

Employee Performance and Attrition Report

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1. Data Extraction: Loading CSV Files into Pandas

I began by extracting the data from the provided CSV files. The project involved three datasets: -

Employee Data: Contains personal and job-related details. - **Attrition Data:** Contains attrition flags and exit interview scores. - **Employee Performance Data:** Contains performance ratings, training hours, and other performance metrics.

I loaded each CSV into a Pandas DataFrame and ensured that the lower-case gender column was removed so that only the Gender column was used. Here is the code I used:

```
# Read CSV files
employee_df = pd.read_csv('employee_data 1.csv')
attrition_df = pd.read_csv('Attrition 1.csv')
performance_df = pd.read_csv('employee_performance_data 1.csv')

# Display initial shapes
print("Employee Data Shape:", employee_df.shape)
print("Attrition Data Shape:", attrition_df.shape)
print("Performance Data Shape:", performance_df.shape)

# Drop lower-case 'gender' column if it exists; keep only the 'Gender' column.
if 'gender' in employee_df.columns:
    employee_df = employee_df.drop(columns=['gender'])
print("Columns in employee_df after dropping 'gender':", employee_df.columns.tolist())
```

2. Data Transformation & Cleaning

After loading the data, I validated the uniqueness of the primary key (Employee_ID) in each dataset to ensure data integrity.

```
# Check uniqueness in employee data
if employee_df['Employee_ID'].is_unique:
    print("Employee_ID is unique in employee_data.")
else:
    print("Employee_ID has duplicates in employee_data.")

# Standardize column name in attrition data and check uniqueness
attrition_df.rename(columns={'employee_ID': 'Employee_ID'}, inplace=True)
if attrition_df['Employee_ID'].is_unique:
    print("Employee_ID is unique in attrition_data.")
else:
    print("Employee_ID has duplicates in attrition_data.")

# Check uniqueness in performance data
if performance_df['Employee_ID'].is_unique:
    print("Employee_ID is unique in performance_data.")
```

```
else:
    print("Employee_ID has duplicates in performance_data.")
```

I then merged the datasets: - I performed an inner join between employee_df and performance_df on Employee_ID to capture only the employees with available performance data. - I then left-joined the resulting DataFrame with attrition_df on Employee_ID.

Since the project required only complete records, I removed any rows that had missing values in either the attrition or Exit_Interview_Score columns.

Just because I don't have the data do not mean that those employee haven't left the company.

```
# Merge employee and performance data on Employee_ID (inner join)
emp_perf_df = pd.merge(employee_df, performance_df, on='Employee_ID', how='inner')
print("Shape after merging employee and performance data:", emp_perf_df.shape)
```

```
# Merge with attrition data (left join)
full_df = pd.merge(emp_perf_df, attrition_df, on='Employee_ID', how='left')
print("Shape before dropping incomplete records:", full_df.shape)
```

```
# Drop rows with missing values for 'attrition' or 'Exit_Interview_Score'
full_df = full_df.dropna(subset=['attrition', 'Exit_Interview_Score'])
print("Shape after dropping rows with missing attrition or exit interview score:",
      full_df.shape)
```

I also merged the first_name and last_name columns into a single name column in the employee dimension later in the process.

3. Creating Fact and Dimension Tables (Star Schema)

I then transformed the cleaned DataFrame into a star schema by creating one fact table and several dimension tables.

Fact Table: fact_employee_performance

This table captures performance metrics along with attrition and exit interview scores. It also includes surrogate key references for departments and job roles.

```
fact_table = full_df[['Employee_ID', 'Performance_Rating', 'Last_Promotion_Year',
                     'Training_Hours', 'Work_Life_Balance', 'Job_Satisfaction',
                     'attrition', 'Exit_Interview_Score']].copy()
```

Dimension Tables

Employee Dimension (dim_employee)

I excluded Department and Job_Role from this dimension, and I merged first_name and last_name into a new name column.

```
# Create Employee Dimension (exclude department and job role)
dim_employee = full_df[['Employee_ID', 'Age', 'first_name', 'last_name', 'Gender',
                       'Education_Level', 'Marital_Status', 'Job_Tenure',
                       'Distance_From_Home']].drop_duplicates()
```

```
# Merge first and last names into a single column 'name'
```

```
dim_employee['Name'] = dim_employee['first_name'] + ' ' + dim_employee['last_name']
dim_employee = dim_employee.drop(columns=['first_name', 'last_name'])
```

Department Dimension (dim_department)

I created a table containing unique departments and added a surrogate key:

```
dim_department = full_df[['Department']].drop_duplicates().reset_index(drop=True)
dim_department['Department_ID'] = dim_department.index + 1
print("Department Dimension Shape:", dim_department.shape)
```

Role Dimension (dim_role)

Similarly, I created a role dimension table:

```
dim_role = full_df[['Job_Role']].drop_duplicates().reset_index(drop=True)
dim_role['Role_ID'] = dim_role.index + 1
```

Next, I merged the department and role information into the fact table to reference their surrogate keys:

```
# First, add the original department and job role columns to fact table for the lookup.
```

```
fact_table = pd.merge(fact_table, full_df[['Employee_ID', 'Department', 'Job_Role']],
on='Employee_ID', how='left')
```

```
# Merge department ID from dim_department
```

```
fact_table = pd.merge(fact_table, dim_department, on='Department', how='left')
```

```
# Merge role ID from dim_role
```

```
fact_table = pd.merge(fact_table, dim_role, on='Job_Role', how='left')
```

```
# Remove redundant text columns (Department and Job_Role) after merging IDs
```

```
fact_table.drop(columns=['Department', 'Job_Role'], inplace=True)
```

```
print("Fact Table Shape:", fact_table.shape)
```

4. Removing Duplicate Employee_ID Records

Although I ensured data integrity during transformation, I also implemented a method to remove duplicate Employee_ID records directly from the fact_employee_performance table.

In SQL:

After loading the transformed data into MySQL, I used the following SQL code to remove any duplicate records from the fact_employee_performance table. To work around MySQL safe update mode, I disabled safe updates for the session:

```
-- Disable safe update mode for this session
```

```
SET SQL_SAFE_UPDATES = 0;
```

```
-- Add a temporary auto-increment primary key column
```

```
ALTER TABLE fact_employee_performance
```

```
ADD COLUMN temp_id INT AUTO_INCREMENT PRIMARY KEY;
```

```
-- Delete duplicate rows, keeping the row with the smallest temp_id for each Employee_ID
```

```
DELETE f1
FROM fact_employee_performance f1
INNER JOIN fact_employee_performance f2
    ON f1.Employee_ID = f2.Employee_ID
    AND f1.temp_id > f2.temp_id;
```

```
-- Remove the temporary column
```

```
ALTER TABLE fact_employee_performance
DROP COLUMN temp_id;
```

This SQL code ensures that only one record per Employee_ID remains in the fact table.

5. Loading Transformed Data into MySQL

I used SQLAlchemy to connect to the MySQL database and loaded the fact and dimension tables into their respective tables. Here is the code snippet:

```
from sqlalchemy import create_engine
# MySQL connection details
username = 'root'
password = '12345'
host = 'localhost'
port = '3306'
database = 'case3'
engine = create_engine(f'mysql+pymysql://{username}:{password}@{host}:{port}/{database}')

# Load tables into MySQL
fact_table.to_sql('fact_employee_performance', con=engine, if_exists='replace', index=False)
dim_employee.to_sql('dim_employee', con=engine, if_exists='replace', index=False)
dim_department.to_sql('dim_department', con=engine, if_exists='replace', index=False)
dim_role.to_sql('dim_role', con=engine, if_exists='replace', index=False)

print("Data loaded to MySQL successfully.")
```

6. KPI Tracking & Monitoring

- DAX measures

- Attrition Rate:

Attrition Rate =

DIVIDE(

CALCULATE(COUNTROWS(fact_employee_performance),
fact_employee_performance[attrition] = TRUE),

COUNTROWS(fact_employee_performance)

)

- **Retention Rate:**

Retention Rate = 1 - [Attrition Rate]

- **Average Tenure:**

Average Tenure = AVERAGE(dim_employee[Job_Tenure])

- **Department-wise Employee Score:**

Average Employee Satisfaction =
AVERAGE(fact_employee_performance[Job_Satisfaction])

- **Average Performance Rating:**

Average Performance Rating =
AVERAGE(fact_employee_performance[Performance_Rating])

- **Average Exit Interview Satisfaction Score:**

Average Exit Interview Score =
AVERAGE(fact_employee_performance[Exit_Interview_Score])

- **Department-wise Attrition Rate:**

Dept Attrition Rate =

DIVIDE(

CALCULATE(COUNTROWS(fact_employee_performance),
fact_employee_performance[attrition] = TRUE),

COUNTROWS(fact_employee_performance)

)

- Employee Satisfaction Score:

```
25 -- 1. Employee Satisfaction Score (using Job_Satisfaction as a proxy)
26 • SELECT AVG(Job_Satisfaction) AS avg_employee_satisfaction
27 FROM fact_employee_performance;
```

Result Grid
avg_employee_satisfaction
2.8346

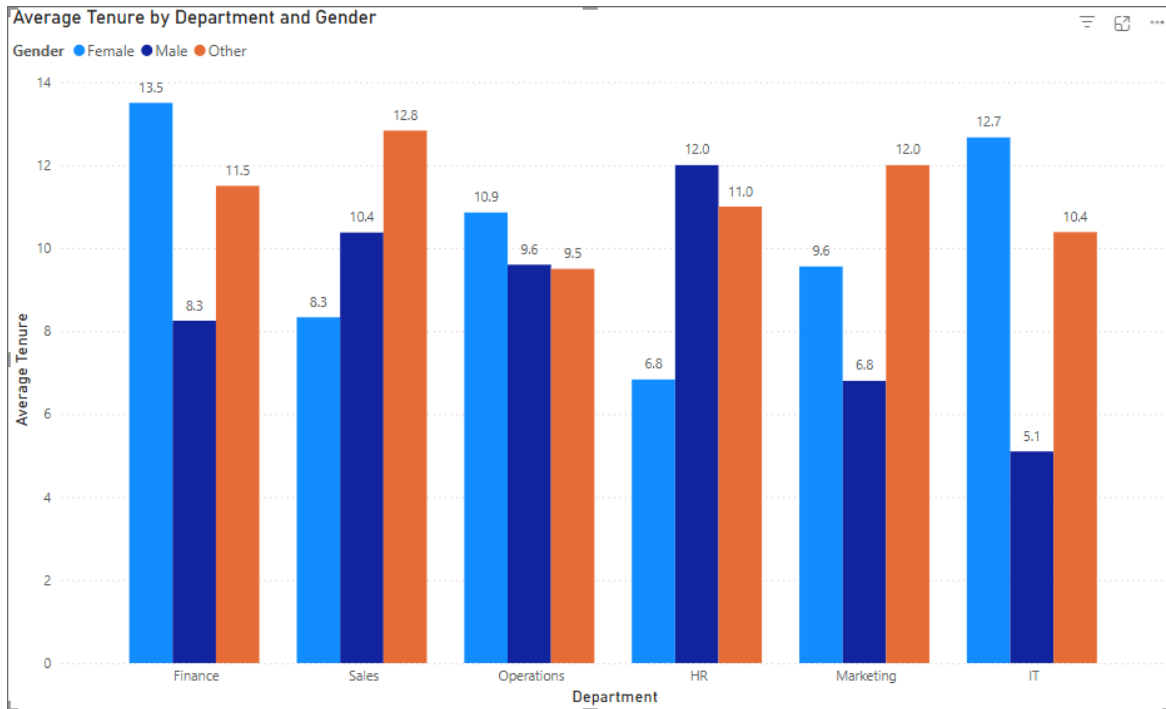
- Average Tenure:

```

29 -- 2. Average Tenure (from the employee dimension)
30 • SELECT AVG(Job_Tenure) AS avg_tenure
31 FROM dim_employee;

```

Result Grid	Filter Rows:	Export:	Wrap Cell Content
avg_tenure			
9.8898			



- Attrition Rate:

```

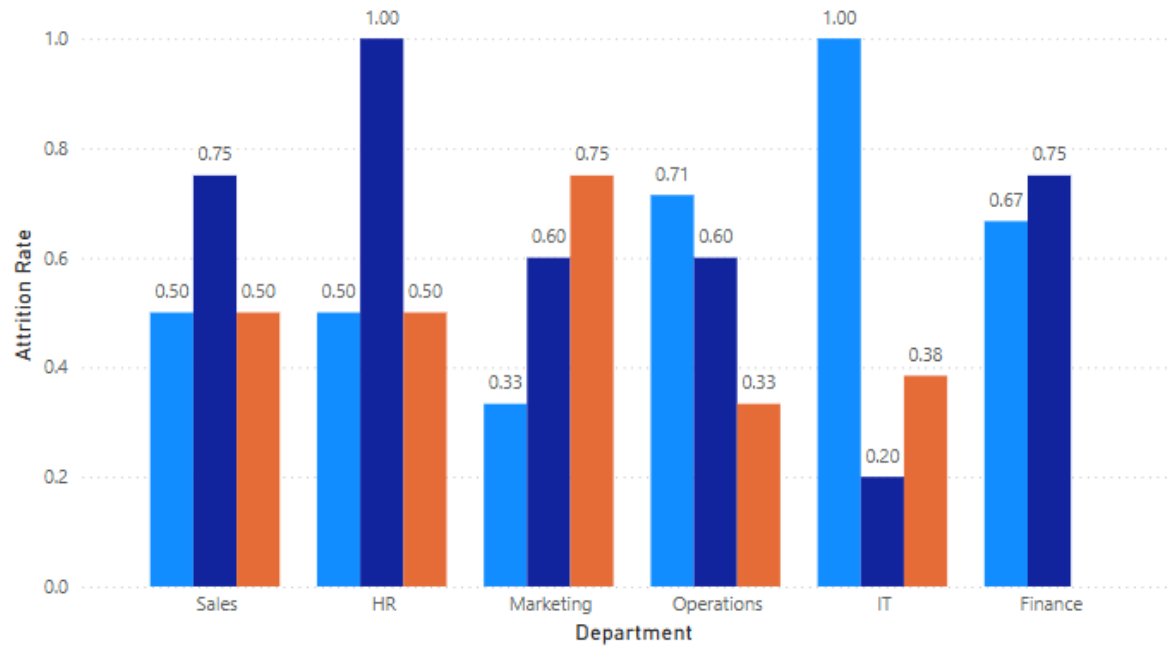
33 -- 3. Attrition Rate: Percentage of employees who left
34 • SELECT
35 (SUM(CASE WHEN attrition = TRUE THEN 1 ELSE 0 END) / COUNT(*)) * 100 AS attrition_rate_percentage
36 FROM fact_employee_performance;
37

```

Result Grid	Filter Rows:	Export:	Wrap Cell Content
attrition_rate_percentage			
48.0315			

Attrition Rate by Department and Gender

Gender ● Female ● Male ● Other



- Performance Rating Distribution:

```

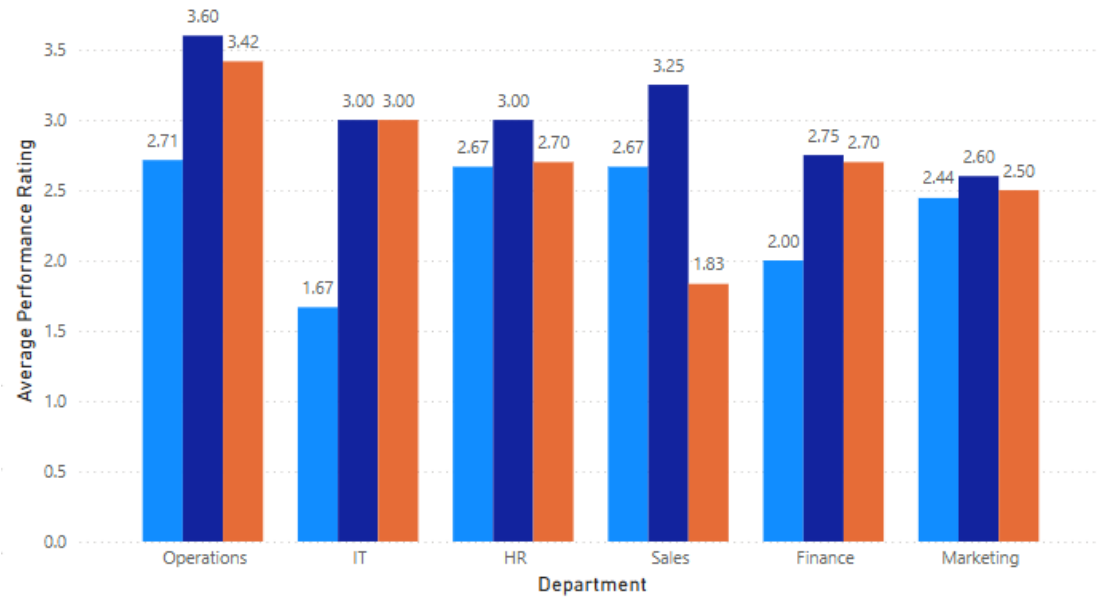
38  -- 4. Performance Rating Distribution: Count employees by performance rating
39  ●  SELECT
40      Performance_Rating,
41      COUNT(*) AS employee_count
42  FROM fact_employee_performance
43  GROUP BY Performance_Rating
44  ORDER BY Performance_Rating;
45

```

Result Grid			Filter Rows:	Export:	Wrap Cell Content:
	Performance_Rating	employee_count			
▶	1	28			
	2	31			
	3	27			
	4	24			
	5	17			

Average Performance Rating by Department and Gender

Gender ● Female ● Male ● Other



- Department-wise Attrition Trends:

```

46 -- 5. Department-wise Attrition Trends: Attrition rate per department
47 • SELECT
48     d.Department,
49     COUNT(*) AS total_employees,
50     SUM(CASE WHEN f.attrition = TRUE THEN 1 ELSE 0 END) AS total_attritions,
51     (SUM(CASE WHEN f.attrition = TRUE THEN 1 ELSE 0 END) / COUNT(*)) * 100 AS attrition_rate_percentage
52 FROM fact_employee_performance f
53 JOIN dim_department d ON f.Department_ID = d.Department_ID
54 GROUP BY d.Department;
55

```

Result Grid				
Filter Rows:		Export:		
Department	total_employees	total_attritions	attrition_rate_percentage	
IT	26	10	38.4615	
Marketing	18	9	50.0000	
Finance	20	7	35.0000	
HR	19	11	57.8947	
Operations	24	12	50.0000	
Sales	20	12	60.0000	

- Exit Interview Sentiment Analysis:

Given below are average Exit_Interview_Score per department. I cannot do Text analysis because there is no text/transcript to analyse.


```

56 • SELECT
57     d.Department,
58     AVG(f.Exit_Interview_Score) AS avg_exit_interview_score
59 FROM
60     fact_employee_performance f
61 JOIN
62     dim_department d
63     ON f.Department_ID = d.Department_ID
64 GROUP BY
65     d.Department;
66

```

Result Grid		Filter Rows:	Export:	Wrap Cell Content:
Department	avg_exit_interview_score			
IT	3.1153846153846154			
Marketing	3.388888888888889			
Finance	2.9			
HR	3.0526315789473686			
Operations	3.375			
Sales	3.15			

- Attrition Rate, Retention Rate, Average Tenure, Average Performance Rating, Average Performance Rating

2.83

Average Employee Satisfaction

2.77

Average Performance Rating

0.52

Retention Rate

3.17

Average Exit Interview Score

9.89

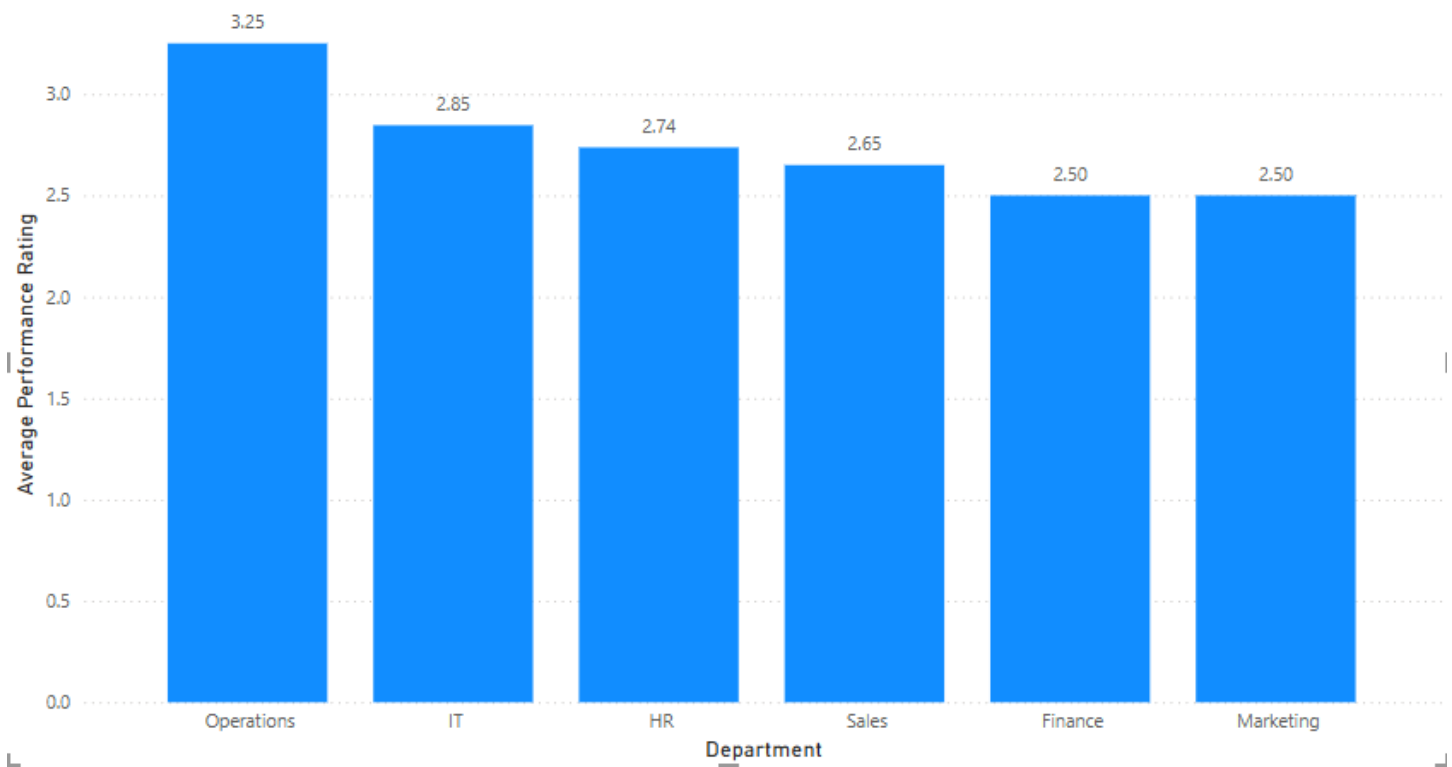
Average Tenure

0.48

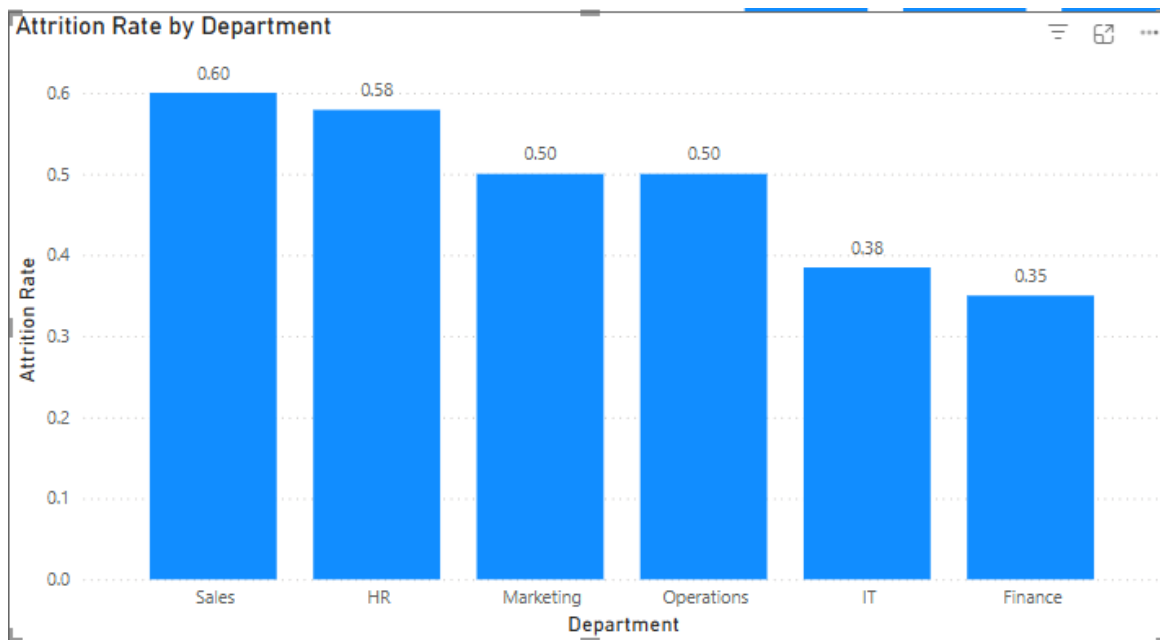
Attrition Rate

- Department-wise Employee Score – I assumed performance rating is same as employee code.

Average Performance Rating by Department



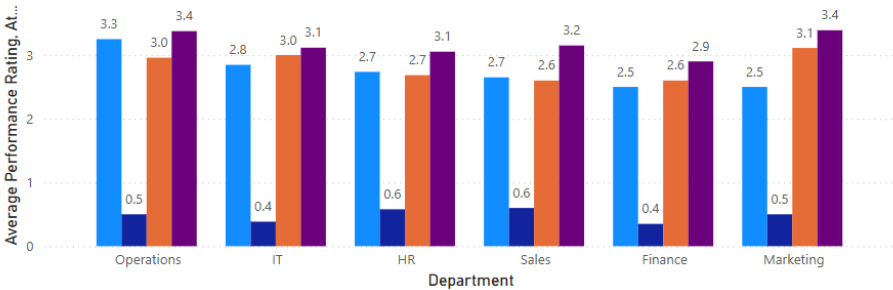
- Department wise Attrition Rate



- Overall

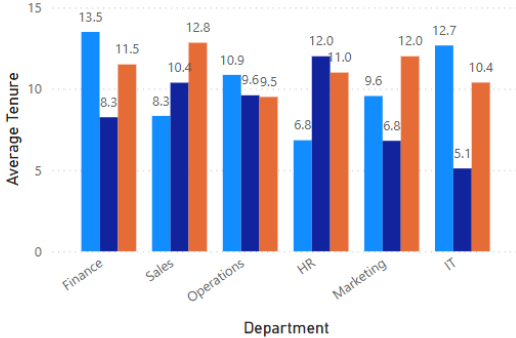
Average Performance Rating, Attrition Rate, Average Employee Satisfaction and Average Exit Interview Score by Department

● Average Performance Rating ● Attrition Rate ● Average Employee Satisfaction ● Average Exit Interview Score



Average Tenure by Department and Gender

Gender ● Female ● Male ● Other



Training_Hours	attrition	Distance_From_Home
197	False	1
196	False	44
196	True	31
193	True	11
192	False	30
190	False	23
190	True	37
187	False	28
182	False	33
181	False	29
181	True	21
180	False	39
180	True	10
179	True	39
177	False	37
176	False	6

Job_Role, Education_Level

^ ☐ Data Analyst

☐ Bachelor's

☐ Master's

☐ PhD

^ ☐ Developer

^ ☐ HR Specialist

^ ☐ Manager

^ ☐ Marketing Lead

^ ☐ Senior Developer

2.83

Average Employee Satisfaction

2.77

Average Performance Rating

0.52

Retention Rate

3.17

Average Exit Interview Score

9.89

Average Tenure

0.48

Attrition Rate

7. Conclusion

Department-Level Observations:

- **HR** appears to have the **highest performance rating** and **highest employee satisfaction** among departments. Correspondingly, it shows a **lower attrition rate** and relatively higher exit interview scores.
 - **Interpretation:** HR's strong performance and job satisfaction likely contribute to reduced turnover.
- **Marketing** exhibits the **highest attrition rate** alongside the **lowest satisfaction** and **lowest exit interview scores**.
 - **Interpretation:** High turnover may be tied to lower satisfaction; it suggests a need for deeper investigation into work conditions, role expectations, or leadership in Marketing.
- **IT** and **Finance** fall somewhere in the middle, with moderate performance ratings and satisfaction. However, Finance's attrition rate is somewhat high, indicating room for improvement.
- **Operations** has moderately high attrition but not as severe as Marketing, suggesting some departmental-specific issues.

Average Tenure Differences:

- **HR** employees tend to have **longer average tenure**, suggesting higher retention and possibly better internal mobility or more favorable work conditions.
- **Marketing** tends to show **shorter average tenure**, aligning with the higher attrition rate. This could point to burnout, role dissatisfaction, or a mismatch in job expectations.

Overall Company Metrics:

- **Average Employee Satisfaction** is around **2.83** (on the scale shown). This is neither very high nor extremely low, but it does leave room for improvement.
- **Average Performance Rating** is **2.77**, indicating that most employees are performing moderately. Departments like HR stand out with slightly higher averages, while Marketing and Finance might need targeted performance management interventions.
- **Average Exit Interview Score** is **2.52**, which suggests that employees who do leave have mixed feelings. Departments with particularly low scores (like Marketing) should investigate root causes—possibly leadership issues, workload concerns, or career development opportunities.
- **Attrition Rate** of **0.48** (48%) is notably high. This signals that nearly half of the workforce observed may be leaving in the measured period. Reducing attrition, especially in high-turnover departments, should be a top priority.
- **Average Tenure** is around **9.89 years**, which is reasonably long overall, but it likely skews higher in departments like HR and lower in Marketing.

Actionable Insights & Recommendations:

- **Focus on Marketing:** With the highest attrition rate and lowest satisfaction, it's crucial to investigate whether employees have clear career paths, sufficient resources, and supportive management.
- **Boost Overall Satisfaction:** Since satisfaction correlates with lower attrition, HR interventions—like flexible schedules, better recognition, and clearer promotion paths—could improve retention.
- **Continue HR Best Practices:** The HR department's relatively high satisfaction and lower attrition can be used as a case study for best practices—potentially replicating them in other departments.