize=14)
plt.xlabel("Number of Employees", fontsize=12)
plt.ylabel("Job Role", fontsize=12)

plt.show()
```

```
Unique Number of Employees by Job Role:
JobRole
Sales Executive              327
Software Engineer            294
Data Scientist               261
Machine Learning Engineer    146
Senior Software Engineer     132
Sales Representative          83
Engineering Manager           75
Analytics Manager             52
Manager                       37
HR Executive                  28
Recruiter                     24
HR Business Partner            7
HR Manager                     4
Name: count, dtype: int64
```

```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/631614572.py:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=unique_jobrole_counts.values, y=unique_jobrole_counts.index, palette="Set2")
```

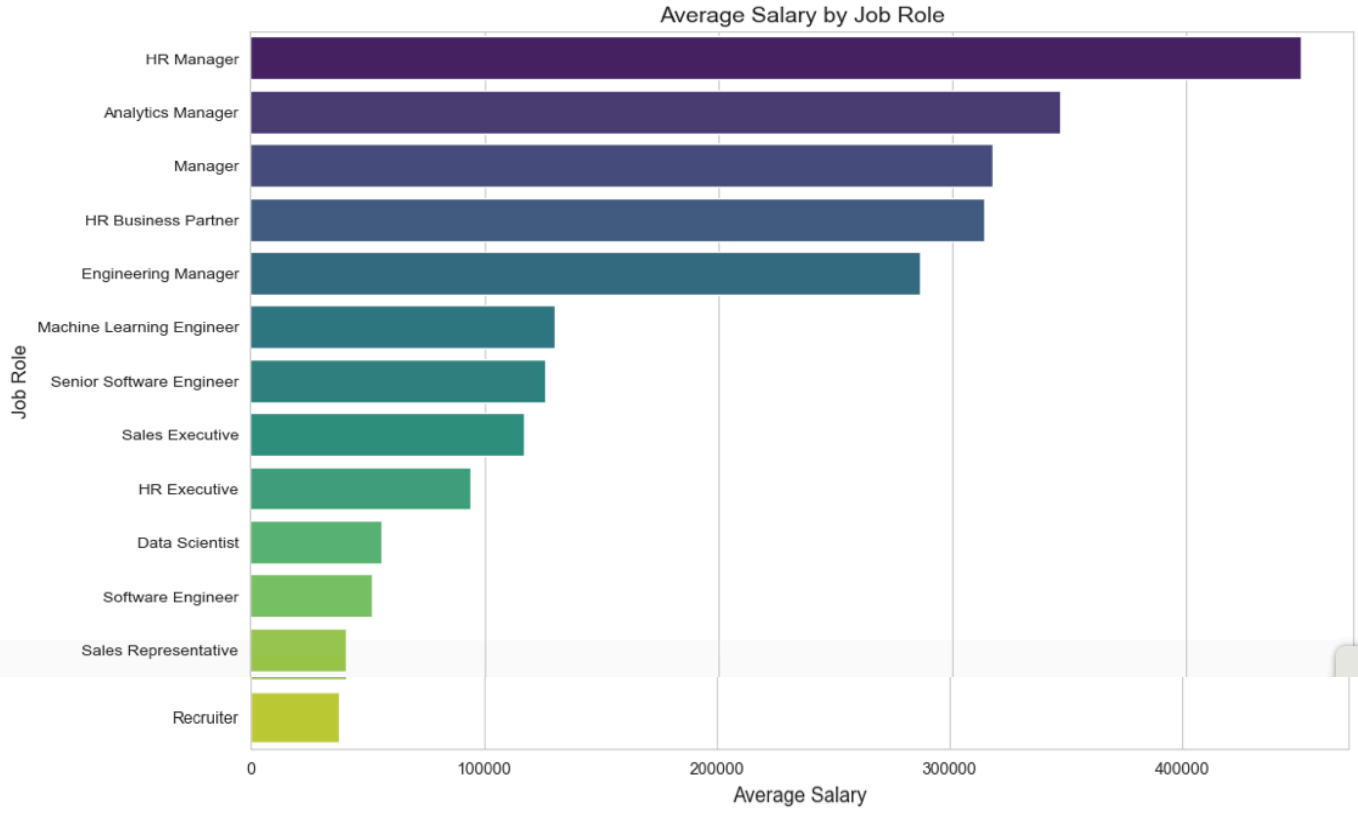


[51…

```
# 3. Calculate the average salary by job role for unique employees
avg_salary_by_jobrole = merged_df.groupby("EmployeeID")[["JobRole", "Salary"]].first().groupby("JobRol

print("Average Salary by Job Role:")
print(avg_salary_by_jobrole)

# Visualize the average salary by job role
plt.figure(figsize=(12, 8))
sns.barplot(x=avg_salary_by_jobrole.values, y=avg_salary_by_jobrole.index, palette="viridis")

plt.title("Average Salary by Job Role", fontsize=14)
plt.xlabel("Average Salary", fontsize=12)
plt.ylabel("Job Role", fontsize=12)

plt.show()
```

```
Average Salary by Job Role:
JobRole
HR Manager                    449330.750000
Analytics Manager             346484.230769
Manager                       317531.054054
HR Business Partner           314002.428571
Engineering Manager           286258.506667
Machine Learning Engineer     130164.616438
Senior Software Engineer      126161.295455
Sales Executive               117195.538226
HR Executive                   94362.321429
Data Scientist                 56079.494253
Software Engineer              51967.051020
Sales Representative           40656.421687
Recruiter                      37647.500000
Name: Salary, dtype: float64
```

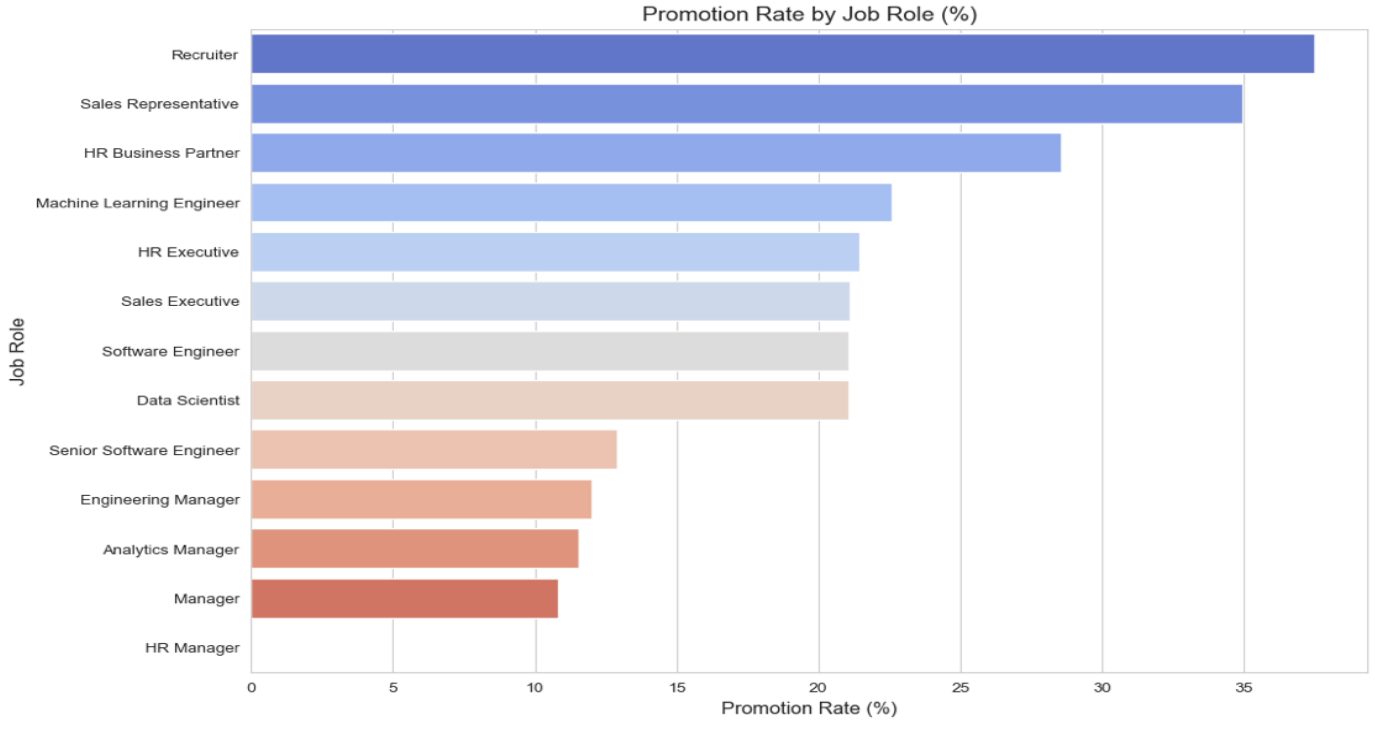
```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/952937992.py:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=avg_salary_by_jobrole.values, y=avg_salary_by_jobrole.index, palette="viridis")
```



[53…]
```
# 4. What is the salary distribution based on years of experience?
# Identify employees who have been promoted (YearsSinceLastPromotion == 0 indicates a recent promotion)
promoted_employees = merged_df[merged_df["YearsSinceLastPromotion"] == 0]

# Calculate the number of promoted employees by job role (unique employees only)
promotion_by_jobrole = promoted_employees.groupby("EmployeeID")["JobRole"].first().value_counts()

# Total unique employees by job role (for comparison)
total_by_jobrole = merged_df.groupby("EmployeeID")["JobRole"].first().value_counts()

# Calculate promotion rate by job role (% of promoted employees per role)
promotion_rate_by_jobrole = (promotion_by_jobrole / total_by_jobrole * 100).fillna(0).sort_values(asce

print("Promotion Rate by Job Role (%):")
print(promotion_rate_by_jobrole)

# Visualize promotion rate by job role
plt.figure(figsize=(12, 8))
sns.barplot(x=promotion_rate_by_jobrole.values, y=promotion_rate_by_jobrole.index, palette="coolwarm")

plt.title("Promotion Rate by Job Role (%)", fontsize=14)
plt.xlabel("Promotion Rate (%)", fontsize=12)
plt.ylabel("Job Role", fontsize=12)

plt.show()
```

```
Promotion Rate by Job Role (%):
JobRole
Recruiter                     37.500000
Sales Representative          34.939759
HR Business Partner           28.571429
Machine Learning Engineer     22.602740
HR Executive                  21.428571
Sales Executive               21.100917
Software Engineer             21.088435
Data Scientist                21.072797
Senior Software Engineer      12.878788
Engineering Manager           12.000000
Analytics Manager             11.538462
Manager                       10.810811
HR Manager                     0.000000
Name: count, dtype: float64
```

```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/2626743584.py:19: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=promotion_rate_by_jobrole.values, y=promotion_rate_by_jobrole.index, palette="coolwar
m")
```

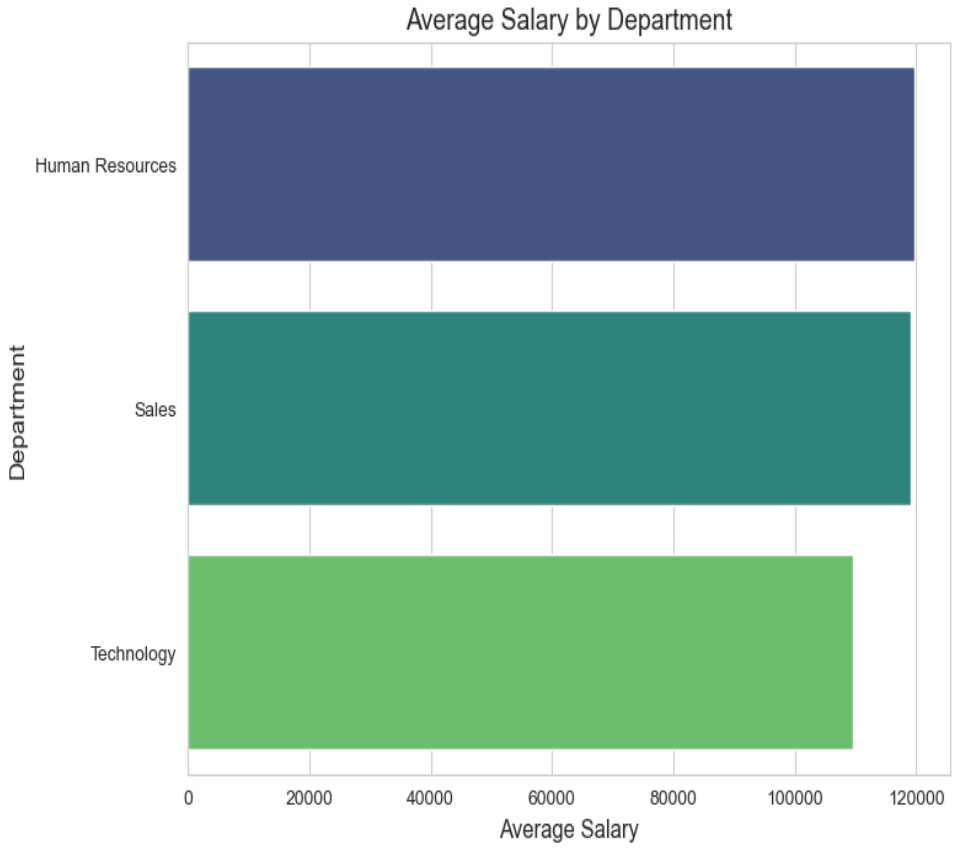


[55…

```
# 5 Calculate the average salary by department for unique employees
avg_salary_by_department = merged_df.groupby("EmployeeID")[["Department", "Salary"]].first().groupby("I

print("Average Salary by Department:")
print(avg_salary_by_department)

# Visualize the average salary by department
plt.figure(figsize=(8, 6))
sns.barplot(x=avg_salary_by_department.values, y=avg_salary_by_department.index, palette="viridis")

plt.title("Average Salary by Department", fontsize=14)
plt.xlabel("Average Salary", fontsize=12)
plt.ylabel("Department", fontsize=12)

plt.show()
```

```
Average Salary by Department:
Department
Human Resources    119698.809524
Sales              119117.609865
Technology         109655.122789
Name: Salary, dtype: float64
```

```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/3839542891.py:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=avg_salary_by_department.values, y=avg_salary_by_department.index, palette="viridis")
```

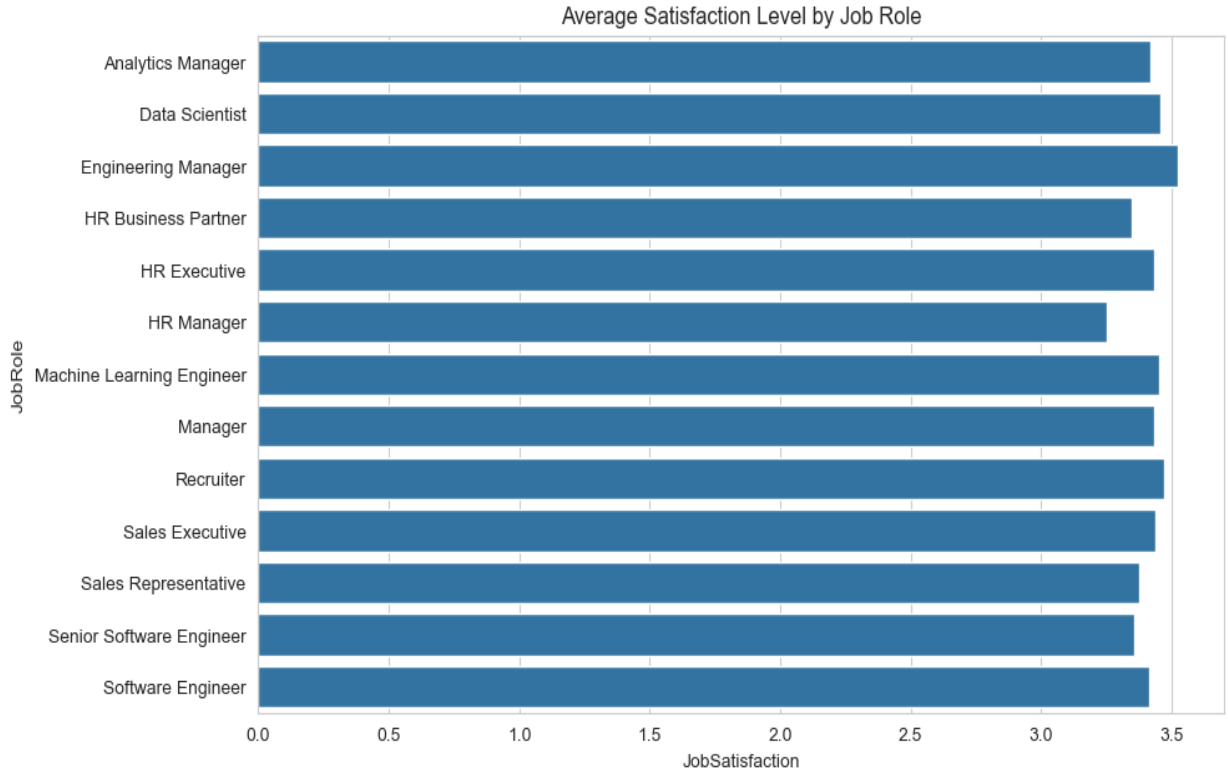


[57…]
```
# Second Categoty
# Employee Satisfaction & Engagement
```

[59…]
```
# 6. What is the average satisfaction level across different job roles?
# Average satisfaction by job role
avg_satisfaction_by_role = merged_df.groupby('JobRole')['JobSatisfaction'].mean().reset_index()
print(avg_satisfaction_by_role)

# Visualization
plt.figure(figsize=(10, 6))
sns.barplot(x='JobSatisfaction', y='JobRole', data=avg_satisfaction_by_role, ci=None)
plt.title("Average Satisfaction Level by Job Role")
plt.show()
```

```
                    JobRole  JobSatisfaction
0           Analytics Manager         3.418269
1              Data Scientist         3.457353
2         Engineering Manager         3.526490
3         HR Business Partner         3.347826
4               HR Executive         3.434783
5                 HR Manager         3.250000
6   Machine Learning Engineer         3.453405
7                     Manager         3.435714
8                   Recruiter         3.469799
9             Sales Executive         3.435897
10       Sales Representative         3.378323
11   Senior Software Engineer         3.356275
12          Software Engineer         3.413043
```

```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/1379388627.py:8: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=None` for the same effect.

  sns.barplot(x='JobSatisfaction', y='JobRole', data=avg_satisfaction_by_role, ci=None)
```

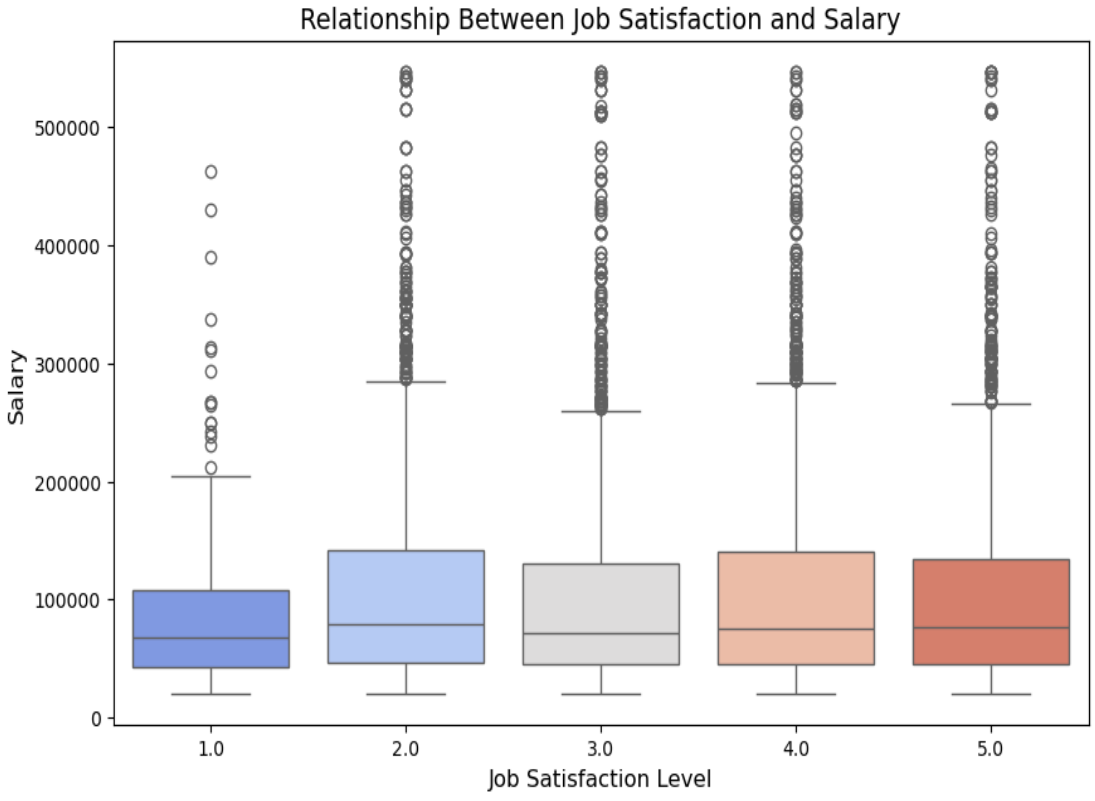


[28…

```python
# 7 Calculate average salary by satisfaction level for unique employees
unique_df = merged_df.drop_duplicates (subset=[ 'EmployeeID' ])
salary_by_satisfaction = unique_df.groupby("EmployeeID")[["JobSatisfaction", "Salary"]].first().groupby

print("Average Salary by Job Satisfaction Level:")
print(salary_by_satisfaction)


# Visualizing the relationship between job satisfaction and salary
plt.figure(figsize=(10, 6))
sns.boxplot(data=merged_df, x="JobSatisfaction", y="Salary", palette="coolwarm")

plt.title("Relationship Between Job Satisfaction and Salary", fontsize=14)
plt.xlabel("Job Satisfaction Level", fontsize=12)
plt.ylabel("Salary", fontsize=12)

plt.show()
```

```
Average Salary by Job Satisfaction Level:
JobSatisfaction
1.0    120500.333333
2.0    116695.341463
3.0    104914.106312
4.0    113217.044444
5.0    120707.823718
Name: Salary, dtype: float64
```

```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_29168/2446902177.py:11: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x`
variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(data=merged_df, x="JobSatisfaction", y="Salary", palette="coolwarm")
```



[65…]
```
# 8. Do employees with higher education levels report higher satisfaction?
# Average satisfaction by education level
satisfaction_by_edu = merged_df.groupby('EducationLevel')['JobSatisfaction'].mean().reset_index()
print(satisfaction_by_edu)
```

```
            EducationLevel  JobSatisfaction
0                Bachelors         3.440015
1                 Doctorate         3.298578
2              High School         3.460400
3                  Masters         3.435146
4  No Formal Qualifications         3.377381
```

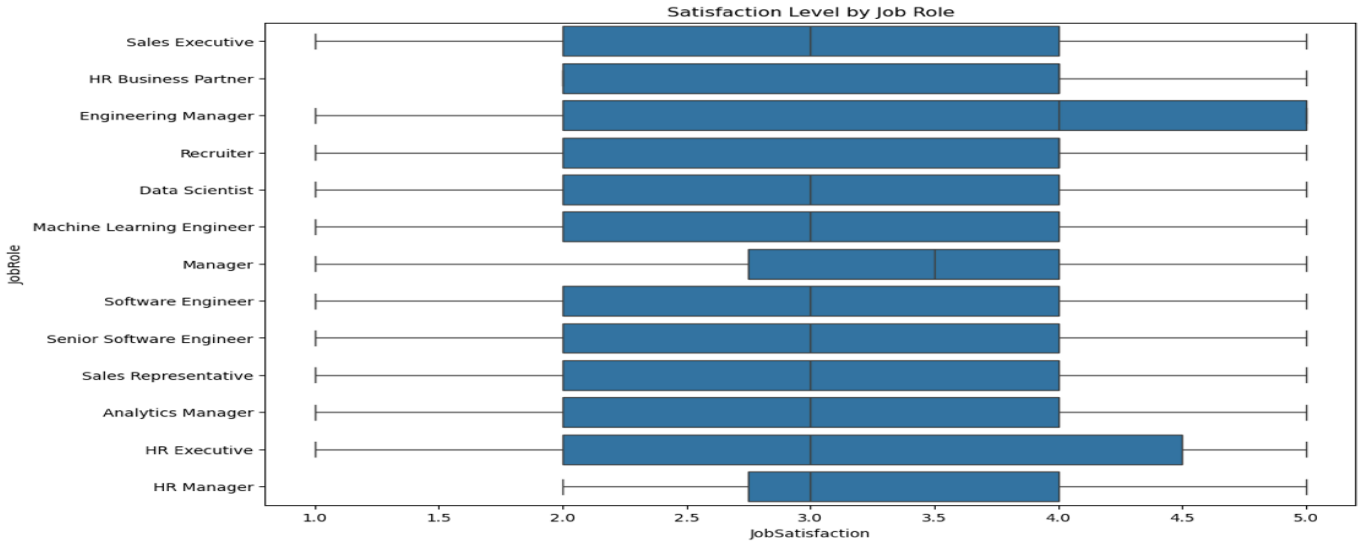
[69…]
```
# 9. Which departments have the most satisfied and least satisfied employees?
# Average satisfaction by department
satisfaction_by_dept = merged_df.groupby('Department')['JobSatisfaction'].mean().reset_index()
print(satisfaction_by_dept.sort_values('JobSatisfaction', ascending=False))
```

```
        Department  JobSatisfaction
0  Human Resources         3.435644
2       Technology         3.434578
1            Sales         3.422057
```

[47…

```python
# 10. Does job role impact satisfaction level?
import pandas as pd

# Function to classify satisfaction levels based on numerical values
def classify_satisfaction(avg_satisfaction):
    rounded_value = round(avg_satisfaction)  # Round to the nearest integer
    if rounded_value == 1:
        return 'Very Dissatisfied'
    elif rounded_value == 2:
        return 'Dissatisfied'
    elif rounded_value == 3:
        return 'Neutral'
    elif rounded_value == 4:
        return 'Satisfied'
    elif rounded_value == 5:
        return 'Very Satisfied'
    else:
        return 'Neutral'  # Default to 'Neutral' for non-exact values

# Group data by JobRole and calculate the average JobSatisfaction
job_satisfaction_summary = merged_df.groupby("JobRole")["JobSatisfaction"].mean().reset_index()

# Round the average satisfaction value to match SQL behavior
job_satisfaction_summary["AverageSatisfaction"] = job_satisfaction_summary["JobSatisfaction"].round(6)

# Apply classification function to categorize satisfaction levels
job_satisfaction_summary["SatisfactionCategory"] = job_satisfaction_summary["AverageSatisfaction"].app

# Print results
print("Job Role Impact on Satisfaction Level: ")
for index, row in job_satisfaction_summary.iterrows():
    print(f" *{row['JobRole']}: Avg Satisfaction = {row['AverageSatisfaction']:.6f}, "
          f"Category = {row['SatisfactionCategory']}")

# Satisfaction level by job role
plt.figure(figsize=(12, 8))
sns.boxplot(x='JobSatisfaction', y='JobRole', data=merged_df)
plt.title('Satisfaction Level by Job Role')
plt.show()
```

```
Job Role Impact on Satisfaction Level:
 *Analytics Manager: Avg Satisfaction = 3.418269, Category = Neutral
 *Data Scientist: Avg Satisfaction = 3.457353, Category = Neutral
 *Engineering Manager: Avg Satisfaction = 3.526490, Category = Satisfied
 *HR Business Partner: Avg Satisfaction = 3.347826, Category = Neutral
 *HR Executive: Avg Satisfaction = 3.434783, Category = Neutral
 *HR Manager: Avg Satisfaction = 3.250000, Category = Neutral
 *Machine Learning Engineer: Avg Satisfaction = 3.453405, Category = Neutral
 *Manager: Avg Satisfaction = 3.435714, Category = Neutral
 *Recruiter: Avg Satisfaction = 3.469799, Category = Neutral
 *Sales Executive: Avg Satisfaction = 3.435897, Category = Neutral
 *Sales Representative: Avg Satisfaction = 3.378323, Category = Neutral
 *Senior Software Engineer: Avg Satisfaction = 3.356275, Category = Neutral
 *Software Engineer: Avg Satisfaction = 3.413043, Category = Neutral
```



[73…]
```
# Third Categoty
# Attrition & Turnover Analysis
```

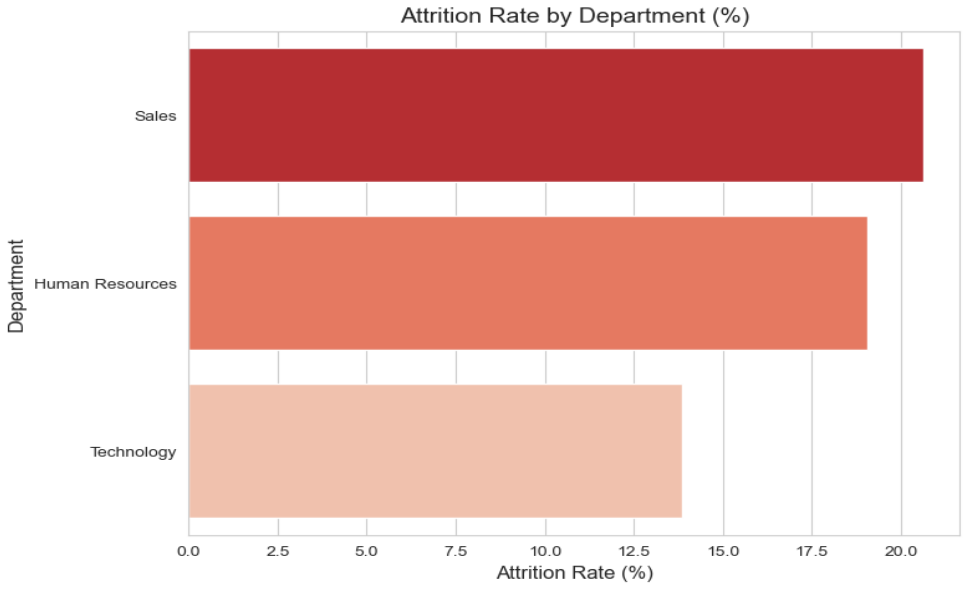
[75…]
```
# 11. What is the overall employee attrition rate?
# Attrition rate

# Remove duplicate entries based on EmployeeID to ensure unique employees
unique_df = merged_df.drop_duplicates(subset=['EmployeeID'])

# Calculate the attrition rate after removing duplicates
attrition_rate = unique_df['Attrition'].value_counts(normalize=True) * 100

# Print the attrition rate
print(attrition_rate)
```

```
Attrition
No     83.877551
Yes    16.122449
Name: proportion, dtype: float64
```

[77…]
```
# 12. Which department has the highest employee turnover?
# Ensure unique employees before calculating attrition rate
unique_employees = merged_df.drop_duplicates(subset=['EmployeeID'])

# Calculate attrition rate per department
attrition_by_dept = unique_employees.groupby('Department')['Attrition'].apply(lambda x: (x == 'Yes').m

# Sort by attrition rate in descending order
print(attrition_by_dept.sort_values('Attrition', ascending=False))

# Visualize attrition rate by department
sorted_data = attrition_by_dept.sort_values("Attrition", ascending=False)

plt.figure(figsize=(8, 6))
sns.barplot(x=sorted_data["Attrition"], y=sorted_data["Department"], palette="Reds_r", order=sorted_da

plt.title("Attrition Rate by Department (%)", fontsize=14)
plt.xlabel("Attrition Rate (%)", fontsize=12)
plt.ylabel("Department", fontsize=12)

plt.show()
```

```
         Department  Attrition
1             Sales  20.627803
0   Human Resources  19.047619
2        Technology  13.839750
```

```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/1859184016.py:15: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=sorted_data["Attrition"], y=sorted_data["Department"], palette="Reds_r", order=sorted_
data["Department"])
```

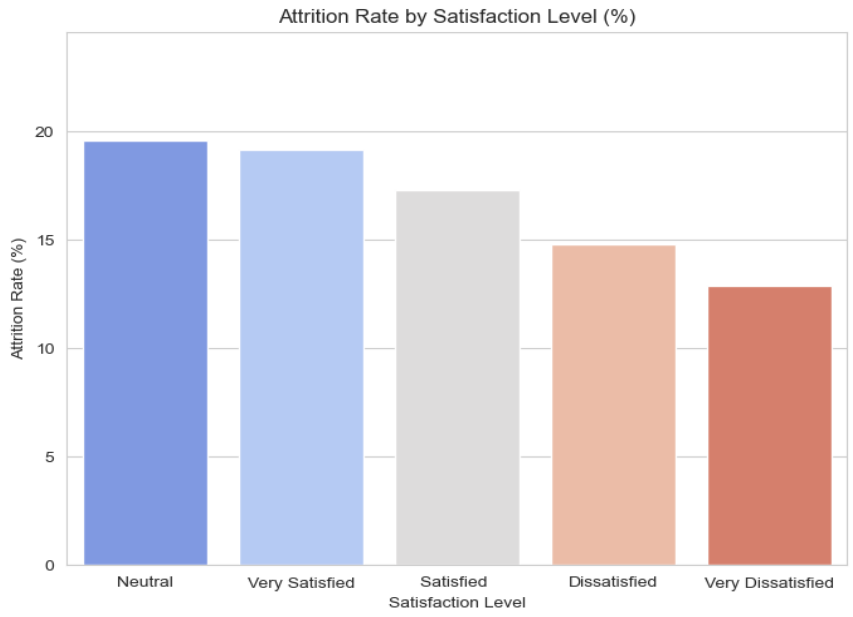


[79…

```
# 13. Is there a connection between satisfaction level and attrition?
# Ensure unique employees by EmployeeID before calculation (drop duplicates)
unique_employees = merged_df.drop_duplicates(subset=['EmployeeID'])

# Group by SatisfactionLevel and calculate the required metrics
attrition_by_satisfaction = unique_employees.groupby('SatisfactionLevel').agg(
    TotalEmployees=('EmployeeID', 'count'),  # Count total unique employees in each satisfaction level
    AttritionEmployees=('Attrition', lambda x: (x == 'Yes').sum())  # Count unique employees who have a
)

# Calculate the attrition rate for each satisfaction level
attrition_by_satisfaction['AttritionRate'] = (attrition_by_satisfaction['AttritionEmployees'] / attrit

# Sort by AttritionRate in descending order
attrition_by_satisfaction = attrition_by_satisfaction.sort_values('AttritionRate', ascending=False).re

# Print the result to show the attrition by satisfaction level
print(attrition_by_satisfaction)

# Visualization - Create a histogram for JobSatisfaction, distinguishing by Attrition

plt.figure(figsize=(8, 6))
sns.barplot(x='SatisfactionLevel', y='AttritionRate', data=attrition_by_satisfaction, palette='coolwar

# Customize plot
plt.title('Attrition Rate by Satisfaction Level (%)')
plt.xlabel('Satisfaction Level')
plt.ylabel('Attrition Rate (%)')
plt.ylim(0, max(attrition_by_satisfaction['AttritionRate']) + 5)  # Set y-limit dynamically

# Show the plot
plt.show()
```

	SatisfactionLevel	TotalEmployees	AttritionEmployees	AttritionRate
0	Neutral	424	83	19.575472
1	Very Satisfied	417	80	19.184652
2	Satisfied	381	66	17.322835
3	Dissatisfied	27	4	14.814815
4	Very Dissatisfied	31	4	12.903226

```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/96147670.py:23: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x='SatisfactionLevel', y='AttritionRate', data=attrition_by_satisfaction, palette='coolw
arm')
```

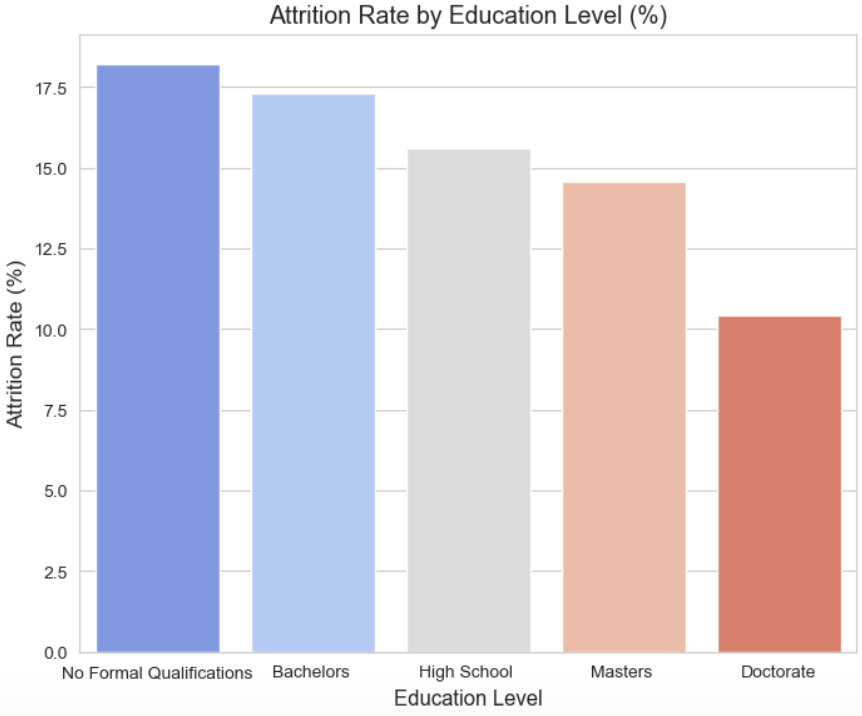


[81…

```
# 14. Do employees with higher education levels have lower attrition rates?
# Calculate attrition rate by education level using unique employees
attrition_by_education = merged_df.groupby("EmployeeID")[["EducationLevel", "Attrition"]].first()

# Count total unique employees and employees who left per education level
total_by_education = attrition_by_education["EducationLevel"].value_counts()
attrition_counts = attrition_by_education[attrition_by_education["Attrition"] == "Yes"]["EducationLeve

# Calculate attrition rate (% of employees who left per education level)
attrition_rate_by_education = (attrition_counts / total_by_education * 100).fillna(0).sort_values(asce

print("Attrition Rate by Education Level (%):")
print(attrition_rate_by_education)

# Visualize attrition rate by education level
plt.figure(figsize=(8, 6))
sns.barplot(x=attrition_rate_by_education.index, y=attrition_rate_by_education.values, palette="coolwa

plt.title("Attrition Rate by Education Level (%)", fontsize=14)
plt.xlabel("Education Level", fontsize=12)
plt.ylabel("Attrition Rate (%)", fontsize=12)

plt.show()
```

```
Attrition Rate by Education Level (%):
EducationLevel
No Formal Qualifications    18.235294
Bachelors                   17.307692
High School                 15.602837
Masters                     14.572864
Doctorate                   10.416667
Name: count, dtype: float64
```

```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/2642233808.py:17: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=attrition_rate_by_education.index, y=attrition_rate_by_education.values, palette="cool
warm")
```

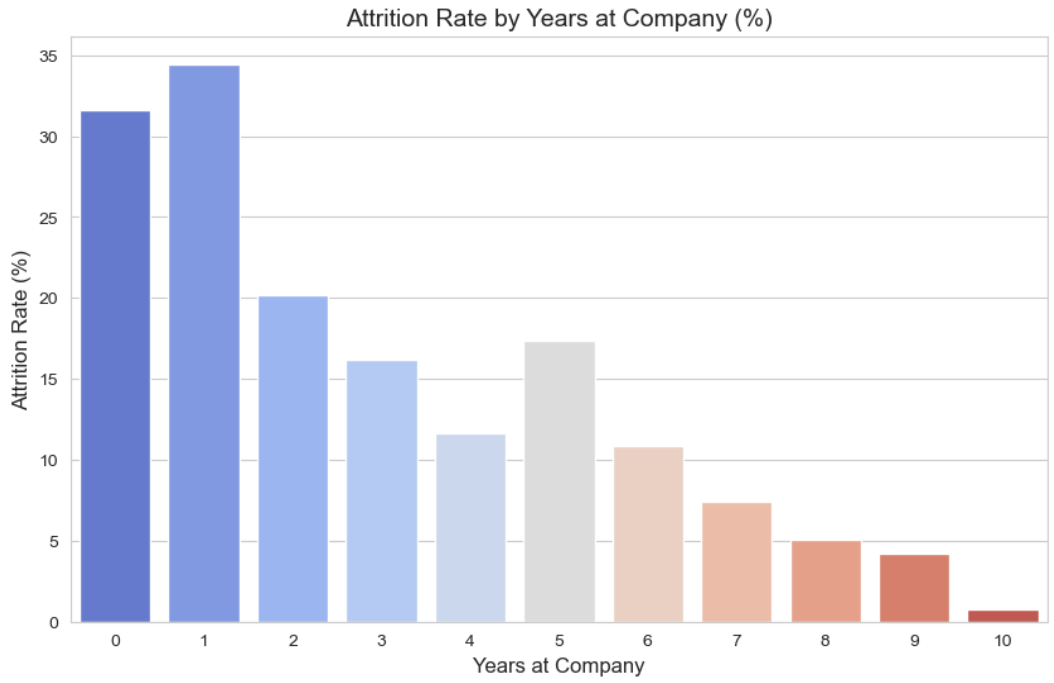


[83…

```
# 15. How does tenure (years at company) impact attrition?
# Calculate attrition rate by tenure (YearsAtCompany) using unique employees
attrition_by_tenure = merged_df.groupby("EmployeeID")[["YearsAtCompany", "Attrition"]].first()

# Count total unique employees and employees who left per tenure level
total_by_tenure = attrition_by_tenure["YearsAtCompany"].value_counts()
attrition_counts = attrition_by_tenure[attrition_by_tenure["Attrition"] == "Yes"]["YearsAtCompany"].va

# Calculate attrition rate (% of employees who left per tenure level)
attrition_rate_by_tenure = (attrition_counts / total_by_tenure * 100).fillna(0).sort_values(ascending=

print("Attrition Rate by Years at Company (%):")
print(attrition_rate_by_tenure)

# Visualize attrition rate by years at company
plt.figure(figsize=(10, 6))
sns.barplot(x=attrition_rate_by_tenure.index, y=attrition_rate_by_tenure.values, palette="coolwarm")

plt.title("Attrition Rate by Years at Company (%)", fontsize=14)
plt.xlabel("Years at Company", fontsize=12)
plt.ylabel("Attrition Rate (%)", fontsize=12)

plt.show()
```

```
Attrition Rate by Years at Company (%):
YearsAtCompany
1     34.463277
0     31.578947
2     20.161290
5     17.391304
3     16.216216
4     11.627907
6     10.891089
7      7.438017
8      5.042017
9      4.237288
10     0.781250
Name: count, dtype: float64
```

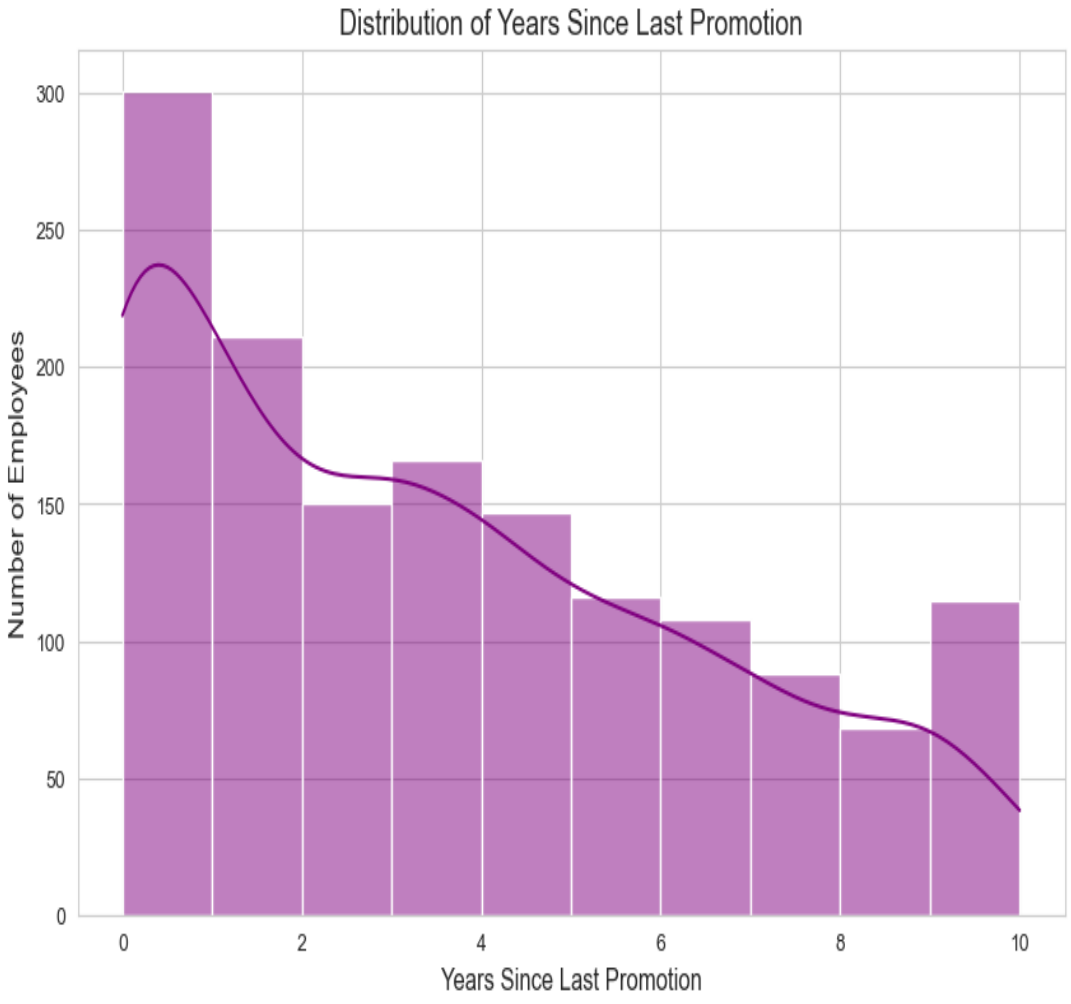
```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/409883378.py:17: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=attrition_rate_by_tenure.index, y=attrition_rate_by_tenure.values, palette="coolwarm")
```



[85…]
```
# Fourth Categoty
# Promotion & Career Growth
```

[87…]
```
# 16. How long does it take, on average, for employees to receive a promotion?
# Average time to promotion
avg_time_to_promotion = merged_df.groupby("EmployeeID")["YearsSinceLastPromotion"].first().mean()

print(f"Average Time to Promotion: {avg_time_to_promotion:.2f} years")

# Visualizing distribution of years since last promotion
plt.figure(figsize=(10, 6))
sns.histplot(merged_df.groupby("EmployeeID")["YearsSinceLastPromotion"].first(), bins=10, kde=True, co

plt.title("Distribution of Years Since Last Promotion", fontsize=14)
plt.xlabel("Years Since Last Promotion", fontsize=12)
plt.ylabel("Number of Employees", fontsize=12)

plt.show()
```

```
Average Time to Promotion: 3.44 years
```

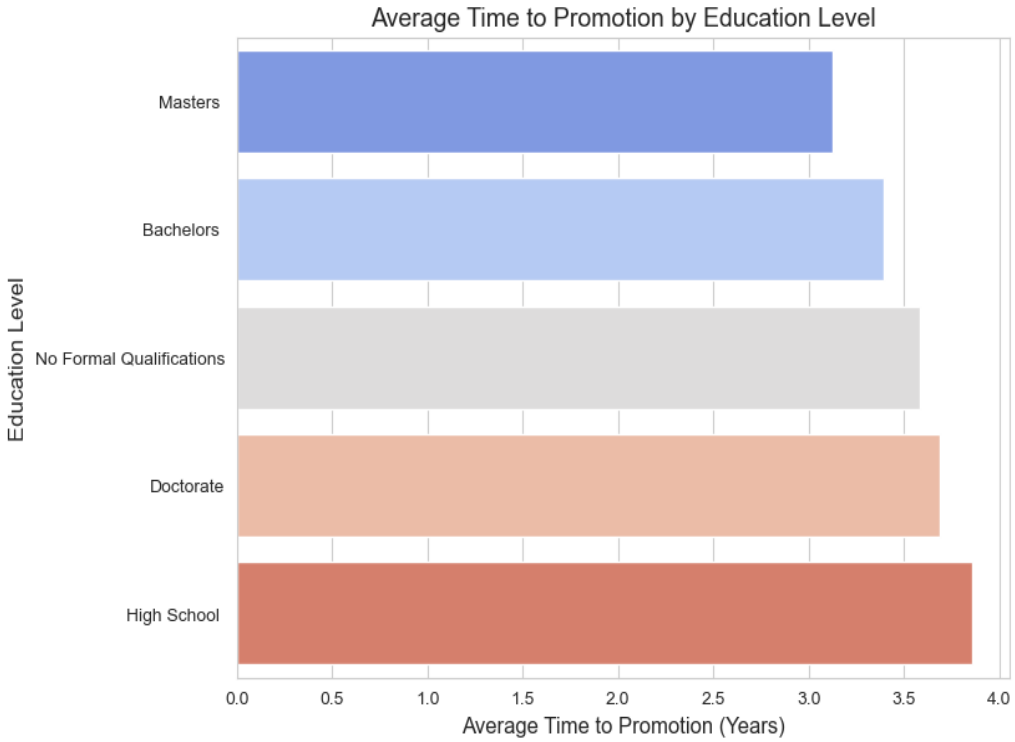


[89…

```python
# 17. Is there a correlation between education level and promotion frequency?
# Promotion rate by education level
# Calculate promotion frequency by education level using unique employees
promotion_by_education = merged_df.groupby("EmployeeID")[["EducationLevel", "YearsSinceLastPromotion"]]

# Calculate the average time to promotion for each education level
avg_promotion_by_education = promotion_by_education.groupby("EducationLevel")["YearsSinceLastPromotion"

print("Average Time to Promotion by Education Level (Years):")
print(avg_promotion_by_education)

# Visualizing the relationship between education level and promotion frequency
plt.figure(figsize=(8, 6))
sns.barplot(x=avg_promotion_by_education.values, y=avg_promotion_by_education.index, palette="coolwarm"

plt.title("Average Time to Promotion by Education Level", fontsize=14)
plt.xlabel("Average Time to Promotion (Years)", fontsize=12)
plt.ylabel("Education Level", fontsize=12)

plt.show()
```

```
Average Time to Promotion by Education Level (Years):
EducationLevel
Masters                     3.123116
Bachelors                   3.393357
No Formal Qualifications    3.582353
Doctorate                   3.687500
High School                 3.858156
Name: YearsSinceLastPromotion, dtype: float64
```

```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/3214222776.py:14: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=avg_promotion_by_education.values, y=avg_promotion_by_education.index, palette="coolwa
rm")
```

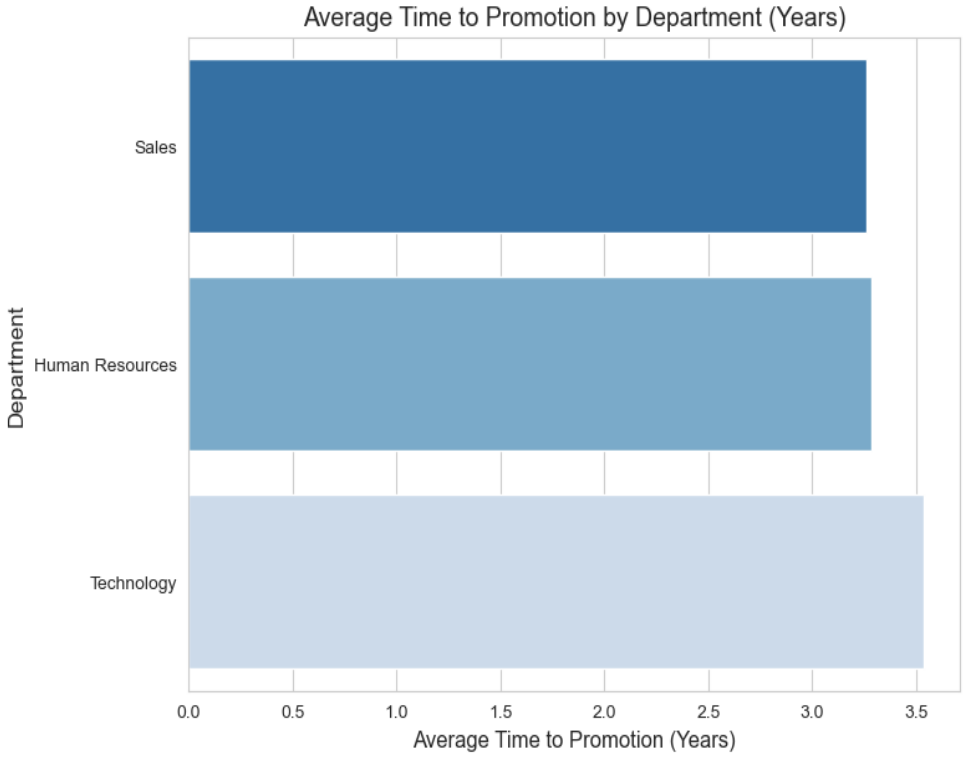


[91…]

```
# 18. Which departments promote employees the fastest and the slowest?
# Promotion rate by department
# Calculate the average time to promotion by department using unique employees
promotion_by_department = merged_df.groupby("EmployeeID")[["Department", "YearsSinceLastPromotion"]].f

# Compute the average years since last promotion for each department
avg_promotion_by_department = promotion_by_department.groupby("Department")["YearsSinceLastPromotion"]

print("Average Time to Promotion by Department (Years):")
print(avg_promotion_by_department)

# Visualizing the relationship between department and promotion speed
plt.figure(figsize=(8, 6))
sns.barplot(x=avg_promotion_by_department.values, y=avg_promotion_by_department.index, palette="Blues_

plt.title("Average Time to Promotion by Department (Years)", fontsize=14)
plt.xlabel("Average Time to Promotion (Years)", fontsize=12)
plt.ylabel("Department", fontsize=12)

plt.show()
```

```
Average Time to Promotion by Department (Years):
Department
Sales                3.260090
Human Resources      3.285714
Technology           3.534860
Name: YearsSinceLastPromotion, dtype: float64
```

```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/2322969403.py:14: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=avg_promotion_by_department.values, y=avg_promotion_by_department.index, palette="Blue
s_r")
```

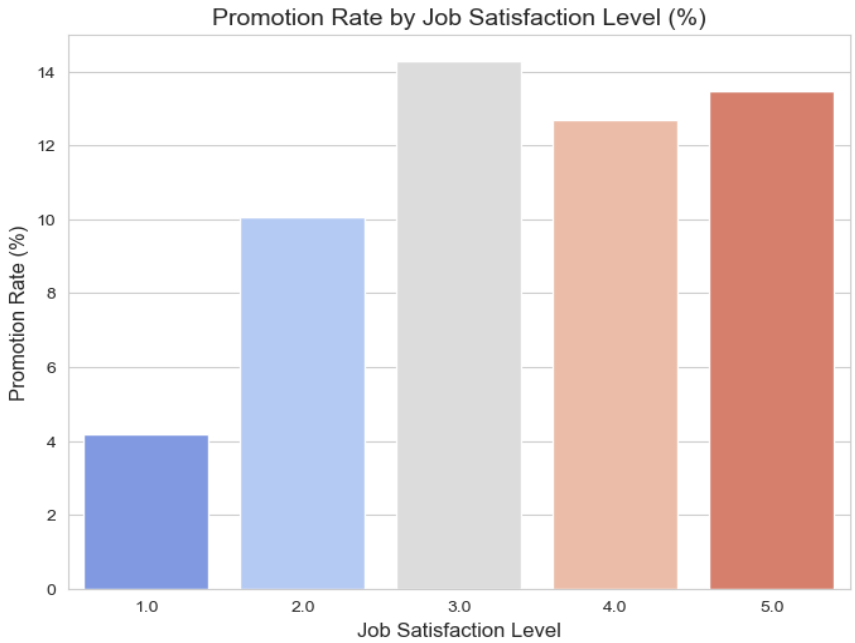


[93…

```
# 19. What percentage of satisfied employees receive promotions?
# Promotion rate for highly satisfied employees
# Identify promoted employees (YearsSinceLastPromotion == 0 indicates a recent promotion)
promoted_employees = merged_df[merged_df["YearsSinceLastPromotion"] == 0]

# Calculate total unique employees by satisfaction level
total_by_satisfaction = merged_df.groupby("EmployeeID")[["JobSatisfaction", "YearsSinceLastPromotion"]

# Calculate number of promoted employees by satisfaction level
promoted_by_satisfaction = promoted_employees.groupby("EmployeeID")["JobSatisfaction"].first().value_c

# Calculate promotion rate by satisfaction level (% of promoted employees per satisfaction level)
promotion_rate_by_satisfaction = (promoted_by_satisfaction / total_by_satisfaction * 100).fillna(0).so

print("Promotion Rate by Job Satisfaction Level (%):")
print(promotion_rate_by_satisfaction)

# Visualizing promotion rate by satisfaction level
plt.figure(figsize=(8, 6))
sns.barplot(x=promotion_rate_by_satisfaction.index, y=promotion_rate_by_satisfaction.values, palette="

plt.title("Promotion Rate by Job Satisfaction Level (%)", fontsize=14)
plt.xlabel("Job Satisfaction Level", fontsize=12)
plt.ylabel("Promotion Rate (%)", fontsize=12)

plt.show()
```

```
Promotion Rate by Job Satisfaction Level (%):
JobSatisfaction
1.0     4.166667
2.0    10.060976
3.0    14.285714
4.0    12.698413
5.0    13.461538
Name: count, dtype: float64
```

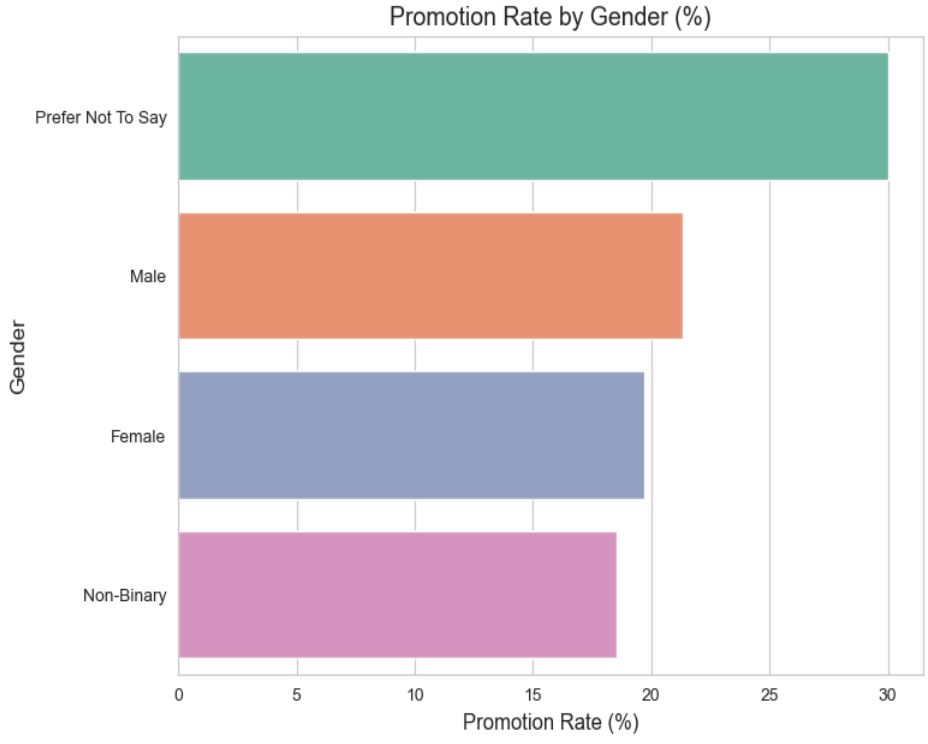
```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/4244127750.py:20: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=promotion_rate_by_satisfaction.index, y=promotion_rate_by_satisfaction.values, palette
="coolwarm")
```



[95…]
```python
# 20. Does gender impact promotion opportunities?
# Promotion rate by gender
# Calculate promotion rate by gender using unique employees
promotion_by_gender = promoted_employees.groupby("EmployeeID")["Gender"].first().value_counts()

# Calculate total unique employees by gender for comparison
total_by_gender = merged_df.groupby("EmployeeID")["Gender"].first().value_counts()

# Calculate promotion rate by gender (% of promoted employees per gender)
promotion_rate_by_gender = (promotion_by_gender / total_by_gender * 100).fillna(0).sort_values(ascendi

print("Promotion Rate by Gender (%):")
print(promotion_rate_by_gender)

# Visualizing promotion rate by gender
plt.figure(figsize=(8, 6))
sns.barplot(x=promotion_rate_by_gender.values, y=promotion_rate_by_gender.index, palette="Set2")

plt.title("Promotion Rate by Gender (%)", fontsize=14)
plt.xlabel("Promotion Rate (%)", fontsize=12)
plt.ylabel("Gender", fontsize=12)

plt.show()
```

```
Promotion Rate by Gender (%):
Gender
Prefer Not To Say    30.000000
Male                 21.351767
Female               19.703704
Non-Binary           18.548387
Name: count, dtype: float64
```

```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/2755841693.py:17: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=promotion_rate_by_gender.values, y=promotion_rate_by_gender.index, palette="Set2")
```



jupyter Depi_HR_Project Last Checkpoint: 19 hours ago

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Trusted

Code

JupyterLab Python 3 (ipykernel)

[10…
```
# Additional Questions
```

[11…
```
# 21. Calculate the total salary of all employees
total_salary = merged_df.drop_duplicates(subset="EmployeeID")["Salary"].sum()
total_salary
```

[11… 166046052

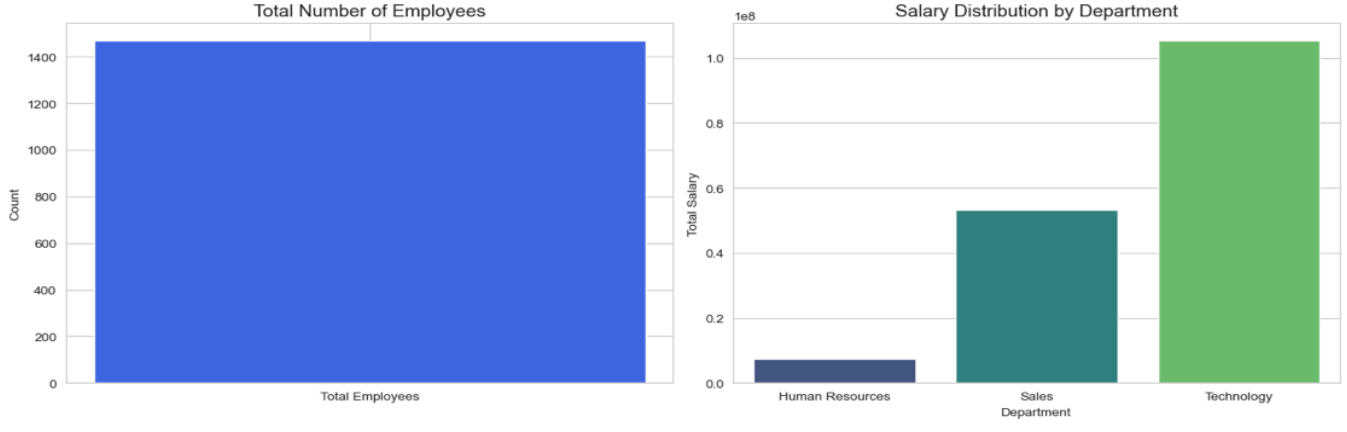
[12…
```
# 22. Calculate total salary distribution by department
salary_distribution = merged_df.drop_duplicates(subset="EmployeeID").groupby("Department")["Salary"].s
# Display the salary distribution
salary_distribution
```

[12…

	Department	Salary
0	Human Resources	7541025
1	Sales	53126454
2	Technology	105378573

[12…
```
# 22. Calculate total salary distribution by department
# Visualizing total salary distribution by department
# Set plot style
sns.set_style("whitegrid")

# Create a figure with subplots
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Total Number of Employees - Bar Chart
axes[0].bar(["Total Employees"], [total_employees], color="royalblue")
axes[0].set_title("Total Number of Employees", fontsize=14)
axes[0].set_ylabel("Count")

# Salary Distribution by Department - Bar Chart
sns.barplot(data=salary_distribution, x="Department", y="Salary", ax=axes[1], palette="viridis")
axes[1].set_title("Salary Distribution by Department", fontsize=14)
axes[1].set_ylabel("Total Salary")

# Adjust layout and display the plots
plt.tight_layout()
plt.show()
```

```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/2400868859.py:15: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(data=salary_distribution, x="Department", y="Salary", ax=axes[1], palette="viridis")
```



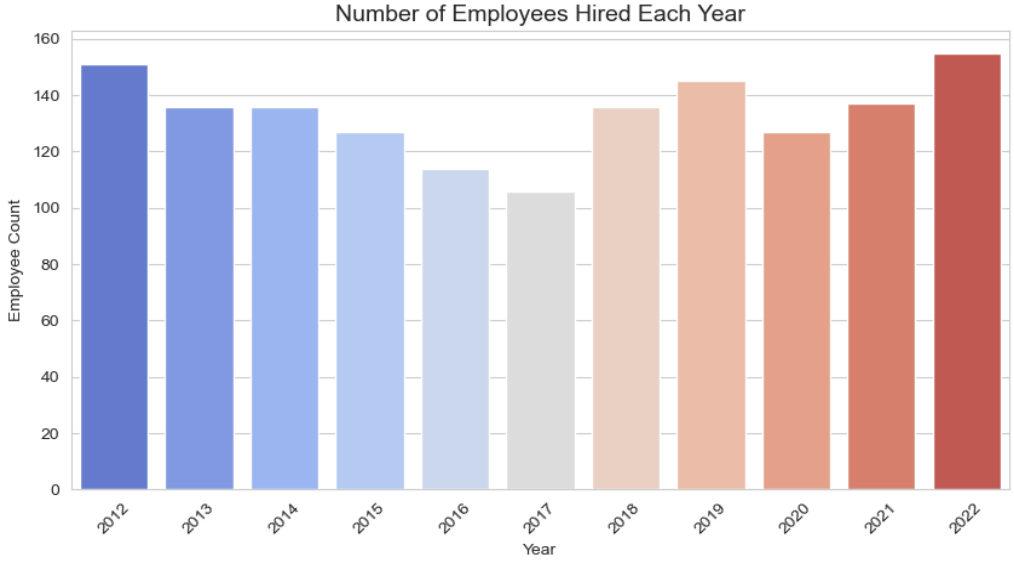
[16…]
```python
# 23. Calculate the number of employees hired in each year
# Convert HireDate to datetime format
merged_df["HireDate"] = pd.to_datetime(merged_df["HireDate"], errors="coerce")

# Remove duplicates to ensure each employee is counted once
unique_employees = merged_df.drop_duplicates(subset="EmployeeID")

# Extract year from HireDate and count employees per year
employee_count_by_year = unique_employees.groupby(unique_employees["HireDate"].dt.year)["EmployeeID"].
# Display the result
employee_count_by_year
```

[16…]

	HireDate	EmployeeID
0	2012	151
1	2013	136
2	2014	136
3	2015	127
4	2016	114
5	2017	106
6	2018	136
7	2019	145
8	2020	127
9	2021	137
10	2022	155

[16…]
```python
# 23. Calculate the number of employees hired in each year
# Visualizing the number of employees in each year
# Plot the data
plt.figure(figsize=(10, 5))
sns.barplot(data=employee_count_by_year, x="Year", y="EmployeeCount", palette="coolwarm")

# Add labels and title
plt.title("Number of Employees Hired Each Year", fontsize=14)
plt.xlabel("Year")
plt.ylabel("Employee Count")
plt.xticks(rotation=45)

# Show the plot
plt.show()
```

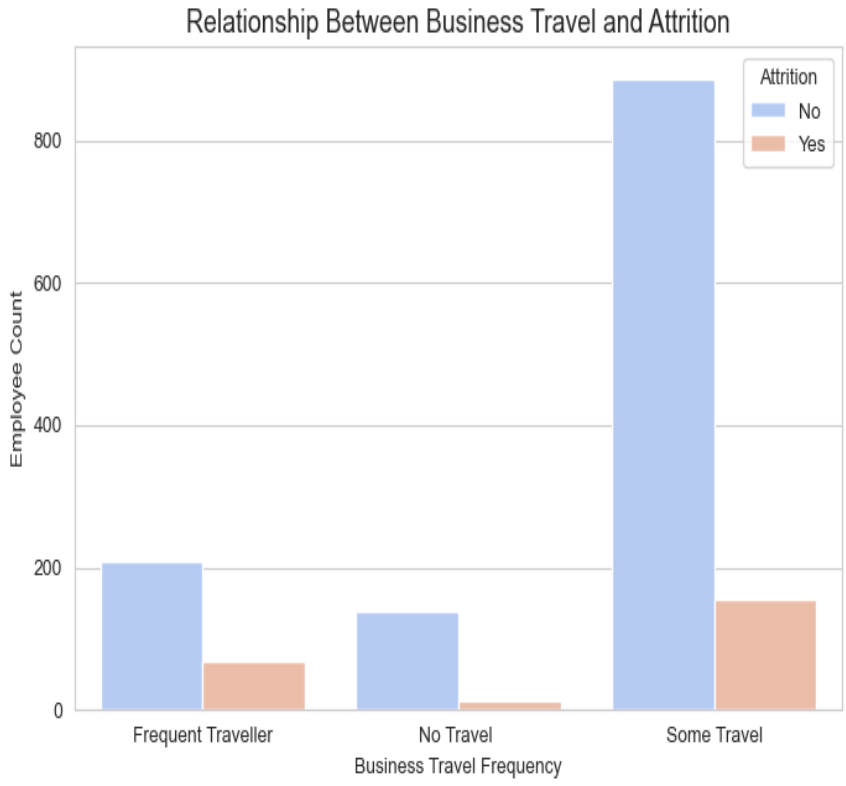
```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/2530743306.py:5: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(data=employee_count_by_year, x="Year", y="EmployeeCount", palette="coolwarm")
```



[17…
```
# 24. Calculate the Number of Embployees based on BusinessTravel and Attrition
#Count employees by BusinessTravel and Attrition
business_travel_attrition = merged_df.groupby(["BusinessTravel", "Attrition"])["EmployeeID"].nunique()
business_travel_attrition.columns = ["BusinessTravel", "Attrition", "EmployeeCount"]

# Display the result
print (business_travel_attrition)
```

	BusinessTravel	Attrition	EmployeeCount
0	Frequent Traveller	No	208
1	Frequent Traveller	Yes	69
2	No Travel	No	138
3	No Travel	Yes	12
4	Some Travel	No	887
5	Some Travel	Yes	156

[17…
```
# 24. Calculate the Number of Embployees based on BusinessTravel and Attrition
# Plot the data
plt.figure(figsize=(8, 5))
sns.barplot(data=business_travel_attrition, x="BusinessTravel", y="EmployeeCount", hue="Attrition", pa

# Add labels and title
plt.title("Relationship Between Business Travel and Attrition", fontsize=14)
plt.xlabel("Business Travel Frequency")
plt.ylabel("Employee Count")

# Show the plot
plt.show()
```

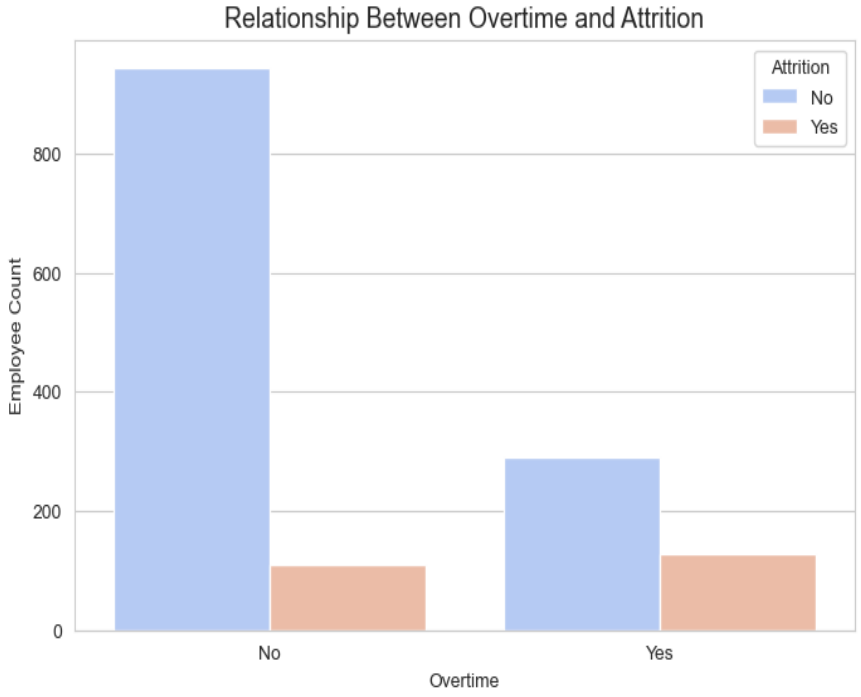


[18…]
```
# 25. Calculate the Number of Employees based on OverTime and Attrition
# Count employees by OverTime and Attrition
overtime_attrition = merged_df.groupby(["OverTime", "Attrition"])["EmployeeID"].nunique().reset_index(
overtime_attrition.columns = ["OverTime", "Attrition", "EmployeeCount"]

# Display the result
overtime_attrition
```

[18…]

	OverTime	Attrition	EmployeeCount
0	No	No	944
1	No	Yes	110
2	Yes	No	289
3	Yes	Yes	127

[18…]
```
# 25. Calculate the Number of Employees based on OverTime and Attrition
# Plot the data
plt.figure(figsize=(8, 5))
sns.barplot(data=overtime_attrition, x="OverTime", y="EmployeeCount", hue="Attrition", palette="coolwa

# Add labels and title
plt.title("Relationship Between Overtime and Attrition", fontsize=14)
plt.xlabel("Overtime")
plt.ylabel("Employee Count")

# Show the plot
plt.show()
```

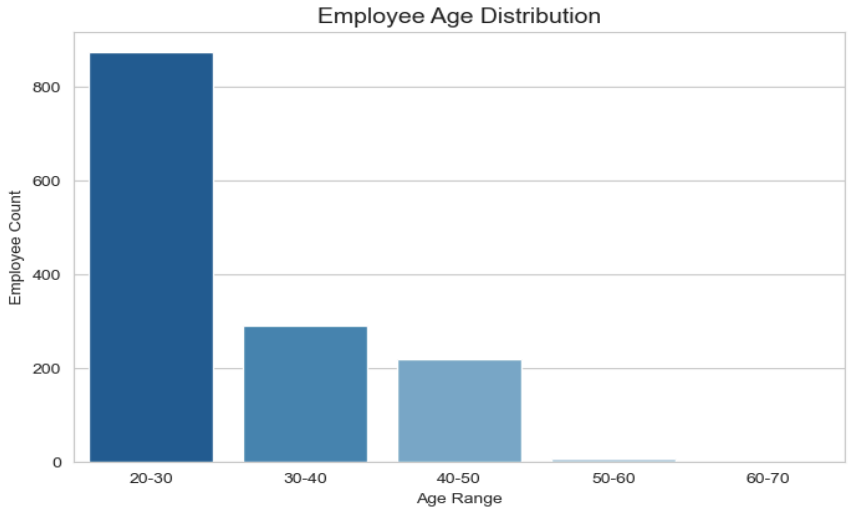


[20…]
```python
# 26.1 Define the age ranges of Employees
bins = [20, 30, 40, 50, 60, 70]
labels = ["20-30", "30-40", "40-50", "50-60", "60-70"]

# Remove duplicate employees by EmployeeID (if necessary) before calculating age range
merged_df_unique = merged_df.drop_duplicates(subset="EmployeeID")

# Assign each employee to an age range using .loc to avoid SettingWithCopyWarning
merged_df_unique.loc[:, "AgeRange"] = pd.cut(merged_df_unique["Age"], bins=bins, labels=labels, right=

# Count employees in each age range
age_range_count = merged_df_unique["AgeRange"].value_counts().reset_index()
age_range_count.columns = ["AgeRange", "EmployeeCount"]

# Display the result
print(age_range_count)

# 26.2 Find the minimum and maximum age of employees (no duplicates)
# Drop rows where Age is NaN (if any)
merged_df_unique = merged_df_unique.dropna(subset=['Age'])

min_age, max_age = merged_df_unique['Age'].min(), merged_df_unique['Age'].max()

# Display the results for minimum and maximum age
print(f"Age Range of Employees: {min_age} - {max_age}")

# 26.3 Find the age group with the most employees
# Find the age range with the most employees
max_age_range = age_range_count.loc[age_range_count["EmployeeCount"].idxmax()]

# Display the result for the age group with the most employees
print(f"The age range with the most employees is {max_age_range['AgeRange']} with {max_age_range['Empl
```

```
  AgeRange  EmployeeCount
0    20-30            874
1    30-40            289
2    40-50            219
3    50-60              7
4    60-70              0
Age Range of Employees: 18 - 51
The age range with the most employees is 20-30 with 874 employees.
```

[20…]
```python
# 26.1 Define the age ranges of Employees
# Plot the data
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8, 5))  # Size of the plot
sns.barplot(data=age_range_count, x="AgeRange", y="EmployeeCount", palette="Blues_r")

# Add labels and title
plt.title("Employee Age Distribution", fontsize=14)
plt.xlabel("Age Range")
plt.ylabel("Employee Count")

# Show the plot
plt.show()
```

```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/3134220879.py:7: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(data=age_range_count, x="AgeRange", y="EmployeeCount", palette="Blues_r")
```



[22…]
```
# 27. Calculate the correlation between ManagerRating and JobSatisfaction to assess employee performan
# Remove duplicates by EmployeeID to ensure each employee is counted only once
performance_manager_rating = merged_df[['EmployeeID', 'ManagerRating', 'JobSatisfaction']].drop_duplic

# Calculate the mean of JobSatisfaction based on ManagerRating
performance_by_manager_rating = performance_manager_rating.groupby('ManagerRating')['JobSatisfaction']

# Display the results
print(performance_by_manager_rating)
```

	ManagerRating	JobSatisfaction
0	2.0	3.439331
1	3.0	3.461538
2	4.0	3.402353
3	5.0	3.475000

[22…]
```
# 27. Calculate the correlation between ManagerRating and JobSatisfaction to assess employee performan
# Plot the data
# Remove duplicates by EmployeeID to ensure each employee is counted only once
performance_manager_rating = merged_df[['EmployeeID', 'ManagerRating', 'JobSatisfaction']].drop_duplic

# Create a barplot to visualize the average Job Satisfaction based on Manager Rating
plt.figure(figsize=(8, 5))
sns.barplot(x='ManagerRating', y='JobSatisfaction', data=performance_manager_rating, palette='viridis'

# Add labels and title
plt.title('Job Satisfaction based on Manager Rating', fontsize=14)
plt.xlabel('Manager Rating')
plt.ylabel('Average Job Satisfaction')

# Show the plot
plt.show()
```

```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_10217/612261823.py:8: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x`
variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x='ManagerRating', y='JobSatisfaction', data=performance_manager_rating, palette='viridi
s')
```

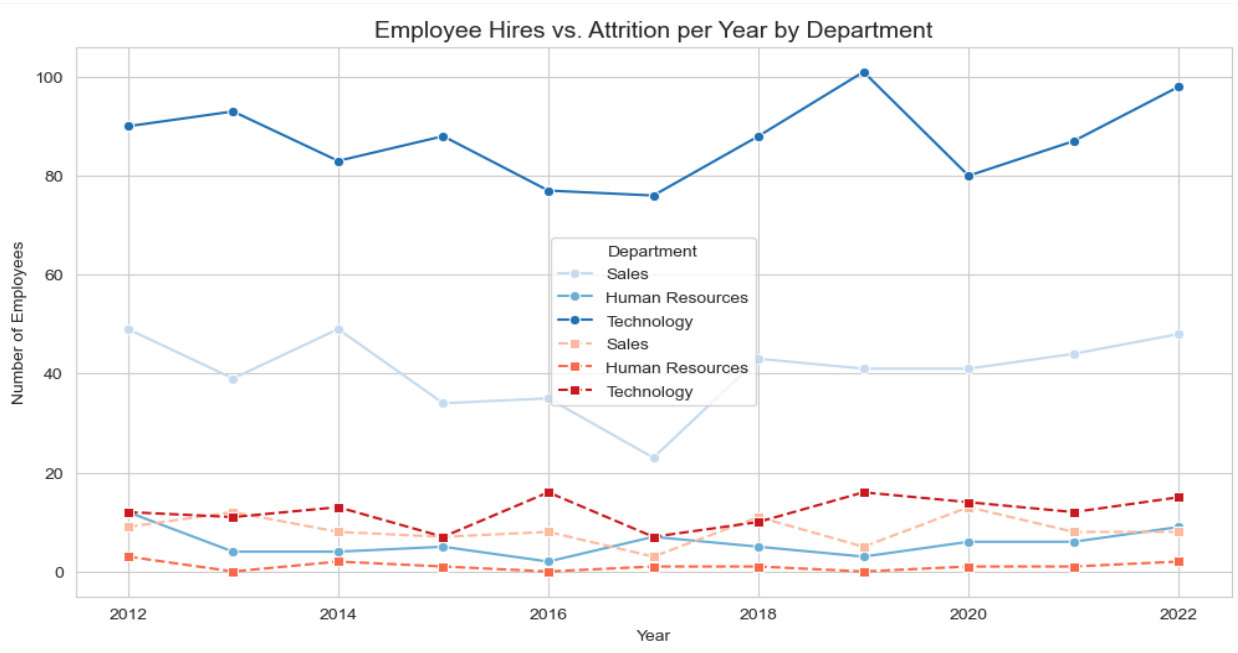
[27…

```python
# 28. Count employees hired per year and Count employees who left (attrition) by each department
import pandas as pd

# Convert Hire Date to datetime
merged_df["HireDate"] = pd.to_datetime(merged_df["HireDate"], errors="coerce")

# Extract Hire Year
merged_df["HireYear"] = merged_df["HireDate"].dt.year

# Identify latest year in dataset
latest_year = merged_df["HireYear"].max()

# Count employees hired per year by department
hire_counts = merged_df.groupby(["HireYear", "Department"])["EmployeeID"].nunique().reset_index()
hire_counts.columns = ["Year", "Department", "EmployeesHired"]

# Count employees who left (attrition) per department
attrition_counts = merged_df[merged_df["Attrition"] == "Yes"].groupby(["HireYear", "Department"])["Emp
attrition_counts.columns = ["Year", "Department", "EmployeesLeft"]

# Get all unique years and departments
all_years = pd.DataFrame({"Year": range(merged_df["HireYear"].min(), latest_year + 1)})
departments = merged_df["Department"].unique()
dept_df = pd.DataFrame({"Department": departments})

# Create a full Year-Department grid
year_dept_grid = all_years.merge(dept_df, how="cross")

# Merge hire and attrition data to ensure all Year-Department combinations exist
workforce_trend = year_dept_grid.merge(hire_counts, on=["Year", "Department"], how="left").fillna(0)
workforce_trend = workforce_trend.merge(attrition_counts, on=["Year", "Department"], how="left").filln

# Convert employee counts to integers
workforce_trend["EmployeesHired"] = workforce_trend["EmployeesHired"].astype(int)
workforce_trend["EmployeesLeft"] = workforce_trend["EmployeesLeft"].astype(int)

# Display the results as numbers
print("Employee Hires and Attrition by Year and Department:")
print(workforce_trend[["Year", "Department", "EmployeesHired", "EmployeesLeft"]])
```

```
Employee Hires and Attrition by Year and Department:
    Year       Department  EmployeesHired  EmployeesLeft
0   2012            Sales              49              9
1   2012  Human Resources              12              3
2   2012       Technology              90             12
3   2013            Sales              39             12
4   2013  Human Resources               4              0
5   2013       Technology              93             11
6   2014            Sales              49              8
7   2014  Human Resources               4              2
8   2014       Technology              83             13
9   2015            Sales              34              7
10  2015  Human Resources               5              1
11  2015       Technology              88              7
12  2016            Sales              35              8
13  2016  Human Resources               2              0
14  2016       Technology              77             16
15  2017            Sales              23              3
16  2017  Human Resources               7              1
17  2017       Technology              76              7
18  2018            Sales              43             11
19  2018  Human Resources               5              1
20  2018       Technology              88             10
21  2019            Sales              41              5
22  2019  Human Resources               3              0
23  2019       Technology             101             16
24  2020            Sales              41             13
25  2020  Human Resources               6              1
26  2020       Technology              80             14
27  2021            Sales              44              8
28  2021  Human Resources               6              1
29  2021       Technology              87             12
30  2022            Sales              48              8
31  2022  Human Resources               9              2
32  2022       Technology              98             15
```

[28…

```python
# 28. Count employees hired per year and Count employees who left (attrition) by each department
# Plot the data
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Convert Hire Date to datetime
merged_df["HireDate"] = pd.to_datetime(merged_df["HireDate"], errors="coerce")

# Extract Hire Year
merged_df["HireYear"] = merged_df["HireDate"].dt.year

# Identify latest year in dataset
latest_year = merged_df["HireYear"].max()

# Count employees hired per year by department
hire_counts = merged_df.groupby(["HireYear", "Department"])["EmployeeID"].nunique().reset_index()
hire_counts.columns = ["Year", "Department", "EmployeesHired"]

# Count employees who left (attrition) per department
attrition_counts = merged_df[merged_df["Attrition"] == "Yes"].groupby(["HireYear", "Department"])["Emp
attrition_counts.columns = ["Year", "Department", "EmployeesLeft"]

# Get all unique years and departments
all_years = pd.DataFrame({"Year": range(merged_df["HireYear"].min(), latest_year + 1)})
departments = merged_df["Department"].unique()
dept_df = pd.DataFrame({"Department": departments})

# Create a full Year-Department grid
year_dept_grid = all_years.merge(dept_df, how="cross")

# Merge hire and attrition data to ensure all Year-Department combinations exist
workforce_trend = year_dept_grid.merge(hire_counts, on=["Year", "Department"], how="left").fillna(0)
workforce_trend = workforce_trend.merge(attrition_counts, on=["Year", "Department"], how="left").fillna

# Convert employee counts to integers
workforce_trend["EmployeesHired"] = workforce_trend["EmployeesHired"].astype(int)
workforce_trend["EmployeesLeft"] = workforce_trend["EmployeesLeft"].astype(int)

# Plot trends
plt.figure(figsize=(12, 6))

# Plot hires
sns.lineplot(data=workforce_trend, x="Year", y="EmployeesHired", hue="Department", marker="o", linesty

# Plot attrition
sns.lineplot(data=workforce_trend, x="Year", y="EmployeesLeft", hue="Department", marker="s", linestyl

# Labels and title
plt.title("Employee Hires vs. Attrition per Year by Department", fontsize=14)
plt.xlabel("Year")
plt.ylabel("Number of Employees")
plt.legend(title="Department")

# Show the plot
plt.show()
```



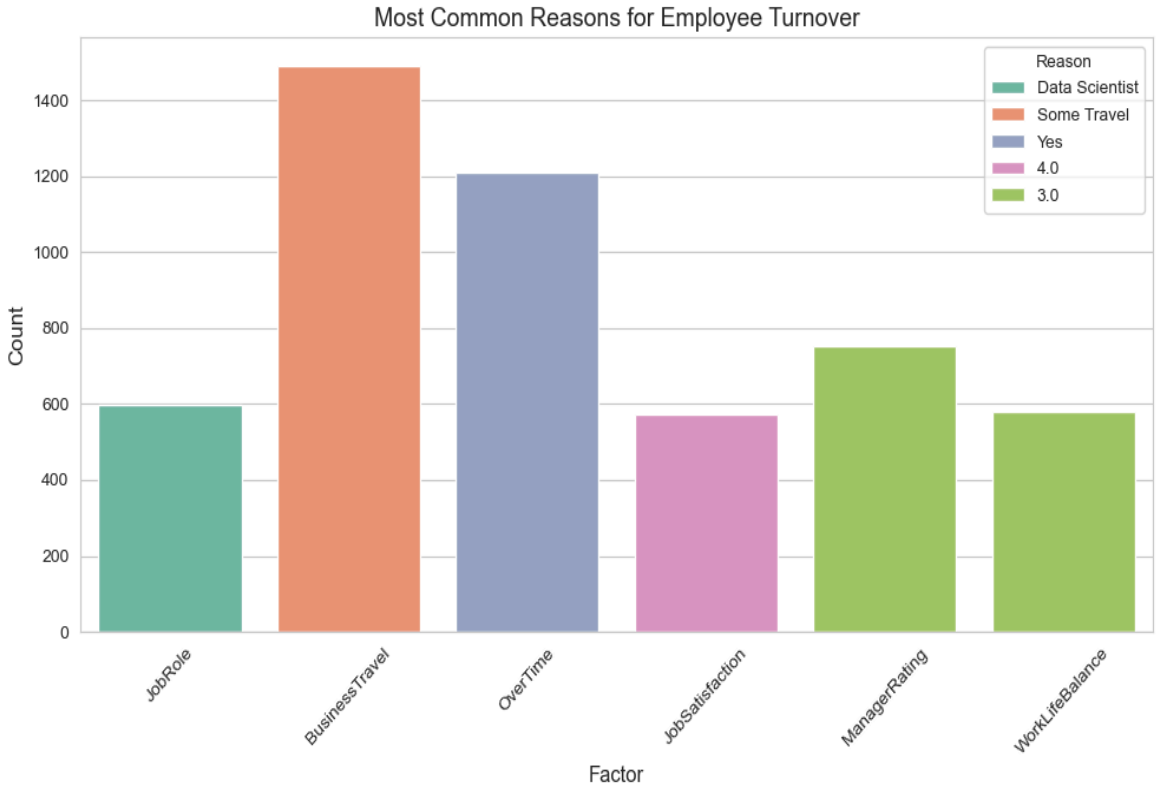
[34…

```python
# 29. What is the most common reason for employee turnover?
# 29. What is the most common reason for employee turnover?
# Filter only employees who left (Attrition = 'Yes'), ensuring each employee is counted once
attrition_data = merged_df[merged_df["Attrition"] == "Yes"].drop_duplicates(subset=["EmployeeID"])

# Define the possible reasons for attrition (adjust based on your dataset)
attrition_factors = ["JobRole", "BusinessTravel", "OverTime", "JobSatisfaction", "ManagerRating", "Worl

# Create a dictionary to store the count of each factor for employees who left
attrition_counts = {factor: attrition_data[factor].value_counts() for factor in attrition_factors}

# Identify the most common reason by finding the value with the highest count
most_common_reasons = {factor: attrition_counts[factor].idxmax() for factor in attrition_factors}

# Display the most common reasons for attrition
print("Most Common Reasons for Employee Turnover:")
for factor, reason in most_common_reasons.items():
    print(f"{factor}: {reason} (Count: {attrition_counts[factor].max()})")



# Filter only employees who left (Attrition = 'Yes')
#attrition_data = merged_df[merged_df["Attrition"] == "Yes"]

# Define the possible reasons for attrition (adjust based on your dataset)
#attrition_factors = ["JobRole", "BusinessTravel", "OverTime", "JobSatisfaction", "ManagerRating", "Wo

# Create a dictionary to store the count of each factor for employees who left
# Count each factor without dropping duplicates
#attrition_counts = {factor: attrition_data[factor].value_counts() for factor in attrition_factors}

# Identify the most common reason by finding the value with the highest count
#most_common_reasons = {factor: attrition_counts[factor].idxmax() for factor in attrition_factors}

# Display the most common reasons for attrition
#print("Most Common Reasons for Employee Turnover:")
#for factor, reason in most_common_reasons.items():
#    print(f"{factor}: {reason} (Count: {attrition_counts[factor].max()})")
```

```
Most Common Reasons for Employee Turnover:
JobRole: Data Scientist (Count: 62)
BusinessTravel: Some Travel (Count: 156)
OverTime: Yes (Count: 127)
JobSatisfaction: 4.0 (Count: 64)
ManagerRating: 4.0 (Count: 82)
WorkLifeBalance: 4.0 (Count: 67)
```

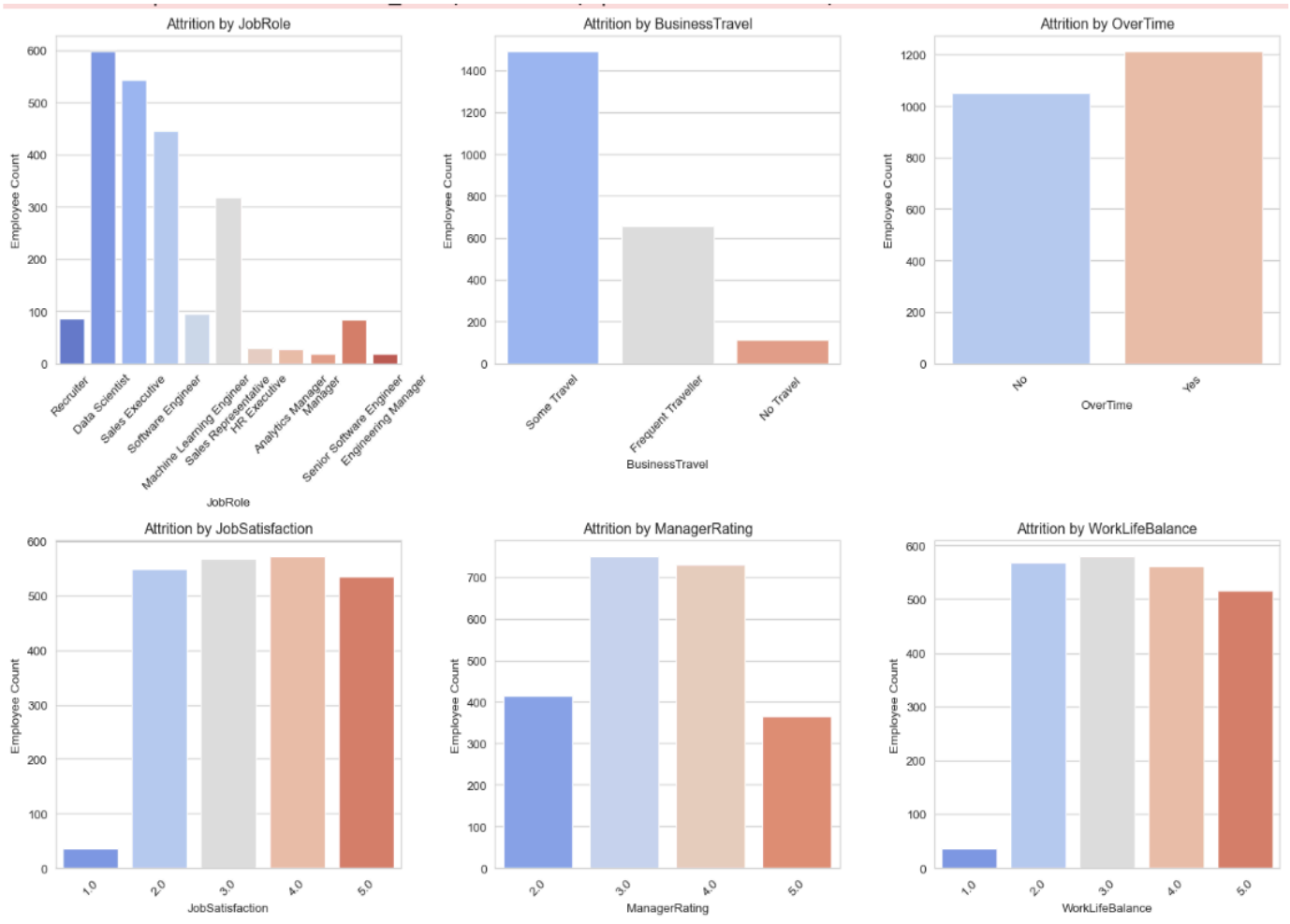
[29…

```python
# 29.1 What is the most common reason for employee turnover?
# Plot the data
import matplotlib.pyplot as plt
import seaborn as sns

# List of the most common reasons for attrition and their counts
factors = ["JobRole", "BusinessTravel", "OverTime", "JobSatisfaction", "ManagerRating", "WorkLifeBalan
reasons = ["Data Scientist", "Some Travel", "Yes", "4.0", "3.0", "3.0"]  # As per your result
counts = [597, 1490, 1211, 573, 751, 580]  # Corresponding counts

# Create a DataFrame for plotting
import pandas as pd
data = pd.DataFrame({
    'Factor': factors,
    'Reason': reasons,
    'Count': counts
})

# Plot the data using seaborn
plt.figure(figsize=(10, 6))
sns.barplot(data=data, x='Factor', y='Count', hue='Reason', palette='Set2')

# Add labels and title
plt.title("Most Common Reasons for Employee Turnover", fontsize=14)
plt.xlabel("Factor", fontsize=12)
plt.ylabel("Count", fontsize=12)
plt.xticks(rotation=45)
plt.tight_layout()

# Show the plot
plt.show()
```



[28…]

```python
# 29.2 What is the most common reason for employee turnover?
# Plot the data
import matplotlib.pyplot as plt
import seaborn as sns

# Filter only employees who left (Attrition = 'Yes')
attrition_data = merged_df[merged_df["Attrition"] == "Yes"]

# Define the possible reasons for attrition (adjust based on your dataset)
attrition_factors = ["JobRole", "BusinessTravel", "OverTime", "JobSatisfaction", "ManagerRating", "Wor

# Create subplots
fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(15, 10))
axes = axes.flatten()

# Plot each factor
for i, factor in enumerate(attrition_factors):
    sns.countplot(data=attrition_data, x=factor, palette="coolwarm", ax=axes[i])
    axes[i].set_title(f"Attrition by {factor}")
    axes[i].set_xlabel(factor)
    axes[i].set_ylabel("Employee Count")
    axes[i].tick_params(axis="x", rotation=45)

# Adjust layout to avoid overlapping
plt.tight_layout()
plt.show()
```



[ ]:

[17…]

```
############################## Ending of Week 2: Analysis Questions Phase
```

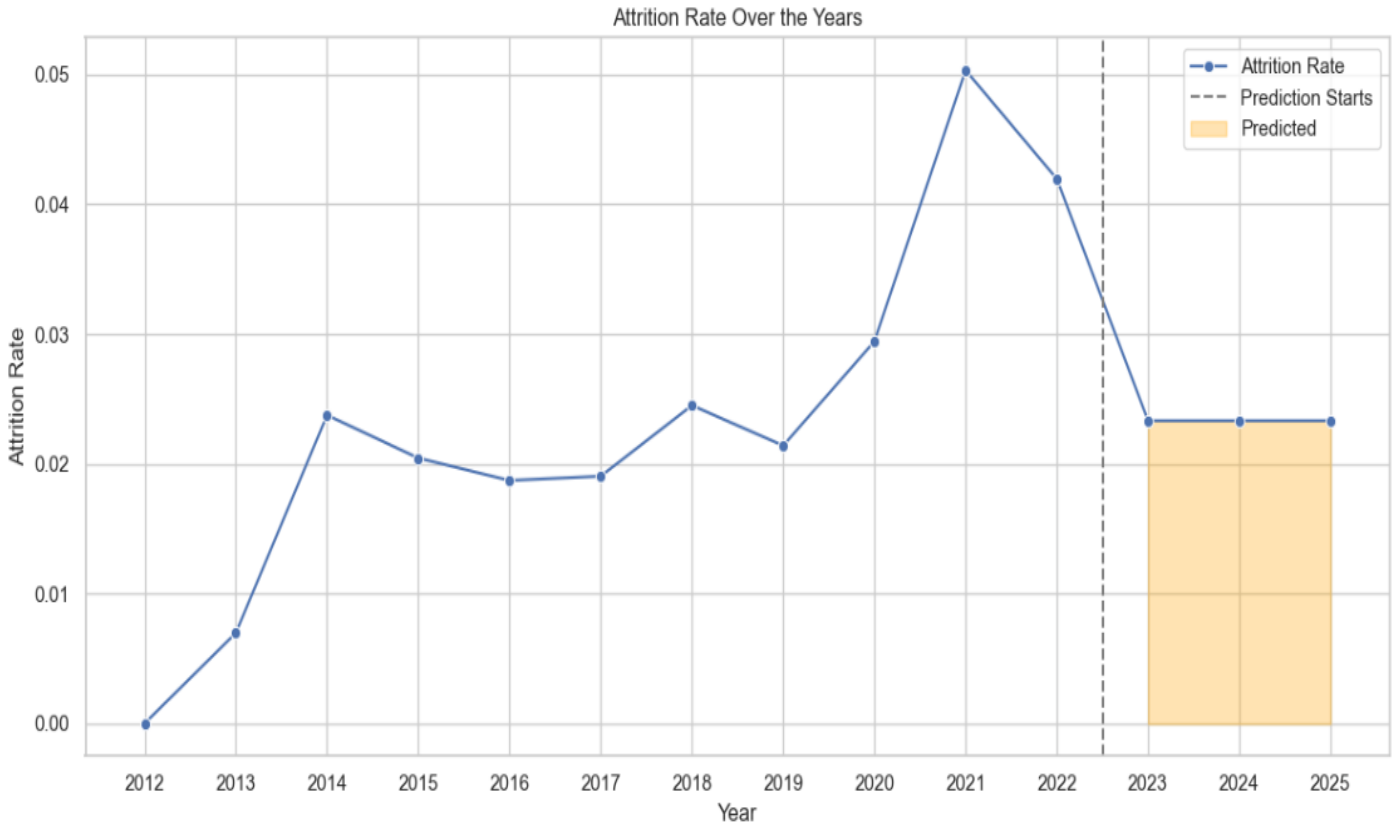
[21…]
```
############################## Week 3: Forecasting Questions Phase
```

[14…]
```
# 1. Predict attrition for the next 5 years
import pandas as pd

# Load and clean data
df = pd.read_csv("/Users/rahmasaadawy/Downloads/Cleaned_HR_Data.csv")
df = df.drop_duplicates(subset="EmployeeID")
df['HireDate'] = pd.to_datetime(df['HireDate'])
df['HireYear'] = df['HireDate'].dt.year
df['ExitYear'] = df.apply(lambda row: row['HireYear'] + row['YearsAtCompany'] if row['Attrition'] == '

# Create a long table with one row per employee per year
records = []
for _, row in df.iterrows():
    start = int(row['HireYear'])  # تحويل لـ int
    end = int(row['ExitYear']) if pd.notnull(row['ExitYear']) else 2022  # تحويل لـ int
    for year in range(start, end + 1):
        records.append({
            'Year': year,
            'EmployeeID': row['EmployeeID'],
            'Exited': 1 if row['ExitYear'] == year else 0
        })

long_df = pd.DataFrame(records)

# Group by year to calculate metrics
summary = long_df.groupby('Year').agg(
    ActiveEmployees=('EmployeeID', 'nunique'),
    ExitedEmployees=('Exited', 'sum')
).reset_index()

# Attrition rate
summary['AttritionRate'] = summary['ExitedEmployees'] / summary['ActiveEmployees']

# Predict for 2023–2025
avg_rate = summary['AttritionRate'].mean()
future_years = pd.DataFrame({
    'Year': [2023, 2024, 2025],
    'ActiveEmployees': [None, None, None],
    'ExitedEmployees': [None, None, None],
    'AttritionRate': [avg_rate] * 3
})

# Combine all
full_summary = pd.concat([summary, future_years], ignore_index=True)
print(full_summary)
```

```
    Year ActiveEmployees ExitedEmployees  AttritionRate
0   2012             151               0       0.000000
1   2013             287               2       0.006969
2   2014             421              10       0.023753
3   2015             538              11       0.020446
4   2016             641              12       0.018721
5   2017             735              14       0.019048
6   2018             857              21       0.024504
7   2019             981              21       0.021407
8   2020            1087              32       0.029439
9   2021            1192              60       0.050336
10  2022            1287              54       0.041958
11  2023            None            None       0.023325
12  2024            None            None       0.023325
13  2025            None            None       0.023325
```

[14…

```python
# 1. Predict attrition for the next 5 years
# Plot the data
import matplotlib.pyplot as plt
import seaborn as sns

# Set the style
sns.set(style="whitegrid")

# Create the plot
plt.figure(figsize=(12, 6))
sns.lineplot(data=full_summary, x="Year", y="AttritionRate", marker="o", label="Attrition Rate")

# Highlight predicted years
plt.axvline(x=2022.5, color='gray', linestyle='--', label='Prediction Starts')
plt.fill_between(full_summary['Year'], full_summary['AttritionRate'], where=full_summary['Year'] > 202
                 color='orange', alpha=0.3, label='Predicted')

# Customize plot
plt.title("Attrition Rate Over the Years")
plt.xlabel("Year")
plt.ylabel("Attrition Rate")
plt.xticks(full_summary['Year'])
plt.legend()
plt.tight_layout()

# Show the plot
plt.show()
```



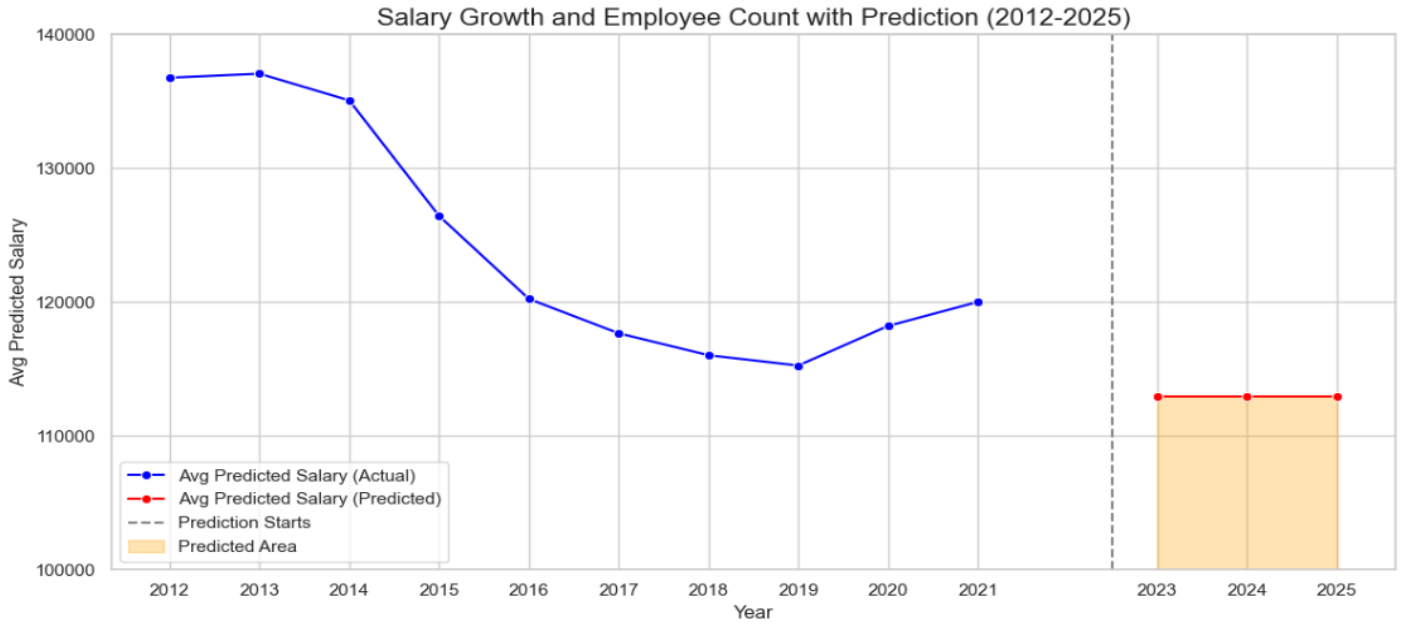
[17…

```python
# 2. Predict Salary Growth Projection for next 3 years
import pandas as pd
import numpy as np

# Load data
df = pd.read_csv("/Users/rahmasaadawy/Downloads/Cleaned_HR_Data.csv")
df = df.drop_duplicates(subset="EmployeeID")

# Ensure correct types
df['HireDate'] = pd.to_datetime(df['HireDate'])
df['HireYear'] = df['HireDate'].dt.year

# Calculate salary history per employee and year
salary_records = []
for _, row in df.iterrows():
    for i in range(row['YearsAtCompany']):
        year = row['HireYear'] + i
        salary = row['Salary']  # Starting salary, we will calculate the growth later
        salary_records.append({
            'Year': year,
            'EmployeeID': row['EmployeeID'],
            'Salary': salary
        })

salary_df = pd.DataFrame(salary_records)

# Calculate salary growth rate per employee
salary_df_sorted = salary_df.sort_values(['EmployeeID', 'Year'])
salary_df_sorted['PrevSalary'] = salary_df_sorted.groupby('EmployeeID')['Salary'].shift(1)
salary_df_sorted['GrowthRate'] = (salary_df_sorted['Salary'] - salary_df_sorted['PrevSalary']) / salary
avg_growth_rate = salary_df_sorted['GrowthRate'].mean(skipna=True)

# Calculate actual salary data (2012-2022)
actual_summary = salary_df[salary_df['Year'].between(2012, 2022)].groupby('Year').agg(
    EmployeeCount=('EmployeeID', 'nunique'),
    AvgPredictedSalary=('Salary', 'mean')
).reset_index()

# Get current salary of employees (the most recent salary for each)
latest_salaries = df[['EmployeeID', 'Salary']]

# Predict salaries for 2023-2025 based on the average growth rate
predicted_records = []
for year in [2023, 2024, 2025]:
    factor = (1 + avg_growth_rate) ** (year - 2022)  # Apply growth rate over the years
    for _, row in latest_salaries.iterrows():
        predicted_salary = row['Salary'] * factor
        predicted_records.append({
            'Year': year,
            'EmployeeID': row['EmployeeID'],
            'Salary': predicted_salary
        })

predicted_df = pd.DataFrame(predicted_records)

# Aggregate predicted salary data
predicted_summary = predicted_df.groupby('Year').agg(
    EmployeeCount=('EmployeeID', 'nunique'),
    AvgPredictedSalary=('Salary', 'mean')
).reset_index()

# Combine actual and predicted salary data
full_summary = pd.concat([actual_summary, predicted_summary], ignore_index=True)
full_summary = full_summary.sort_values('Year')

# Final output
print(full_summary)
```

	Year	EmployeeCount	AvgPredictedSalary
0	2012	151	136773.927152
1	2013	285	137074.112281
2	2014	411	135078.766423
3	2015	527	126447.557875
4	2016	629	120242.230525
5	2017	721	117671.857143
6	2018	836	116033.796651
7	2019	960	115259.107292
8	2020	1055	118218.837915
9	2021	1132	120017.598940
10	2023	1470	112956.497959
11	2024	1470	112956.497959
12	2025	1470	112956.497959

[16…

```python
# 2. Predict Salary Growth Projection for next 3 years
# Plot the data
import matplotlib.pyplot as plt
import seaborn as sns

# Set the style
sns.set(style="whitegrid")

# Create the plot
plt.figure(figsize=(12, 6))

# Plot the data for actual years (2012-2022)
sns.lineplot(data=full_summary[full_summary['Year'] <= 2022], x="Year", y="AvgPredictedSalary", marker=

# Plot the data for predicted years (2023-2025)
sns.lineplot(data=full_summary[full_summary['Year'] > 2022], x="Year", y="AvgPredictedSalary", marker='

# Highlight predicted years (2023-2025)
plt.axvline(x=2022.5, color='gray', linestyle='--', label='Prediction Starts')
plt.fill_between(full_summary['Year'], full_summary['AvgPredictedSalary'], where=full_summary['Year'] >
                 color='orange', alpha=0.3, label='Predicted Area')

# Customize plot
plt.title("Salary Growth and Employee Count with Prediction (2012-2025)", fontsize=16)
plt.xlabel("Year", fontsize=12)
plt.ylabel("Avg Predicted Salary", fontsize=12)
plt.xticks(full_summary['Year'])
plt.legend()

# Adjust Y-axis to focus on the salary range you requested
plt.ylim(100000, 140000)  # Set range from 100,000 to 140,000
plt.yticks(range(100000, 140001, 10000))  # Set ticks every 10,000

# Show the plot
plt.tight_layout()
plt.show()
```



[17…

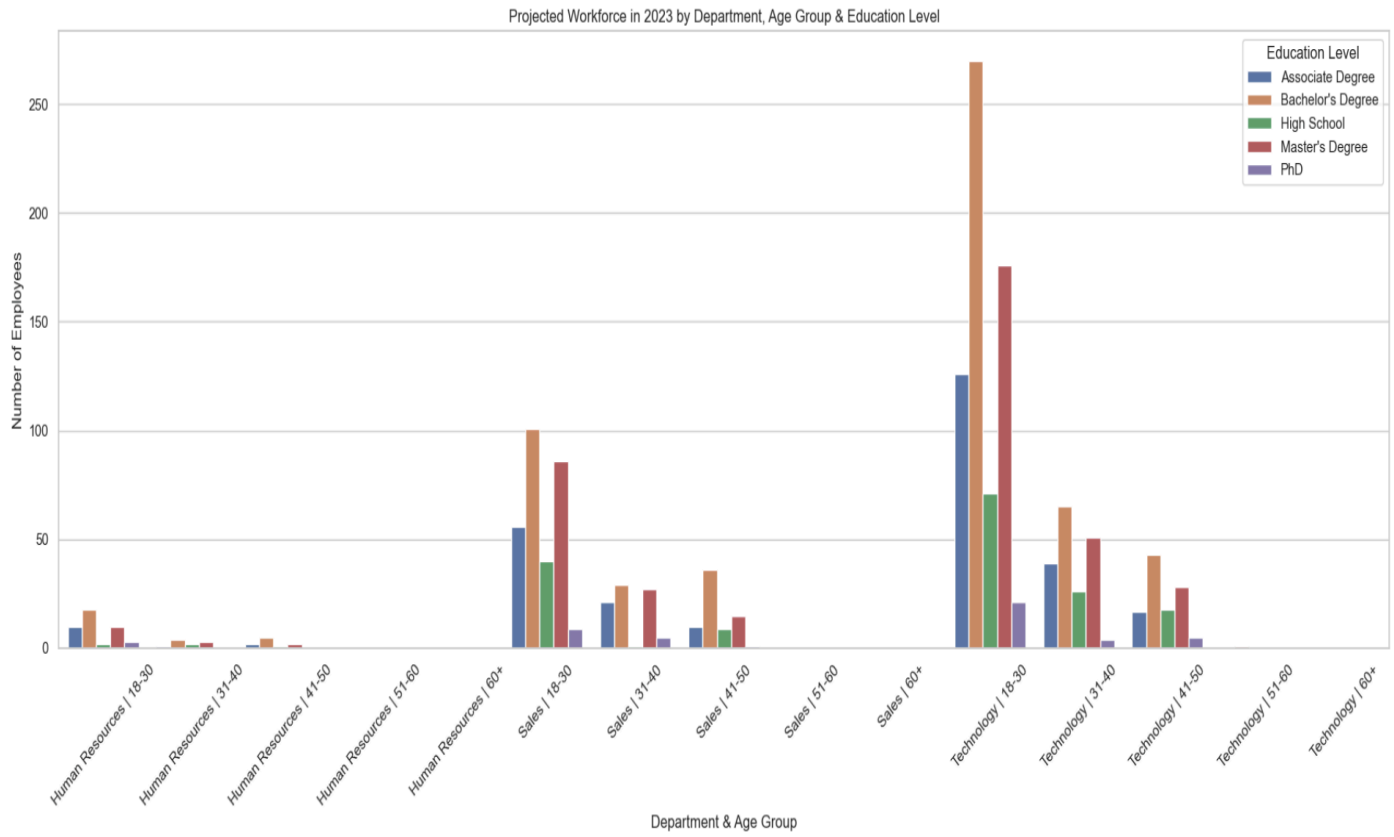
```python
# 3. Predection workforce in 3 years  by Department, Age Group & Education Level
import pandas as pd

# Load and clean data
df = pd.read_csv("/Users/rahmasaadawy/Downloads/Cleaned_HR_Data.csv")
df = df.drop_duplicates(subset="EmployeeID")

# Define Education Mapping
education_mapping = {
    1: 'High School',
    2: 'Associate Degree',
    3: 'Bachelor\'s Degree',
    4: 'Master\'s Degree',
    5: 'PhD'
}

# Map Education column from numeric values to names
df['EducationName'] = df['Education'].map(education_mapping)

# Create AgeGroup based on Age
df['AgeGroup'] = pd.cut(df['Age'], bins=[0, 30, 40, 50, 60, float('inf')],
                        labels=['18-30', '31-40', '41-50', '51-60', '60+'])

# Calculate YearsAtCompany
df['YearsAtCompany'] = pd.to_datetime('today').year - pd.to_datetime(df['HireDate']).dt.year

# Group by Department, AgeGroup, Education and count employees
employee_counts = df.groupby(['Department', 'AgeGroup', 'EducationName']).size().reset_index(name='Emp

# Calculate Growth Rate for each Department, AgeGroup, Education combination
employee_counts['GrowthRate'] = employee_counts.groupby(['Department', 'AgeGroup', 'EducationName'])['

# Define future years (2023, 2024, 2025)
future_years = pd.DataFrame({
    'Year': [2023, 2024, 2025]
})

# Create a cross join between future years and the employee_counts
future_predictions = future_years.merge(employee_counts, how='cross')

# Predict Employee Count for future years
future_predictions['PredictedEmployeeCount'] = future_predictions['EmployeeCount'] * future_prediction

# Display results
result = future_predictions[['Year', 'Department', 'AgeGroup', 'EducationName', 'PredictedEmployeeCoun

# Set pandas to display all rows
pd.set_option('display.max_rows', None)

# Display the result DataFrame with all rows
print(result)
```

```
     Year       Department AgeGroup      EducationName  PredictedEmployeeCount
0    2023  Human Resources    18-30   Associate Degree                    10.0
1    2023  Human Resources    18-30  Bachelor's Degree                    18.0
2    2023  Human Resources    18-30        High School                     2.0
3    2023  Human Resources    18-30    Master's Degree                    10.0
4    2023  Human Resources    18-30                PhD                     3.0
5    2023  Human Resources    31-40   Associate Degree                     1.0
6    2023  Human Resources    31-40  Bachelor's Degree                     4.0
7    2023  Human Resources    31-40        High School                     2.0
8    2023  Human Resources    31-40    Master's Degree                     3.0
9    2023  Human Resources    31-40                PhD                     0.0
10   2023  Human Resources    41-50   Associate Degree                     2.0
11   2023  Human Resources    41-50  Bachelor's Degree                     5.0
12   2023  Human Resources    41-50        High School                     1.0
13   2023  Human Resources    41-50    Master's Degree                     2.0
14   2023  Human Resources    41-50                PhD                     0.0
15   2023  Human Resources    51-60   Associate Degree                     0.0
```

[20…

```python
# 3. Predection workforce in 3 years by Department, Age Group & Education Level
# 3.1 Plot the data for 2023

import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Load and clean data
df = pd.read_csv("/Users/rahmasaadawy/Downloads/Cleaned_HR_Data.csv")
df = df.drop_duplicates(subset="EmployeeID")

# Map education level from numeric values to names
education_mapping = {
    1: 'High School',
    2: 'Associate Degree',
    3: 'Bachelor\'s Degree',
    4: 'Master\'s Degree',
    5: 'PhD'
}
df['EducationName'] = df['Education'].map(education_mapping)

# Create age groups
df['AgeGroup'] = pd.cut(df['Age'], bins=[0, 30, 40, 50, 60, float('inf')],
                        labels=['18-30', '31-40', '41-50', '51-60', '60+'])

# Calculate years at the company
df['YearsAtCompany'] = pd.to_datetime('today').year - pd.to_datetime(df['HireDate']).dt.year

# Group by department, age group, and education
employee_counts = df.groupby(['Department', 'AgeGroup', 'EducationName']).size().reset_index(name='Emp

# Assume fixed growth rate
employee_counts['GrowthRate'] = 1.0

# Define target year
year = 2023
future_predictions = employee_counts.copy()
future_predictions['Year'] = year
future_predictions['PredictedEmployeeCount'] = future_predictions['EmployeeCount'] * future_prediction

# Prepare plot data
data = future_predictions[['Year', 'Department', 'AgeGroup', 'EducationName', 'PredictedEmployeeCount'
data = data.copy()
data['Dept_AgeGroup'] = data['Department'] + ' | ' + data['AgeGroup'].astype(str)

# Plot grouped bar chart
plt.figure(figsize=(18, 8))
sns.barplot(data=data,
            x='Dept_AgeGroup',
            y='PredictedEmployeeCount',
            hue='EducationName',
            errorbar=None)

plt.title(f'Projected Workforce in {year} by Department, Age Group & Education Level')
plt.xlabel('Department & Age Group')
plt.ylabel('Number of Employees')
plt.legend(title='Education Level')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

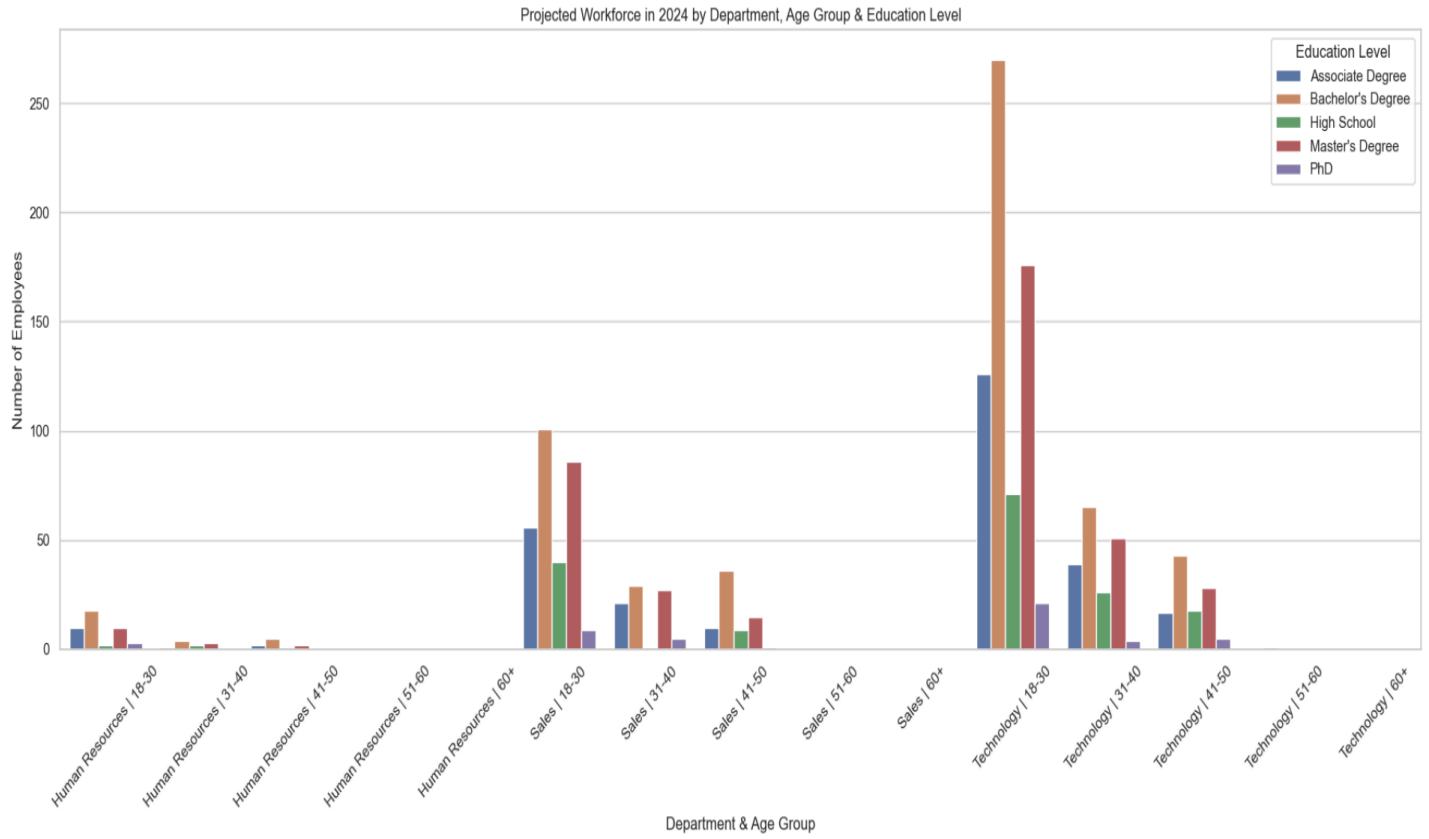
```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_3152/1794388208.py:30: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future version of pandas. Pass observed=False to retain current behavior or observed=True to adopt the future default and silence this warning.
```



[20…

```
# 3. Predection workforce in 3 years by Department, Age Group & Education Level
# 3.2 Plot the data for 2024

import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Load and clean data
df = pd.read_csv("/Users/rahmasaadawy/Downloads/Cleaned_HR_Data.csv")
df = df.drop_duplicates(subset="EmployeeID")

# Map education level from numeric values to names
education_mapping = {
    1: 'High School',
    2: 'Associate Degree',
    3: 'Bachelor\'s Degree',
    4: 'Master\'s Degree',
    5: 'PhD'
}
df['EducationName'] = df['Education'].map(education_mapping)

# Create age groups
df['AgeGroup'] = pd.cut(df['Age'], bins=[0, 30, 40, 50, 60, float('inf')],
                        labels=['18-30', '31-40', '41-50', '51-60', '60+'])

# Calculate years at the company
df['YearsAtCompany'] = pd.to_datetime('today').year - pd.to_datetime(df['HireDate']).dt.year

# Group by department, age group, and education
employee_counts = df.groupby(['Department', 'AgeGroup', 'EducationName']).size().reset_index(name='Emp

# Assume fixed growth rate
employee_counts['GrowthRate'] = 1.0

# Define target year
year = 2024
future_predictions = employee_counts.copy()
future_predictions['Year'] = year
future_predictions['PredictedEmployeeCount'] = future_predictions['EmployeeCount'] * future_prediction

# Prepare plot data
data = future_predictions[['Year', 'Department', 'AgeGroup', 'EducationName', 'PredictedEmployeeCount'
data = data.copy()
data['Dept_AgeGroup'] = data['Department'] + ' | ' + data['AgeGroup'].astype(str)

# Plot grouped bar chart
plt.figure(figsize=(18, 8))
sns.barplot(data=data,
            x='Dept_AgeGroup',
            y='PredictedEmployeeCount',
            hue='EducationName',
            errorbar=None)

plt.title(f'Projected Workforce in {year} by Department, Age Group & Education Level')
plt.xlabel('Department & Age Group')
plt.ylabel('Number of Employees')
plt.legend(title='Education Level')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

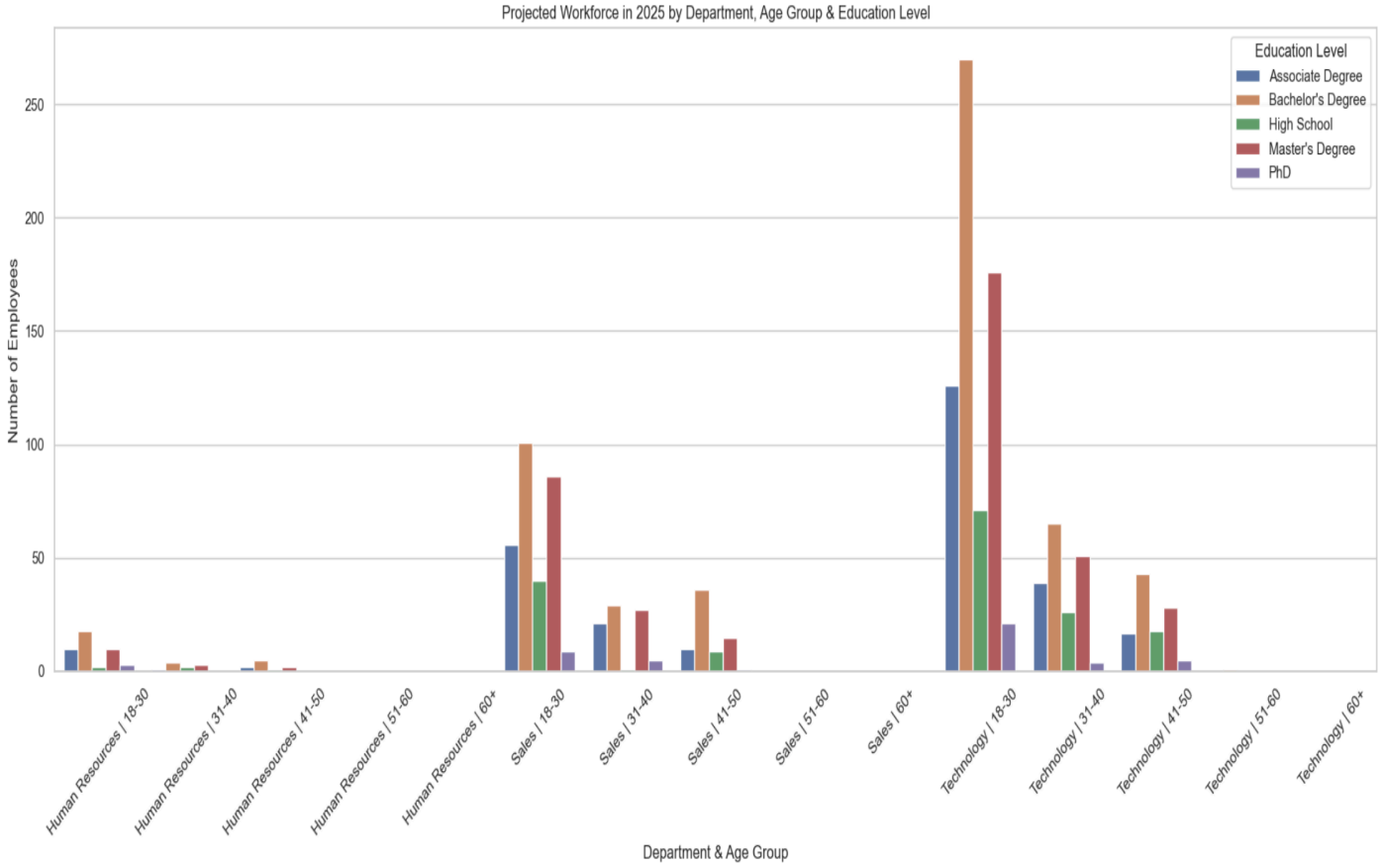
```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_3152/2913596134.py:30: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future version of pandas. Pass observed=False to retain current behavior or observed=True to adopt the future default and silence this warning.
```



[21…

```python
# 3. Predection workforce in 3 years by Department, Age Group & Education Level
# 3.3 Plot the data for 2025

import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Load and clean data
df = pd.read_csv("/Users/rahmasaadawy/Downloads/Cleaned_HR_Data.csv")
df = df.drop_duplicates(subset="EmployeeID")

# Map education level from numeric values to names
education_mapping = {
    1: 'High School',
    2: 'Associate Degree',
    3: 'Bachelor\'s Degree',
    4: 'Master\'s Degree',
    5: 'PhD'
}
df['EducationName'] = df['Education'].map(education_mapping)

# Create age groups
df['AgeGroup'] = pd.cut(df['Age'], bins=[0, 30, 40, 50, 60, float('inf')],
                        labels=['18-30', '31-40', '41-50', '51-60', '60+'])

# Calculate years at the company
df['YearsAtCompany'] = pd.to_datetime('today').year - pd.to_datetime(df['HireDate']).dt.year

# Group by department, age group, and education
employee_counts = df.groupby(['Department', 'AgeGroup', 'EducationName']).size().reset_index(name='Emp

# Assume fixed growth rate
employee_counts['GrowthRate'] = 1.0

# Define target year
year = 2025
future_predictions = employee_counts.copy()
future_predictions['Year'] = year
future_predictions['PredictedEmployeeCount'] = future_predictions['EmployeeCount'] * future_prediction

# Prepare plot data
data = future_predictions[['Year', 'Department', 'AgeGroup', 'EducationName', 'PredictedEmployeeCount']
data = data.copy()
data['Dept_AgeGroup'] = data['Department'] + ' | ' + data['AgeGroup'].astype(str)

# Plot grouped bar chart
plt.figure(figsize=(18, 8))
sns.barplot(data=data,
            x='Dept_AgeGroup',
            y='PredictedEmployeeCount',
            hue='EducationName',
            errorbar=None)

plt.title(f'Projected Workforce in {year} by Department, Age Group & Education Level')
plt.xlabel('Department & Age Group')
plt.ylabel('Number of Employees')
plt.legend(title='Education Level')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

```
/var/folders/03/94ymsk8j2tb7j29w9l6vkzzw0000gn/T/ipykernel_3152/3464113569.py:30: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future version of pandas. Pass observed=False to retain current behavior or observed=True to adopt the future default and silence this warning.
```



[213]:
```
########################## Ending of Week 3: Forecasting Questions Phase
```