HR Data Analytics for Business Decision-Making (MNC Project)

Importing Libraries

In [4]:
```
pip install --upgrade plotly
```

```
Requirement already satisfied: plotly in /usr/local/lib/python3.12/dist-pack
ages (5.24.1)
Collecting plotly
  Downloading plotly-6.3.0-py3-none-any.whl.metadata (8.5 kB)
Requirement already satisfied: narwhals>=1.15.1 in /usr/local/lib/python3.1
2/dist-packages (from plotly) (2.3.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.12/dist-p
ackages (from plotly) (25.0)
Downloading plotly-6.3.0-py3-none-any.whl (9.8 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9.8/9.8 MB 52.4 MB/s eta 0:00:00
Installing collected packages: plotly
  Attempting uninstall: plotly
    Found existing installation: plotly 5.24.1
    Uninstalling plotly-5.24.1:
      Successfully uninstalled plotly-5.24.1
Successfully installed plotly-6.3.0
```

In [3]:
```
!pip install squarify
```

```
Collecting squarify
  Downloading squarify-0.4.4-py3-none-any.whl.metadata (600 bytes)
Downloading squarify-0.4.4-py3-none-any.whl (4.1 kB)
Installing collected packages: squarify
Successfully installed squarify-0.4.4
```

In [5]:
```
import numpy as np
import pandas as pd
import os
import squarify
import matplotlib.pyplot as plt
import plotly.express as px
import plotly.graph_objects as go
import seaborn as sns
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import LabelEncoder
```

In [8]:
```
hr_data = pd.read_csv("/content/HR_Data_MNC.csv")
```

In [9]:
```
hr_data.head(10)
```

Out[9]:

	Unnamed: 0	Employee_ID	Full_Name	Department	Job_Title	Hire_Date	
0	0	EMP0000001	Joshua Nguyen	IT	Software Engineer	2011-08-10	
1	1	EMP0000002	Julie Williams	Marketing	SEO Specialist	2018-03-02	
2	2	EMP0000003	Alyssa Martinez	HR	HR Manager	2023-03-20	
3	3	EMP0000004	Nicholas Valdez	IT	Software Engineer	2023-10-12	
4	4	EMP0000005	Joel Hendricks	Operations	Logistics Coordinator	2024-12-09	
5	5	EMP0000006	Jason Gardner	Operations	Logistics Coordinator	2021-02-23	Zi
6	6	EMP0000007	Julie Wright	Finance	Finance Manager	2016-04-04	K
7	7	EMP0000008	Scott Wilson	Sales	Account Manager	2020-04-04	
8	8	EMP0000009	Cathy Thompson	Finance	Financial Analyst	2018-05-29	S
9	9	EMP0000010	Maria Yu MD	IT	Software Engineer	2015-10-08	

In [10]:
```
hr_data.shape
```

Out[10]:
```
(86754, 12)
```

In [11]:
```
print(hr_data.info(), "\n")
print(hr_data.isnull().sum())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 86754 entries, 0 to 86753
Data columns (total 12 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   Unnamed: 0          86754 non-null  int64  
 1   Employee_ID         86754 non-null  object 
 2   Full_Name           86754 non-null  object 
 3   Department          86754 non-null  object 
 4   Job_Title           86754 non-null  object 
 5   Hire_Date           86753 non-null  object 
 6   Location            86753 non-null  object 
 7   Performance_Rating  86753 non-null  float64
 8   Experience_Years    86753 non-null  float64
 9   Status              86753 non-null  object 
 10  Work_Mode           86753 non-null  object 
 11  Salary_INR          86753 non-null  float64
dtypes: float64(3), int64(1), object(8)
memory usage: 7.9+ MB
None

Unnamed: 0            0
Employee_ID           0
Full_Name             0
Department            0
Job_Title             0
Hire_Date             1
Location              1
Performance_Rating    1
Experience_Years      1
Status                1
Work_Mode             1
Salary_INR            1
dtype: int64
```

In [12]:
```
hr_data.count()
```

Out[12]:

	0
Unnamed: 0	86754
Employee_ID	86754
Full_Name	86754
Department	86754
Job_Title	86754
Hire_Date	86753
Location	86753
Performance_Rating	86753
Experience_Years	86753
Status	86753
Work_Mode	86753
Salary_INR	86753

dtype: int64

In [13]:
```
hr_data.columns
```

Out[13]:
```
Index(['Unnamed: 0', 'Employee_ID', 'Full_Name', 'Department', 'Job_Title',
       'Hire_Date', 'Location', 'Performance_Rating', 'Experience_Years',
       'Status', 'Work_Mode', 'Salary_INR'],
      dtype='object')
```

In [14]:
```
hr_data.columns = hr_data.columns.str.upper()
```

In [15]:
```
hr_data
```

Out[15]:

	UNNAMED: 0	EMPLOYEE_ID	FULL_NAME	DEPARTMENT	JOB_TITLE	HIRI
0	0	EMP0000001	Joshua Nguyen	IT	Software Engineer	201
1	1	EMP0000002	Julie Williams	Marketing	SEO Specialist	201
2	2	EMP0000003	Alyssa Martinez	HR	HR Manager	202
3	3	EMP0000004	Nicholas Valdez	IT	Software Engineer	202
4	4	EMP0000005	Joel Hendricks	Operations	Logistics Coordinator	202
...	...	...	...	...	...	
86749	86749	EMP0086750	Heather Price	HR	HR Director	201
86750	86750	EMP0086751	Robert Jones	Finance	Financial Analyst	202
86751	86751	EMP0086752	Erica Brown	Sales	Sales Executive	201
86752	86752	EMP0086753	Kathleen Mccormick	IT	Software Engineer	202
86753	86753	EMP0086754	Rebecca Wilson	R&D	Lab Technician	

86754 rows × 12 columns

In [16]:
```
# Rename the column
hr_data.rename(columns={'UNNAMED: 0': 'SI.'}, inplace=True)
```

In [17]:
```
# Verify the change
hr_data.head()
```

Out[17]:

	SI.	EMPLOYEE_ID	FULL_NAME	DEPARTMENT	JOB_TITLE	HIRE_DATE	L(
0	0	EMP0000001	Joshua Nguyen	IT	Software Engineer	2011-08-10	I
1	1	EMP0000002	Julie Williams	Marketing	SEO Specialist	2018-03-02	Ant C
2	2	EMP0000003	Alyssa Martinez	HR	HR Manager	2023-03-20	Chri Sau
3	3	EMP0000004	Nicholas Valdez	IT	Software Engineer	2023-10-12	Shelb An
4	4	EMP0000005	Joel Hendricks	Operations	Logistics Coordinator	2024-12-09	Lake P.

In [18]:
```
hr_data.count()
```

Out[18]:

	0
SI.	86754
EMPLOYEE_ID	86754
FULL_NAME	86754
DEPARTMENT	86754
JOB_TITLE	86754
HIRE_DATE	86753
LOCATION	86753
PERFORMANCE_RATING	86753
EXPERIENCE_YEARS	86753
STATUS	86753
WORK_MODE	86753
SALARY_INR	86753

dtype: int64

In [19]:
```
hr_data.describe()
```

Out[19]:

	SI.	PERFORMANCE_RATING	EXPERIENCE_YEARS	SALARY_IN
count	86754.000000	86753.000000	86753.000000	8.675300e+0
mean	43376.500000	3.004784	5.026097	8.951380e+0
std	25043.866964	1.414780	3.615067	4.007010e+0
min	0.000000	1.000000	0.000000	3.002550e+0
25%	21688.250000	2.000000	2.000000	6.154810e+0
50%	43376.500000	3.000000	5.000000	8.103920e+0
75%	65064.750000	4.000000	8.000000	1.072905e+0
max	86753.000000	5.000000	15.000000	2.997010e+0

1. What is the distribution of Employee Status (Active, Resigned, Retired, Terminated)?

In [20]:

```
# Check unique values in STATUS column
hr_data['STATUS'].value_counts()
```

Out[20]:

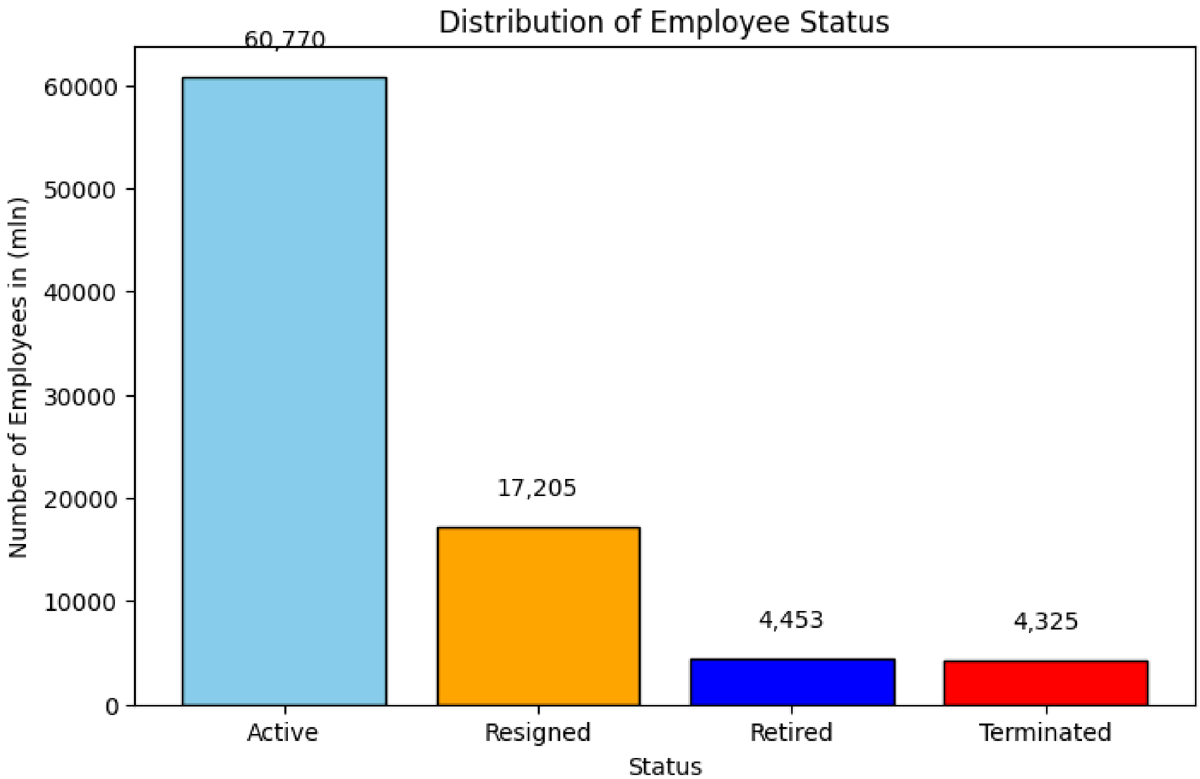
STATUS	count
Active	60770
Resigned	17205
Retired	4453
Terminated	4325

dtype: int64

In [21]:

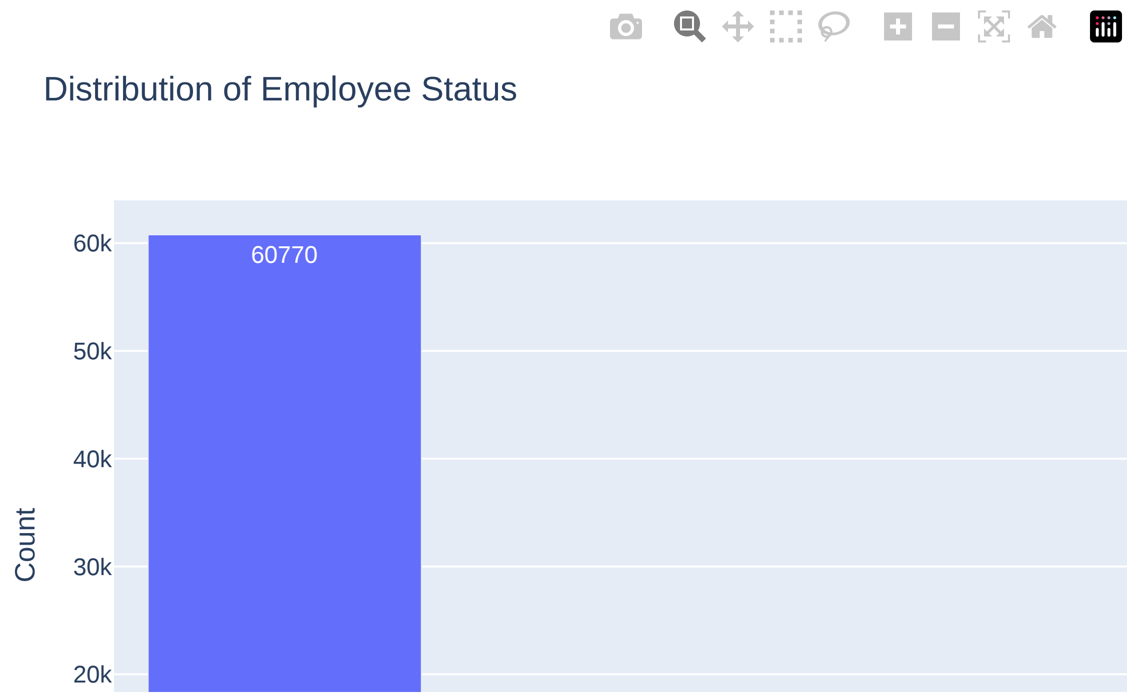
```
import matplotlib.pyplot as plt
from matplotlib.ticker import ScalarFormatter

status_counts = hr_data['STATUS'].value_counts()
colors = ['skyblue', 'orange', 'blue', 'red']

plt.figure(figsize=(8,5))
bars = plt.bar(status_counts.index, status_counts.values, color=colors, edge

# Add values on top
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, height + 2500, f'{height:,}',

# Format y-axis to show normal numbers instead of scientific notation
```

```
plt.gca().yaxis.set_major_formatter(ScalarFormatter())
plt.title('Distribution of Employee Status')
plt.xlabel('Status')
plt.ylabel('Number of Employees in (mln)')
plt.xticks(rotation=0)
plt.show()
```



In [22]:

```
import plotly.express as px

# Prepare the value counts
status_counts = hr_data['STATUS'].value_counts().reset_index()
status_counts.columns = ['Status', 'Count']  # Rename columns properly

# Plot
fig = px.bar(status_counts,
             x='Status',
             y='Count',
             title='Distribution of Employee Status',
             color='Status',
             text='Count')  # Show counts on bars

fig.show()
```



2. What is the distribution of work modes (On-site, Remote)?

In [23]:
```
# Check unique work modes and counts
hr_data['WORK_MODE'].value_counts()
```

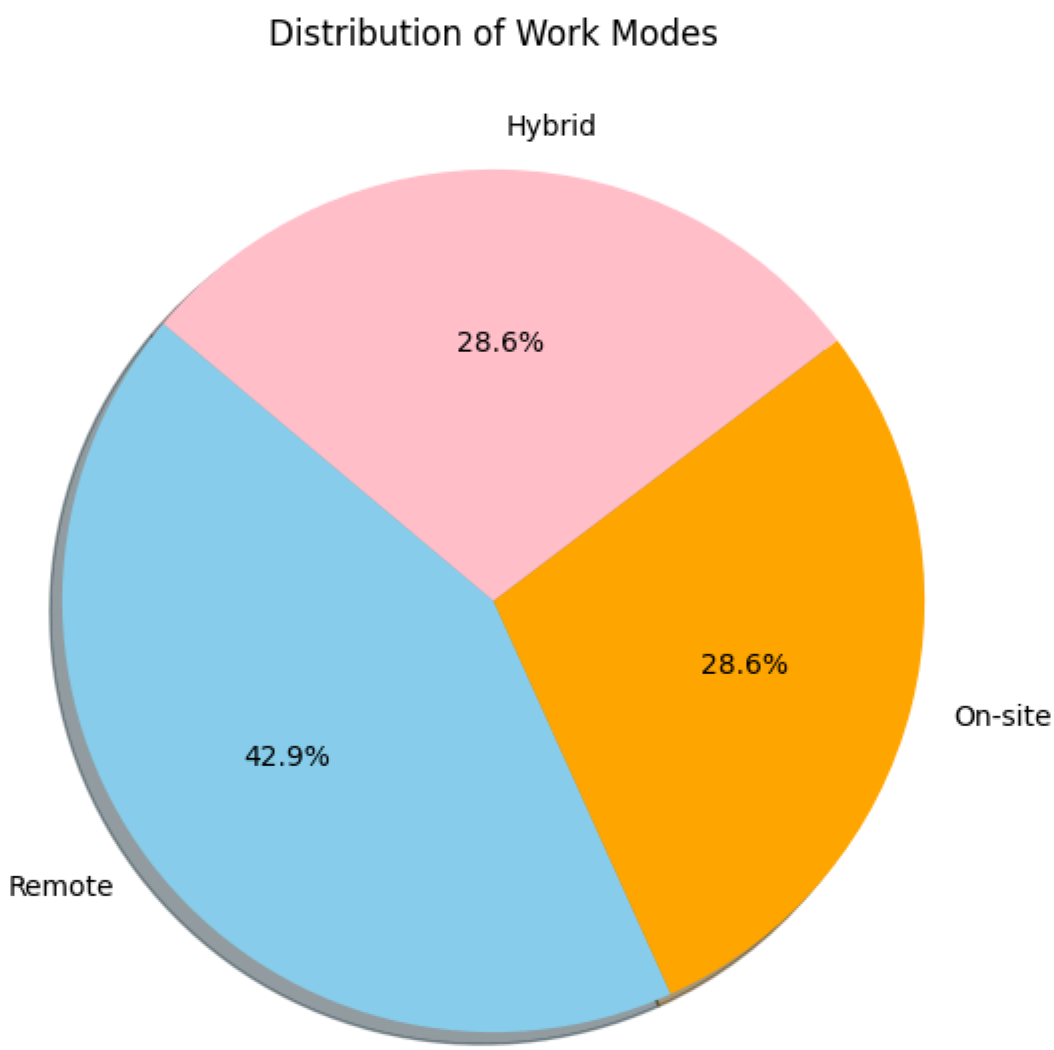
Out[23]:

WORK_MODE	count
On-site	51795
Remote	34958

dtype: int64

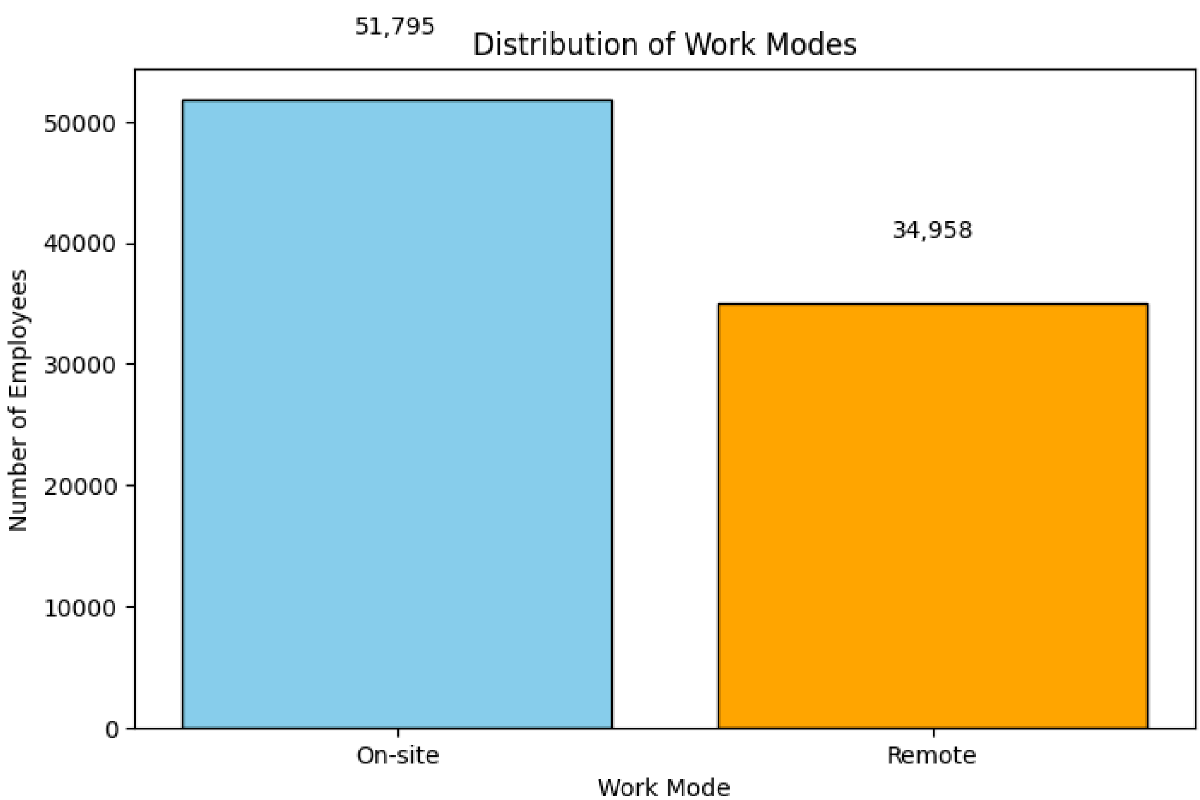
In [24]:
```
import matplotlib.pyplot as plt
import pandas as pd

# Example dataset (you can replace with your actual data)
```

```python
data = ['Remote', 'On-site', 'Hybrid', 'Remote', 'Remote', 'Hybrid', 'On-sit

# Count occurrences of each work mode
work_mode_counts = pd.Series(data).value_counts()

# Define colors (adjust if categories differ)
colors = ['skyblue', 'orange', 'pink']

# Plot pie chart
plt.figure(figsize=(7,7))
plt.pie(work_mode_counts,
        labels=work_mode_counts.index,
        autopct='%1.1f%%',   # Show percentage with 1 decimal
        startangle=140,
        colors=colors,
        shadow=True)

plt.title('Distribution of Work Modes')
plt.show()
```



In [25]:

```python
import matplotlib.pyplot as plt
from matplotlib.ticker import ScalarFormatter

# Count of each work mode
work_mode_counts = hr_data['WORK_MODE'].value_counts()

# Define colors for each work mode
colors = ['skyblue', 'orange', 'green']  # Adjust based on number of categor

# Plot
plt.figure(figsize=(8,5))
bars = plt.bar(work_mode_counts.index, work_mode_counts.values, color=colors

# Add values on top of each bar
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, height + 5000, f'{height:,}',

# Format y-axis to show normal numbers instead of scientific notation
plt.gca().yaxis.set_major_formatter(ScalarFormatter())

plt.title('Distribution of Work Modes')
plt.xlabel('Work Mode')
plt.ylabel('Number of Employees')
plt.xticks(rotation=0)
plt.show()
```

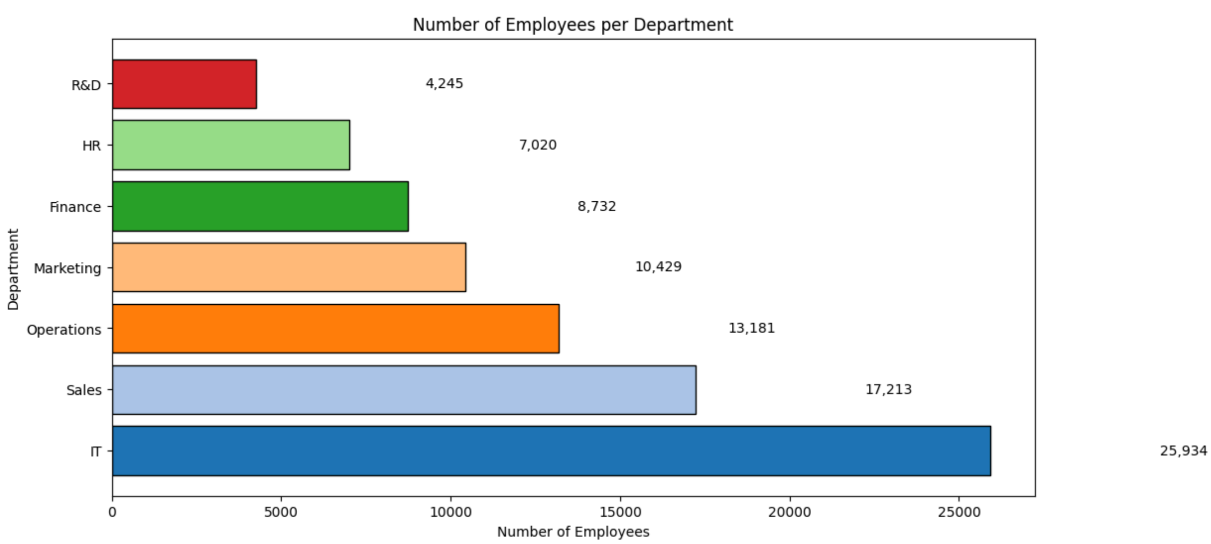


3. How many employees are there in each department?

In [26]:
```
# Count of employees in each department
department_counts = hr_data['DEPARTMENT'].value_counts()

# Display counts
print(department_counts)
```

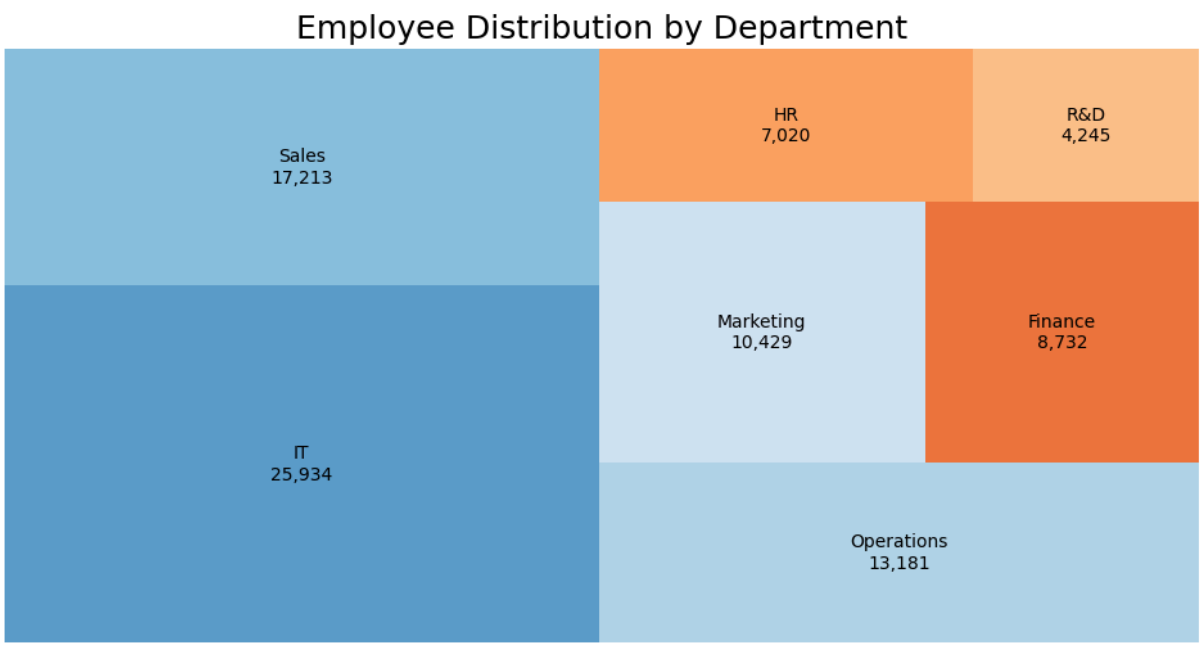
```
DEPARTMENT
IT            25934
Sales         17213
Operations    13181
Marketing     10429
Finance        8732
HR             7020
R&D            4245
Name: count, dtype: int64
```

In [27]:
```
plt.figure(figsize=(12,6))
bars = plt.barh(department_counts.index, department_counts.values, color=plt

# Add values
for bar in bars:
    width = bar.get_width()
    plt.text(width + 5000, bar.get_y() + bar.get_height()/2, f'{width:,}', v

plt.gca().xaxis.set_major_formatter(ScalarFormatter())
plt.xlabel('Number of Employees')
plt.ylabel('Department')
plt.title('Number of Employees per Department')
plt.show()
```



In [28]:
```
import matplotlib.pyplot as plt
import squarify
```

```python
# Sort departments by size (optional, makes treemap look better)
department_counts_sorted = department_counts.sort_values(ascending=False)

# Create color palette (enough colors for all departments)
colors = plt.cm.tab20c.colors  # Use tab20c colormap

# Create the treemap
plt.figure(figsize=(12,6))
squarify.plot(
    sizes=department_counts_sorted.values,
    label=[f"{dept}\n{count:,}" for dept, count in zip(department_counts_sor
    color=colors*10,  # Repeat colors if departments > 20
    alpha=0.8
)

plt.title('Employee Distribution by Department', fontsize=18)
plt.axis('off')  # Remove axes
plt.show()
```



4. What is the average salary by Department?

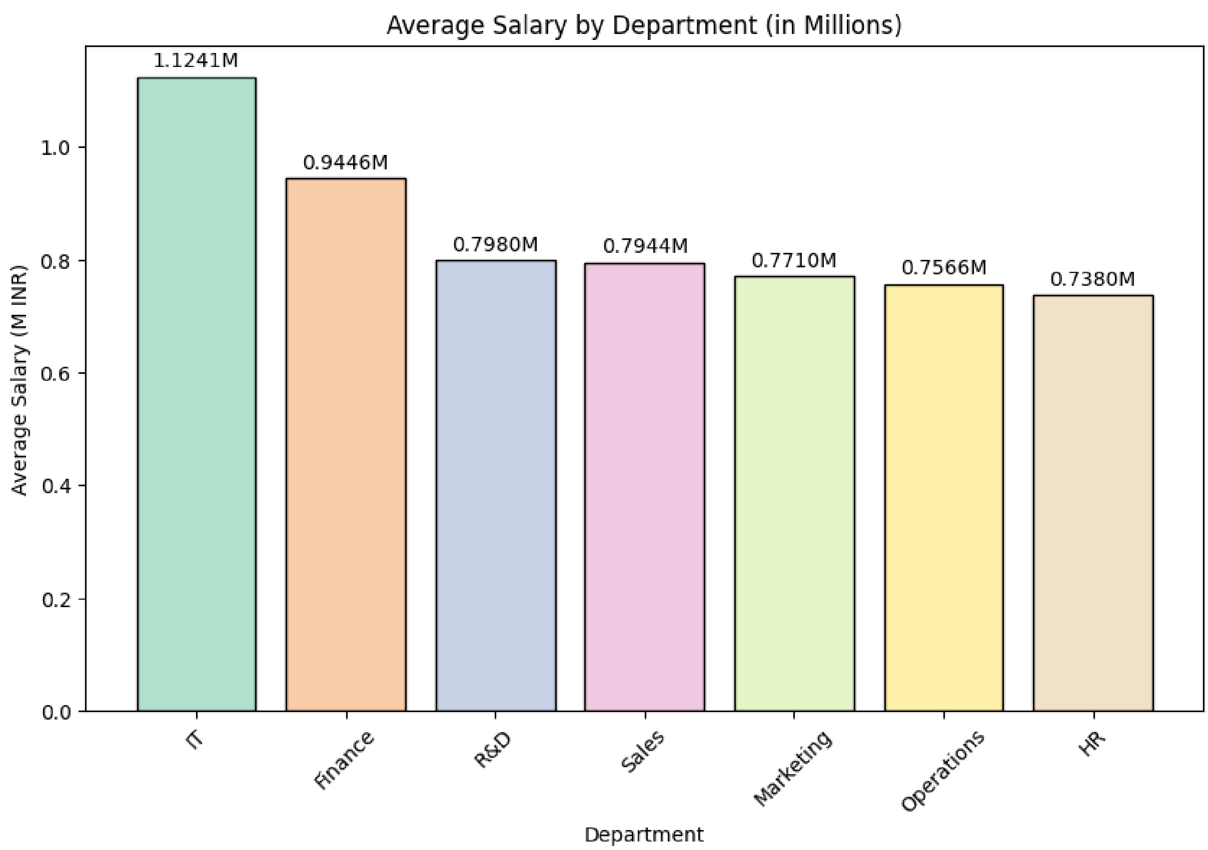
In [29]:

```python
# Average salary per department rounded to 4 decimals
avg_salary_dept = hr_data.groupby('DEPARTMENT')['SALARY_INR'].mean().round(4

# Format output to show as 1.1298 instead of scientific notation
avg_salary_dept_formatted = avg_salary_dept.apply(lambda x: float(f"{x/1e6:.

# Display
print(avg_salary_dept_formatted)
```

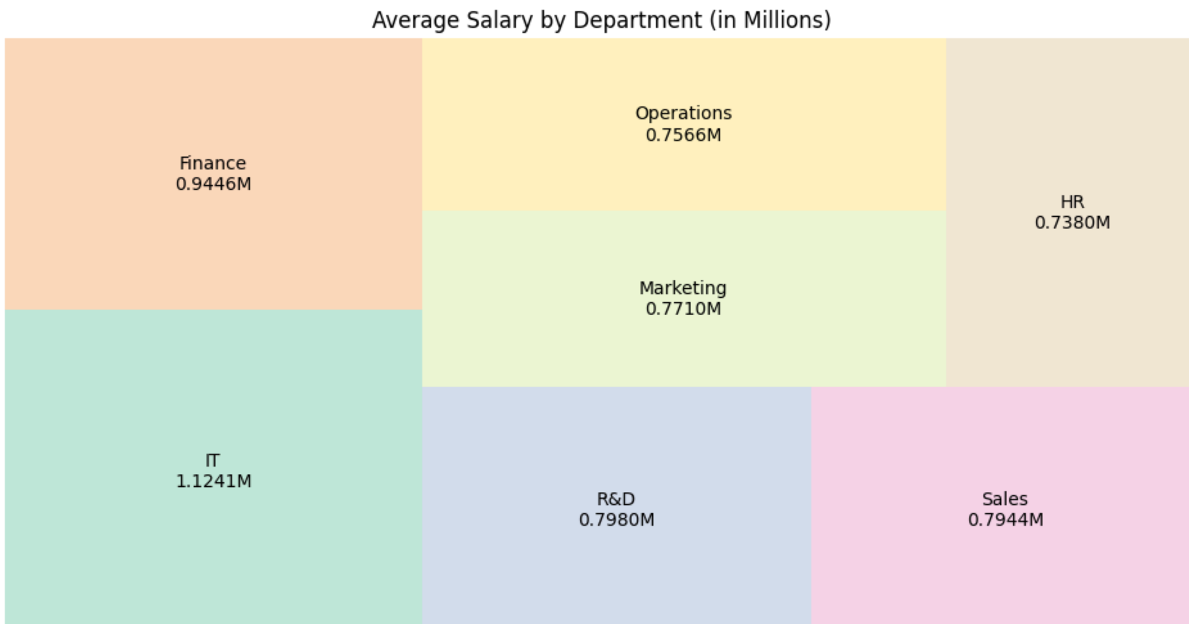
```
DEPARTMENT
IT            1.1241
Finance       0.9446
R&D           0.7980
Sales         0.7944
Marketing     0.7710
Operations    0.7566
HR            0.7380
Name: SALARY_INR, dtype: float64
```

In [30]:

```python
import matplotlib.pyplot as plt

# Colors for bars
colors = plt.cm.Pastel2.colors

plt.figure(figsize=(10,6))
bars = plt.bar(avg_salary_dept.index, avg_salary_dept.values / 1e6, color=co

# Show values on top of each bar
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, height + 0.01, f'{height:.4f}M

plt.title('Average Salary by Department (in Millions)')
plt.xlabel('Department')
plt.ylabel('Average Salary (M INR)')
plt.xticks(rotation=45)
plt.show()
```



In [31]:
```python
import squarify

plt.figure(figsize=(12,6))
squarify.plot(
    sizes=avg_salary_dept.values / 1e6,
    label=[f"{dept}\n{salary:.4f}M" for dept, salary in zip(avg_salary_dept.
    color=colors*10,
    alpha=0.8
)
plt.title('Average Salary by Department (in Millions)')
plt.axis('off')
plt.show()
```



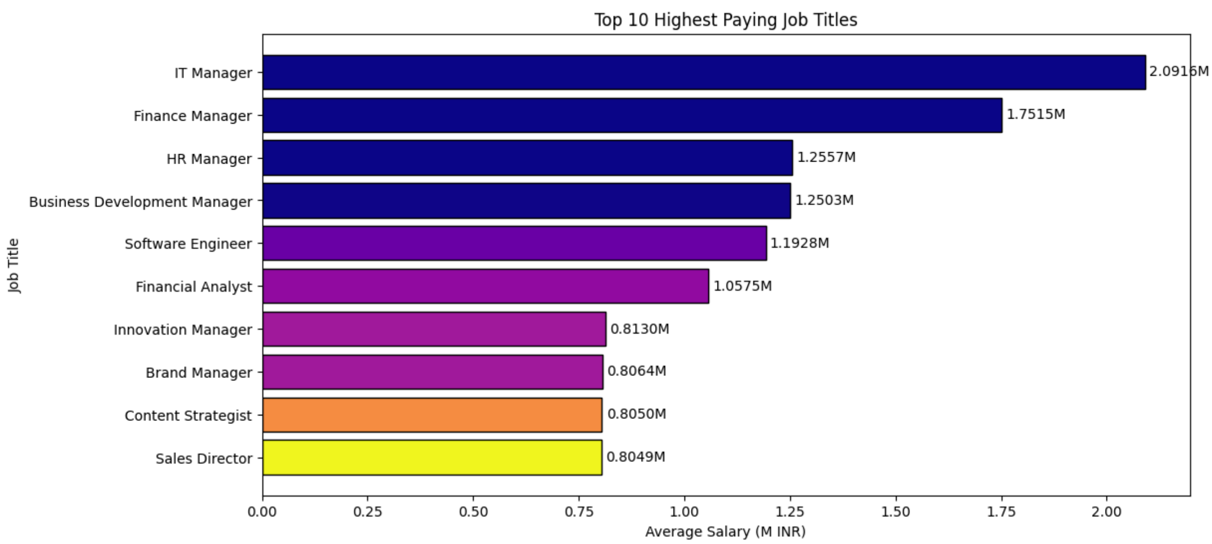
5. Which job title has the highest average salary?

In [32]:
```python
# Average salary per Job Title
avg_salary_job = hr_data.groupby('JOB_TITLE')['SALARY_INR'].mean()

# Find the job title with the highest average salary
highest_salary_job = avg_salary_job.idxmax()
highest_salary_value = avg_salary_job.max()

print(f"Job Title with Highest Average Salary: {highest_salary_job}")
print(f"Average Salary: {highest_salary_value:,.2f} INR")
```

```
Job Title with Highest Average Salary: IT Manager
Average Salary: 2,091,632.61 INR
```

In [33]:
```python
import matplotlib.pyplot as plt
import matplotlib

# Top 10 highest paying jobs
```

```
top_10_jobs = avg_salary_job.sort_values(ascending=False).head(10)

# Normalize salary values for color intensity
norm = matplotlib.colors.Normalize(vmin=min(top_10_jobs.values), vmax=max(to
cmap = plt.cm.plasma  # You can try 'viridis', 'cividis', 'coolwarm'
colors = [cmap(norm(value)) for value in top_10_jobs.values]

# Plot
plt.figure(figsize=(12,6))
bars = plt.barh(top_10_jobs.index[::-1], top_10_jobs.values[::-1]/1e6, color

# Show salary values on bars
for bar, value in zip(bars, top_10_jobs.values[::-1]/1e6):
    plt.text(bar.get_width() + 0.01, bar.get_y() + bar.get_height()/2, f'{va

plt.xlabel('Average Salary (M INR)')
plt.ylabel('Job Title')
plt.title('Top 10 Highest Paying Job Titles')
plt.show()
```

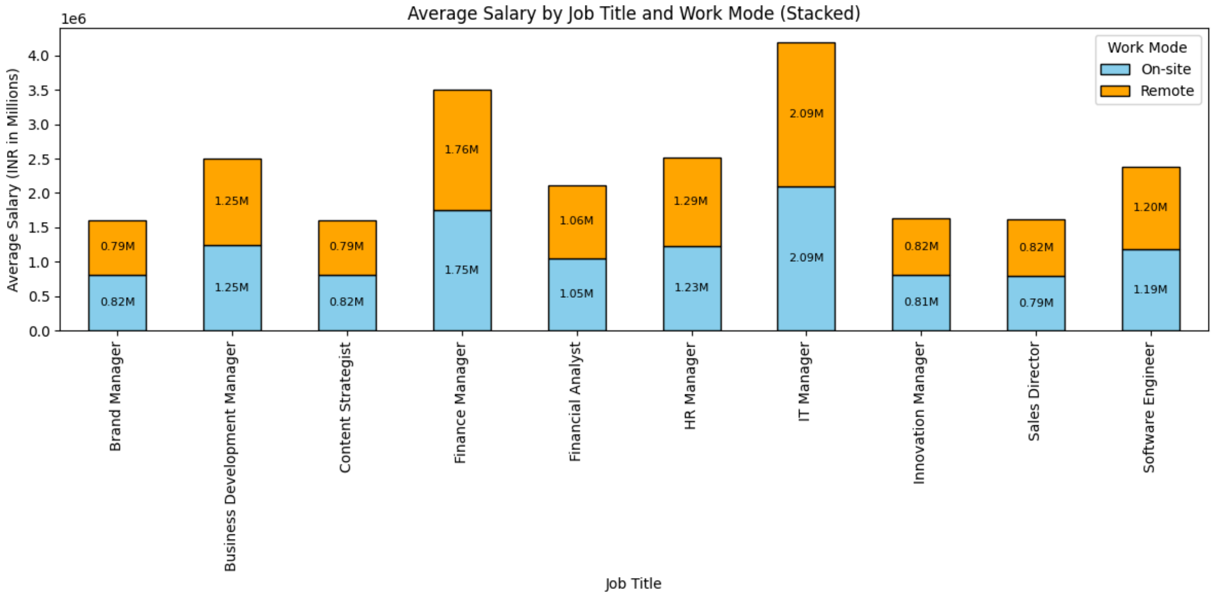


In [34]:
```
# Top 10 highest paying jobs
top_10_jobs_list = avg_salary_job.sort_values(ascending=False).head(10).inde

# Filter dataset for these jobs
top_jobs_data = hr_data[hr_data['JOB_TITLE'].isin(top_10_jobs_list)]

# Group by JOB_TITLE and WORK_MODE, then calculate average salary
stacked_data = top_jobs_data.groupby(['JOB_TITLE', 'WORK_MODE'])['SALARY_INR

# Display
print(stacked_data)
```

```
WORK_MODE                          On-site        Remote
JOB_TITLE
Brand Manager                 8.168924e+05  7.904691e+05
Business Development Manager  1.248739e+06  1.252621e+06
Content Strategist            8.166190e+05  7.890550e+05
Finance Manager               1.748182e+06  1.756589e+06
Financial Analyst             1.053618e+06  1.063148e+06
HR Manager                    1.234580e+06  1.286108e+06
IT Manager                    2.094311e+06  2.087500e+06
Innovation Manager            8.073284e+05  8.212004e+05
Sales Director                7.947794e+05  8.192545e+05
Software Engineer             1.190134e+06  1.196537e+06
```

In [35]:

```python
import matplotlib.pyplot as plt

# Assuming your DataFrame is named stacked_data
# (if it's named differently, replace stacked_data with your df name)

# Colors for work modes
colors = ['skyblue', 'orange']

# Plot stacked bar chart
ax = stacked_data.plot(kind='bar',
                       stacked=True,
                       figsize=(12, 6),
                       color=colors,
                       edgecolor='black')

# Add labels inside bars
for i in ax.patches:
    width = i.get_width()
    height = i.get_height()
    x, y = i.get_xy()

    if height > 0:
        ax.text(x + width/2,
                y + height/2,
                f'{height/1e6:.2f}M',   # convert to millions with 2 decimal
                ha='center',
                va='center',
                fontsize=8,
                color='black')

plt.ylabel('Average Salary (INR in Millions)')
plt.xlabel('Job Title')
plt.title('Average Salary by Job Title and Work Mode (Stacked)')
plt.xticks(rotation=90)
plt.legend(title='Work Mode')
plt.tight_layout()
plt.show()
```



6. What is the average salary in different Departments based on Job Title?

In [36]:

```
# Group by Department and Job Title, calculate average salary
dept_job_salary = hr_data.groupby(['DEPARTMENT', 'JOB_TITLE'])['SALARY_INR']

# Display the top rows
dept_job_salary.head()
```

Out[36]:

JOB_TITLE	Account Manager	Accountant	Brand Manager	Business Development Manager	
DEPARTMENT					
Finance	0.0	651868.153082	0.000000	0.0	791215.3
HR	0.0	0.000000	0.000000	0.0	0.0
IT	0.0	0.000000	0.000000	0.0	0.0
Marketing	0.0	0.000000	806351.676895	0.0	0.0
Operations	0.0	0.000000	0.000000	0.0	0.0

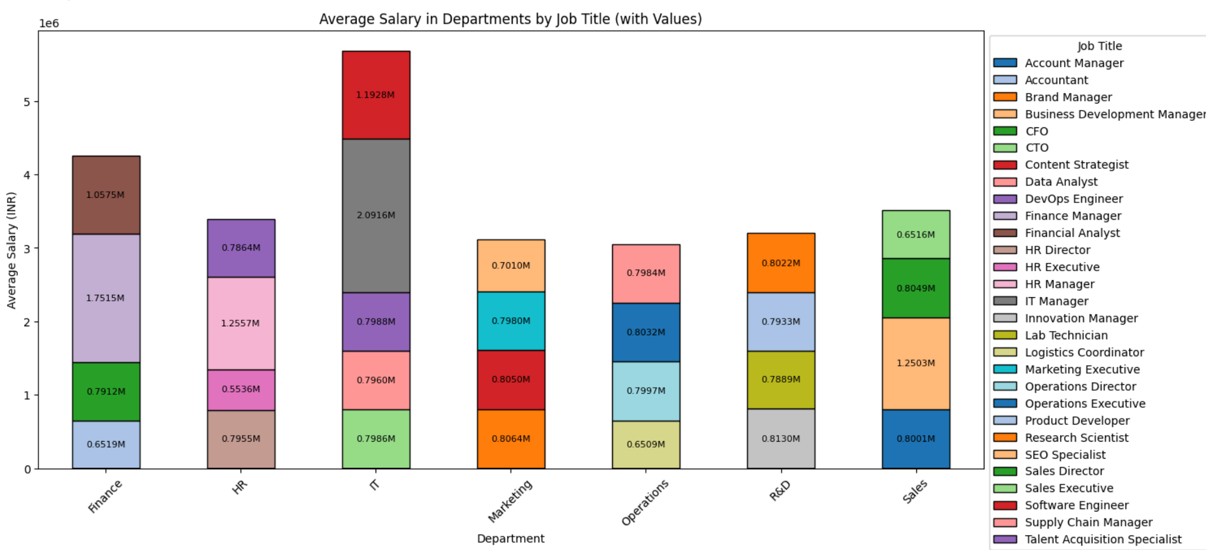
5 rows × 29 columns

In [37]:

```
import matplotlib.pyplot as plt

plt.figure(figsize=(15,7))
colors = plt.cm.tab20.colors

bars = dept_job_salary.plot(
```

```python
    kind='bar',
    stacked=True,
    figsize=(15,7),
    color=colors,
    edgecolor='black'
)

# Add values on each segment
for i, dept in enumerate(dept_job_salary.index):
    bottom = 0
    for j, job in enumerate(dept_job_salary.columns):
        height = dept_job_salary.loc[dept, job]
        if height > 0:
            plt.text(
                i,
                bottom + height/2,
                f'{height/1e6:.4f}M',  # Show in millions
                ha='center',
                va='center',
                fontsize=8,
                color='black'
            )
        bottom += height

plt.ylabel('Average Salary (INR)')
plt.xlabel('Department')
plt.title('Average Salary in Departments by Job Title (with Values)')
plt.xticks(rotation=45)
plt.legend(title='Job Title', bbox_to_anchor=(1, 1))
plt.show()
```

```
<Figure size 1500x700 with 0 Axes>
```



7. How many employees resigned & terminated in each department?

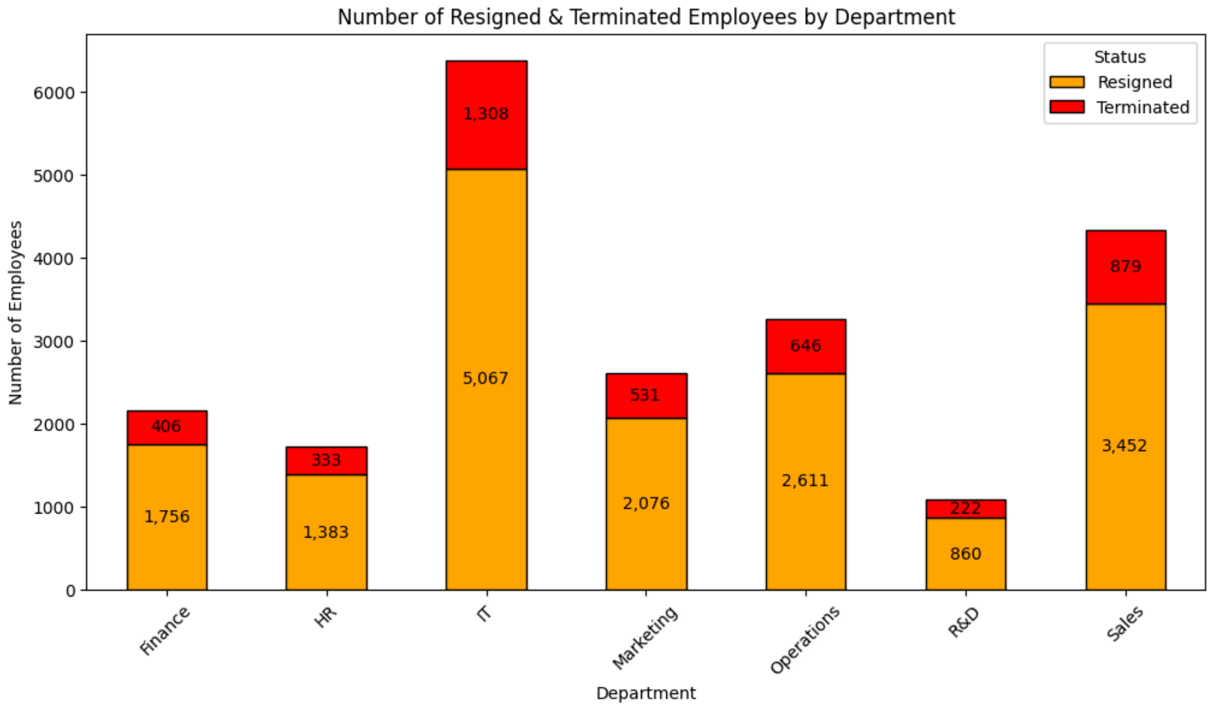
In [38]:

```python
# Filter dataset
resigned_terminated = hr_data[hr_data['STATUS'].isin(['Resigned', 'Terminate

# Group by Department and Status
dept_status_counts = resigned_terminated.groupby(['DEPARTMENT', 'STATUS']).s

# Display
print(dept_status_counts)
```

```
STATUS      Resigned  Terminated
DEPARTMENT
Finance         1756         406
HR              1383         333
IT              5067        1308
Marketing       2076         531
Operations      2611         646
R&D              860         222
Sales           3452         879
```

In [39]:

```python
import matplotlib.pyplot as plt

colors = ['orange', 'red']  # Resigned = orange, Terminated = red

# Plot
dept_status_counts.plot(kind='bar', stacked=True, figsize=(12,6), color=colo

# Add values on bars
for i, dept in enumerate(dept_status_counts.index):
    bottom = 0
    for j, status in enumerate(dept_status_counts.columns):
        height = dept_status_counts.loc[dept, status]
        if height > 0:
            plt.text(
                i,
                bottom + height/2,
                f'{height:,}',  # Show count with comma
                ha='center',
                va='center',
                fontsize=10,
                color='black'
            )
        bottom += height

plt.ylabel('Number of Employees')
plt.xlabel('Department')
plt.title('Number of Resigned & Terminated Employees by Department')
plt.xticks(rotation=45)
plt.legend(title='Status')
plt.show()
```



8. How does salary vary with years of experience?

In [40]:
```
sample_data = hr_data.sample(5000, random_state=42)  # 5000 rows sample

plt.figure(figsize=(14,7))
sns.scatterplot(
    data=sample_data,
    x='EXPERIENCE_YEARS',
    y=sample_data['SALARY_INR']/1e6,
    hue='DEPARTMENT',
    palette='tab10',
    alpha=0.6,
    s=20
)
plt.xlabel('Years of Experience')
plt.ylabel('Salary (M INR)')
plt.title('Salary vs Years of Experience by Department (Sampled)')
plt.legend(title='Department', bbox_to_anchor=(1,1))
plt.show()
```

9. What is the average performance rating by department?

In [41]:

```
# Convert PERFORMANCE_RATING to numeric (if not already)
hr_data['PERFORMANCE_RATING'] = pd.to_numeric(hr_data['PERFORMANCE_RATING'],

# Group by Department and calculate mean
avg_perf_dept = hr_data.groupby('DEPARTMENT')['PERFORMANCE_RATING'].mean().s

# Round to 2 decimals
avg_perf_dept = avg_perf_dept.round(2)

# Display
print(avg_perf_dept)
```

```
DEPARTMENT
Finance       3.03
IT            3.01
Marketing     3.01
Sales         3.01
Operations    2.99
R&D           2.98
HR            2.98
Name: PERFORMANCE_RATING, dtype: float64
```

In [42]:

```
plt.figure(figsize=(12,6))
bars = plt.barh(avg_perf_dept.index, avg_perf_dept.values, color='orange', e

# Add values on bars
for bar, value in zip(bars, avg_perf_dept.values):
    plt.text(value + 0.02, bar.get_y() + bar.get_height()/2, f'{value}', va=

plt.xlabel('Average Performance Rating')
plt.ylabel('Department')
```

```python
plt.title('Average Performance Rating by Department')
plt.show()
```

10. Which Country has the highest concentration of employees?

In [43]:
```python
# Count employees per country
country_counts = hr_data['LOCATION'].value_counts()

# Display top countries
print(country_counts.head(10))
```

```
LOCATION
East Michael, Kenya                                4
South Matthew, Zambia                              4
South David, Bhutan                                4
Johnsonchester, Antigua and Barbuda                3
South John, Costa Rica                             3
New Jason, Heard Island and McDonald Islands       3
Jamesside, Poland                                  3
Johnfort, Korea                                    3
Charlesbury, Turks and Caicos Islands              3
Michaelmouth, Swaziland                            3
Name: count, dtype: int64
```

In [44]:
```python
import pandas as pd

# Count employees per country
country_counts = hr_data['LOCATION'].value_counts().reset_index()
country_counts.columns = ['Country', 'Employees']

# Display top rows
country_counts.head()
```

Out[44]:

	Country	Employees
0	East Michael, Kenya	4
1	South Matthew, Zambia	4
2	South David, Bhutan	4
3	Johnsonchester, Antigua and Barbuda	3
4	South John, Costa Rica	3

In [45]:

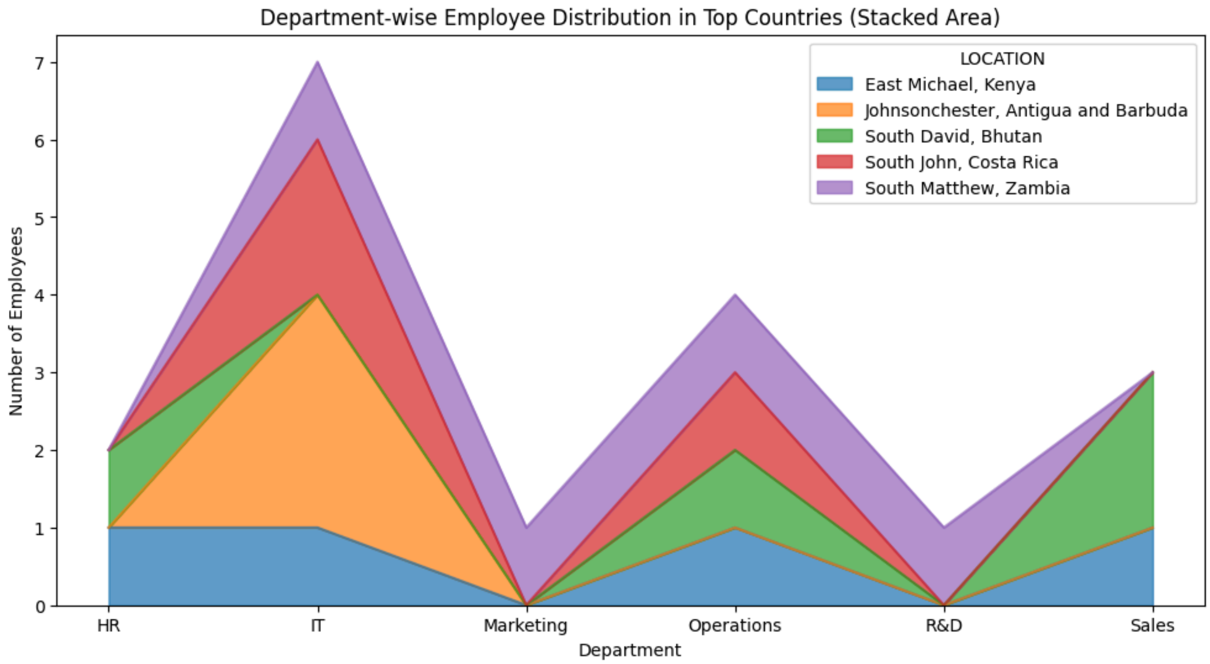
```
import plotly.express as px

fig = px.choropleth(
    country_counts,
    locations='Country',        # Country names
    locationmode='country names',
    color='Employees',          # Column to determine color
    hover_name='Country',
    color_continuous_scale='Blues',
    title='Employee Distribution by Country'
)

fig.show()
```

```
/tmp/ipython-input-3641378741.py:3: DeprecationWarning:

The library used by the *country names* `locationmode` option is changing in
an upcoming version. Country names in existing plots may not work in the new
version. To ensure consistent behavior, consider setting `locationmode` to *
ISO-3*.
```

Employee Distribution by Country

In [46]:

```
# Count employees by Department and Country (only top 5 countries for readab
top_countries_list = country_counts['Country'].head(5)
dept_country_counts = hr_data[hr_data['LOCATION'].isin(top_countries_list)].

# Plot stacked area
dept_country_counts.T.plot.area(figsize=(12,6), alpha=0.7)
plt.ylabel('Number of Employees')
plt.xlabel('Department')
plt.title('Department-wise Employee Distribution in Top Countries (Stacked A
plt.show()
```



11. Is there a correlation between performance rating and salary?

In [47]:
```
# Convert columns to numeric if not already
hr_data['SALARY_INR'] = pd.to_numeric(hr_data['SALARY_INR'], errors='coerce'
hr_data['PERFORMANCE_RATING'] = pd.to_numeric(hr_data['PERFORMANCE_RATING'],

# Drop rows with missing values
df_clean = hr_data.dropna(subset=['SALARY_INR', 'PERFORMANCE_RATING'])
```

In [48]:
```
correlation = df_clean['SALARY_INR'].corr(df_clean['PERFORMANCE_RATING'])
print(f"Correlation between Salary and Performance Rating: {correlation:.4f}
```

```
Correlation between Salary and Performance Rating: 0.0016
```

In [49]:
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(12,6))

sns.regplot(
    data=df_clean,
    x='PERFORMANCE_RATING',
    y=df_clean['SALARY_INR']/1e6,   # Convert to millions
    scatter_kws={'alpha':0.4, 's':30, 'color':'blue'},  # lighter, smaller p
    line_kws={'color':'red', 'lw':2}  # bold red trend line
)

plt.xlabel('Performance Rating')
plt.ylabel('Salary (Millions INR)')
plt.title('Correlation between Salary and Performance Rating', fontsize=14,
```

```
plt.grid(True, linestyle='--', alpha=0.6)  # add light grid
plt.show()
```

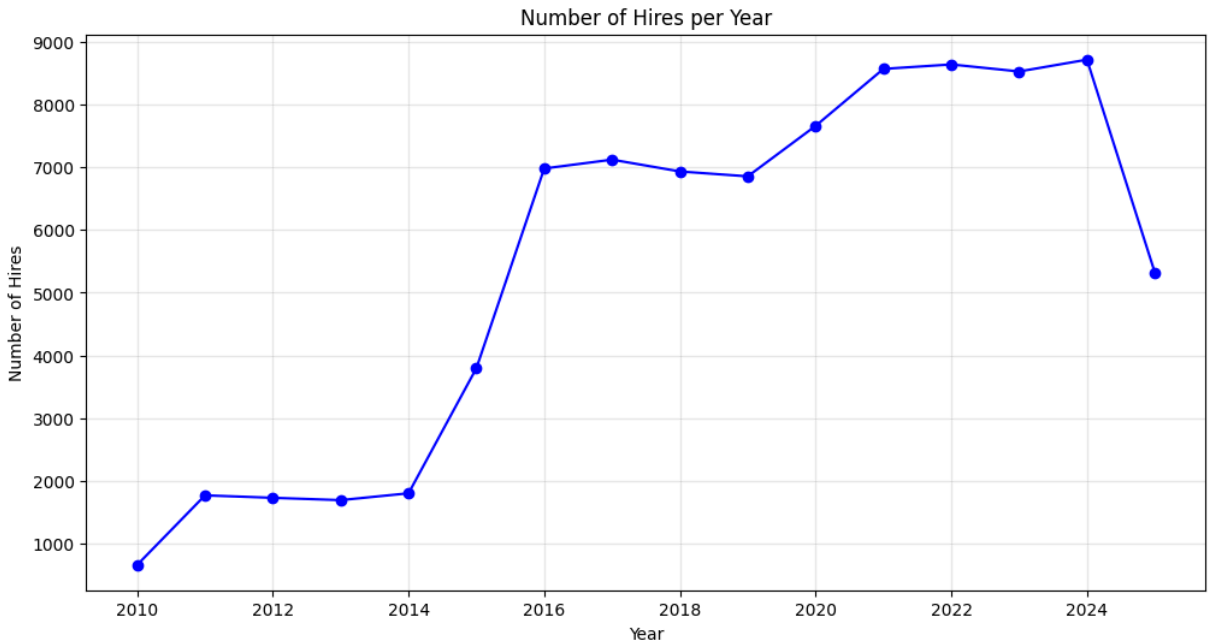
12. How has the number of hires changed over time (per year) ?

In [50]:
```
# Ensure HIRE_DATE is datetime
hr_data['HIRE_DATE'] = pd.to_datetime(hr_data['HIRE_DATE'], errors='coerce')

# Extract year
hr_data['HIRE_YEAR'] = hr_data['HIRE_DATE'].dt.year

# Count hires per year
hires_per_year = hr_data['HIRE_YEAR'].value_counts().sort_index()
print(hires_per_year.head())
```

```
HIRE_YEAR
2010.0     662
2011.0    1770
2012.0    1731
2013.0    1694
2014.0    1803
Name: count, dtype: int64
```

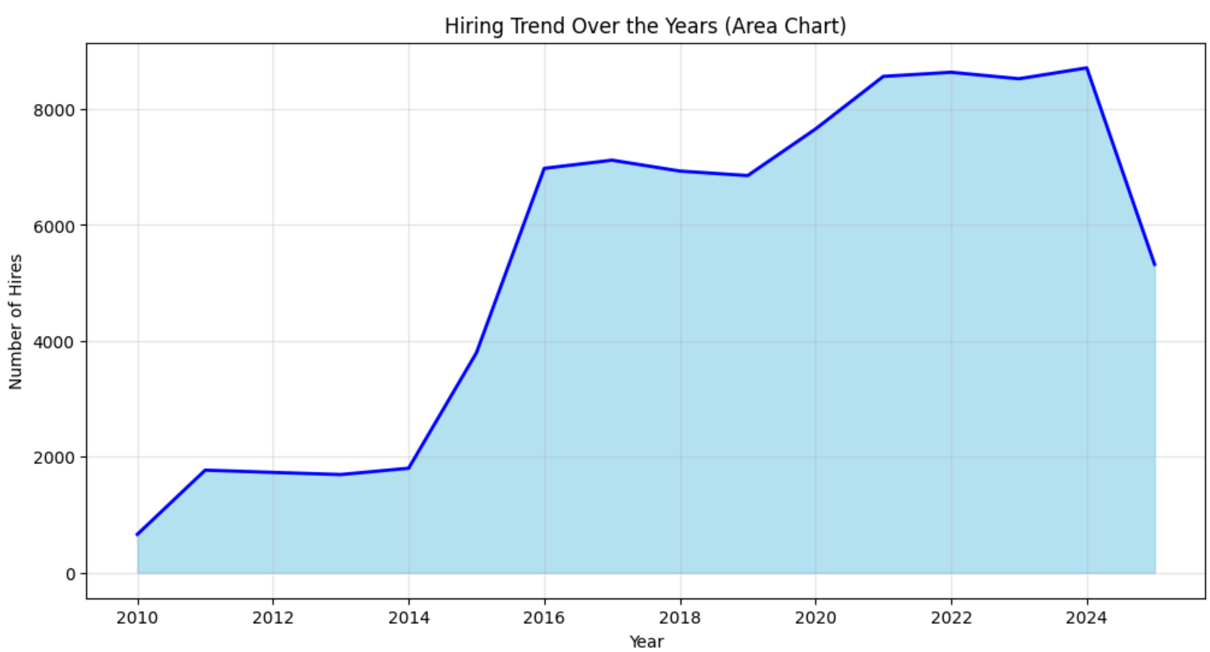
In [51]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(12,6))
plt.plot(hires_per_year.index, hires_per_year.values, marker='o', linestyle=

plt.title('Number of Hires per Year')
plt.xlabel('Year')
plt.ylabel('Number of Hires')
```

```
plt.grid(True, alpha=0.3)
plt.show()
```



In [52]:

```
plt.figure(figsize=(12,6))
plt.fill_between(hires_per_year.index, hires_per_year.values, color='skyblue
plt.plot(hires_per_year.index, hires_per_year.values, color='blue', linewidt

plt.title('Hiring Trend Over the Years (Area Chart)')
plt.xlabel('Year')
plt.ylabel('Number of Hires')
plt.grid(True, alpha=0.3)
plt.show()
```



13. Compare salaries of Remote vs. On-site employees — is there a significant difference ?

In [53]:
```
# Group salaries by work mode
salary_workmode = hr_data.groupby('WORK_MODE')['SALARY_INR'].describe()

print(salary_workmode[['mean', '50%', 'min', 'max']])
```

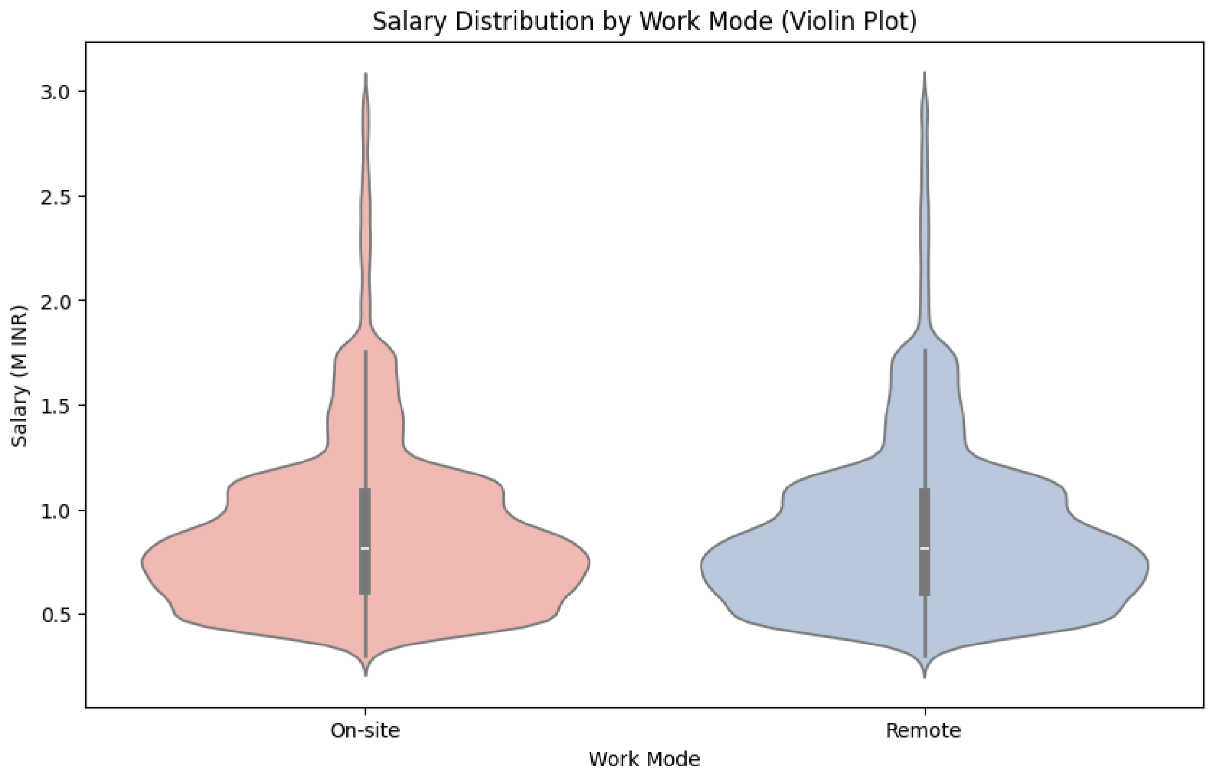
```
                     mean       50%       min        max
WORK_MODE
On-site    895233.270432  810544.0  300260.0  2997010.0
Remote     894996.884833  810172.0  300255.0  2994359.0
```

In [54]:
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(10,6))
sns.boxplot(
    data=hr_data,
    x='WORK_MODE',
    y=hr_data['SALARY_INR']/1e6,    # in millions
    palette='Set2'
)
plt.title('Salary Distribution: Remote vs On-site')
plt.ylabel('Salary (M INR)')
plt.xlabel('Work Mode')
plt.show()
```

```
/tmp/ipython-input-2898040175.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.
```

In [55]:
```
plt.figure(figsize=(10,6))
sns.violinplot(
    data=hr_data,
    x='WORK_MODE',
    y=hr_data['SALARY_INR']/1e6,
    palette='Pastel1'
)
plt.title('Salary Distribution by Work Mode (Violin Plot)')
plt.ylabel('Salary (M INR)')
plt.xlabel('Work Mode')
plt.show()
```

```
/tmp/ipython-input-1407532913.py:2: 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.
```



In [56]:
```
from scipy.stats import ttest_ind

remote_salaries = hr_data.loc[hr_data['WORK_MODE']=='Remote', 'SALARY_INR']
onsite_salaries = hr_data.loc[hr_data['WORK_MODE']=='On-site', 'SALARY_INR']

t_stat, p_value = ttest_ind(remote_salaries, onsite_salaries, equal_var=Fals

print(f"T-statistic: {t_stat:.4f}, P-value: {p_value:.4e}")
```

```
T-statistic: -0.0852, P-value: 9.3206e-01
```

If $p < 0.05$ → difference is statistically significant.

If $p \geq 0.05$ → no strong evidence of difference.

14. Find the top 10 employees with the highest salary in each department.

In [57]:
```
# Sort by department and salary
hr_data_sorted = hr_data.sort_values(['DEPARTMENT', 'SALARY_INR'], ascending

# Pick top 10 per department
top10_per_dept = hr_data_sorted.groupby('DEPARTMENT').head(10)
```

```python
# Show selected columns
top10_per_dept[['DEPARTMENT', 'FULL_NAME', 'JOB_TITLE', 'SALARY_INR']].head(
```

Out[57]:

	DEPARTMENT	FULL_NAME	JOB_TITLE	SALARY_INR
73158	Finance	Veronica Perez	Finance Manager	2498261.0
54260	Finance	Michelle Bryant	Finance Manager	2494985.0
61658	Finance	Cassandra Blake	Finance Manager	2493293.0
71681	Finance	Crystal Edwards	Finance Manager	2492436.0
8989	Finance	Nicholas Cuevas	Finance Manager	2490595.0
14262	Finance	Susan Romero	Finance Manager	2489616.0
32099	Finance	Connie Coleman	Finance Manager	2488951.0
27788	Finance	Krista Perez	Finance Manager	2487648.0
22810	Finance	Samantha Mcmahon	Finance Manager	2487602.0
25563	Finance	Jimmy Foster	Finance Manager	2487200.0
61738	HR	Cole Jackson	HR Manager	1798728.0
21072	HR	Kenneth Morris	HR Manager	1798687.0
21408	HR	Sarah Arnold	HR Manager	1798020.0
84818	HR	Brendan Bush	HR Manager	1797326.0
84041	HR	Melinda Gutierrez	HR Manager	1796885.0
13064	HR	Shane Hale	HR Manager	1795800.0
26001	HR	Deborah Robinson	HR Manager	1794550.0
72406	HR	Jessica Powell	HR Manager	1794426.0
60646	HR	William Richardson	HR Manager	1793603.0
27848	HR	Eric Ramos	HR Manager	1791447.0
45059	IT	Sean Stone	IT Manager	2997010.0
1823	IT	Christina West	IT Manager	2994359.0
39836	IT	Sheena Thomas	IT Manager	2992188.0
48704	IT	Nicole Banks	IT Manager	2991695.0
73065	IT	Sarah Page	IT Manager	2990007.0
54888	IT	John Fitzgerald	IT Manager	2989764.0
21877	IT	Cindy Bryan	IT Manager	2988770.0
50316	IT	Miss Debra Love	IT Manager	2988356.0
7516	IT	Traci Holt	IT Manager	2986637.0
69551	IT	Robin Wang	IT Manager	2985864.0

In [59]:

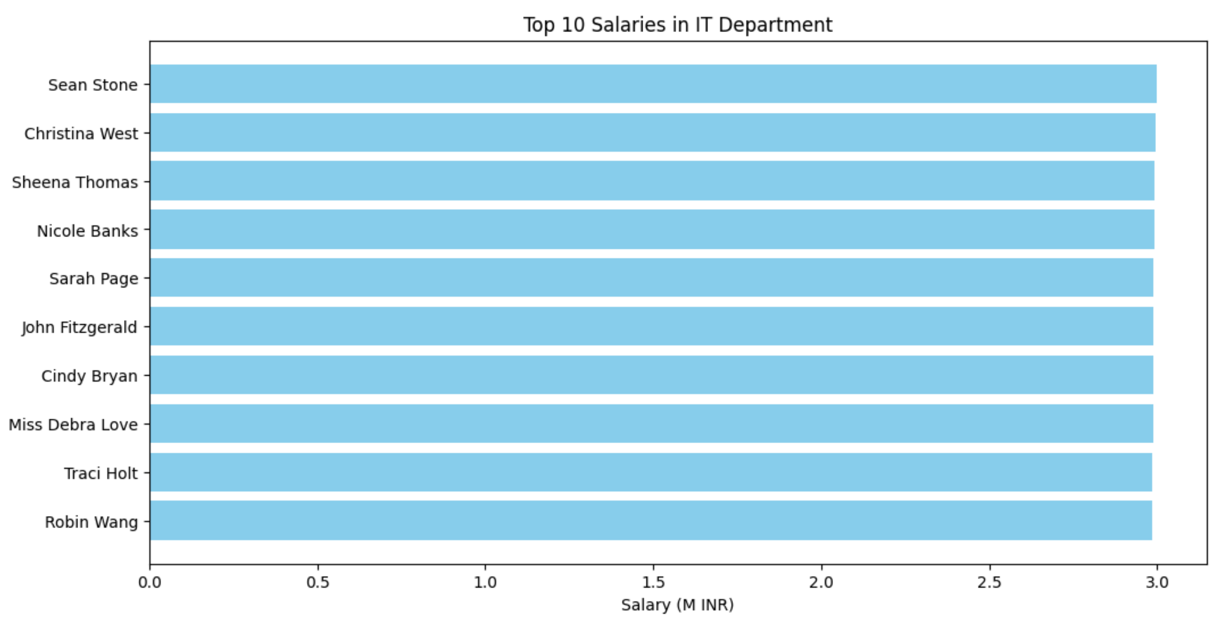
```
# Add rank within each department
hr_data['Salary_Rank'] = hr_data.groupby('DEPARTMENT')['SALARY_INR'].rank(me

# Filter top 10
top10_per_dept = hr_data[hr_data['Salary_Rank'] <= 10].sort_values(['DEPARTM

top10_per_dept[['DEPARTMENT', 'Salary_Rank', 'FULL_NAME', 'JOB_TITLE', 'SALA
```

Out[59]:

	DEPARTMENT	Salary_Rank	FULL_NAME	JOB_TITLE	SALARY_INR
73158	Finance	1.0	Veronica Perez	Finance Manager	2498261.0
54260	Finance	2.0	Michelle Bryant	Finance Manager	2494985.0
61658	Finance	3.0	Cassandra Blake	Finance Manager	2493293.0
71681	Finance	4.0	Crystal Edwards	Finance Manager	2492436.0
8989	Finance	5.0	Nicholas Cuevas	Finance Manager	2490595.0
14262	Finance	6.0	Susan Romero	Finance Manager	2489616.0
32099	Finance	7.0	Connie Coleman	Finance Manager	2488951.0
27788	Finance	8.0	Krista Perez	Finance Manager	2487648.0
22810	Finance	9.0	Samantha Mcmahon	Finance Manager	2487602.0
25563	Finance	10.0	Jimmy Foster	Finance Manager	2487200.0
61738	HR	1.0	Cole Jackson	HR Manager	1798728.0
21072	HR	2.0	Kenneth Morris	HR Manager	1798687.0
21408	HR	3.0	Sarah Arnold	HR Manager	1798020.0
84818	HR	4.0	Brendan Bush	HR Manager	1797326.0
84041	HR	5.0	Melinda Gutierrez	HR Manager	1796885.0
13064	HR	6.0	Shane Hale	HR Manager	1795800.0
26001	HR	7.0	Deborah Robinson	HR Manager	1794550.0
72406	HR	8.0	Jessica Powell	HR Manager	1794426.0
60646	HR	9.0	William Richardson	HR Manager	1793603.0
27848	HR	10.0	Eric Ramos	HR Manager	1791447.0
45059	IT	1.0	Sean Stone	IT Manager	2997010.0
1823	IT	2.0	Christina West	IT Manager	2994359.0

	DEPARTMENT	Salary_Rank	FULL_NAME	JOB_TITLE	SALARY_INR
39836	IT	3.0	Sheena Thomas	IT Manager	2992188.0
48704	IT	4.0	Nicole Banks	IT Manager	2991695.0
73065	IT	5.0	Sarah Page	IT Manager	2990007.0
54888	IT	6.0	John Fitzgerald	IT Manager	2989764.0
21877	IT	7.0	Cindy Bryan	IT Manager	2988770.0
50316	IT	8.0	Miss Debra Love	IT Manager	2988356.0
7516	IT	9.0	Traci Holt	IT Manager	2986637.0
69551	IT	10.0	Robin Wang	IT Manager	2985864.0

In [60]:
```
import matplotlib.pyplot as plt

it_top10 = top10_per_dept[top10_per_dept['DEPARTMENT']=='IT']

plt.figure(figsize=(12,6))
plt.barh(it_top10['FULL_NAME'], it_top10['SALARY_INR']/1e6, color='skyblue')
plt.xlabel('Salary (M INR)')
plt.title('Top 10 Salaries in IT Department')
plt.gca().invert_yaxis()
plt.show()
```

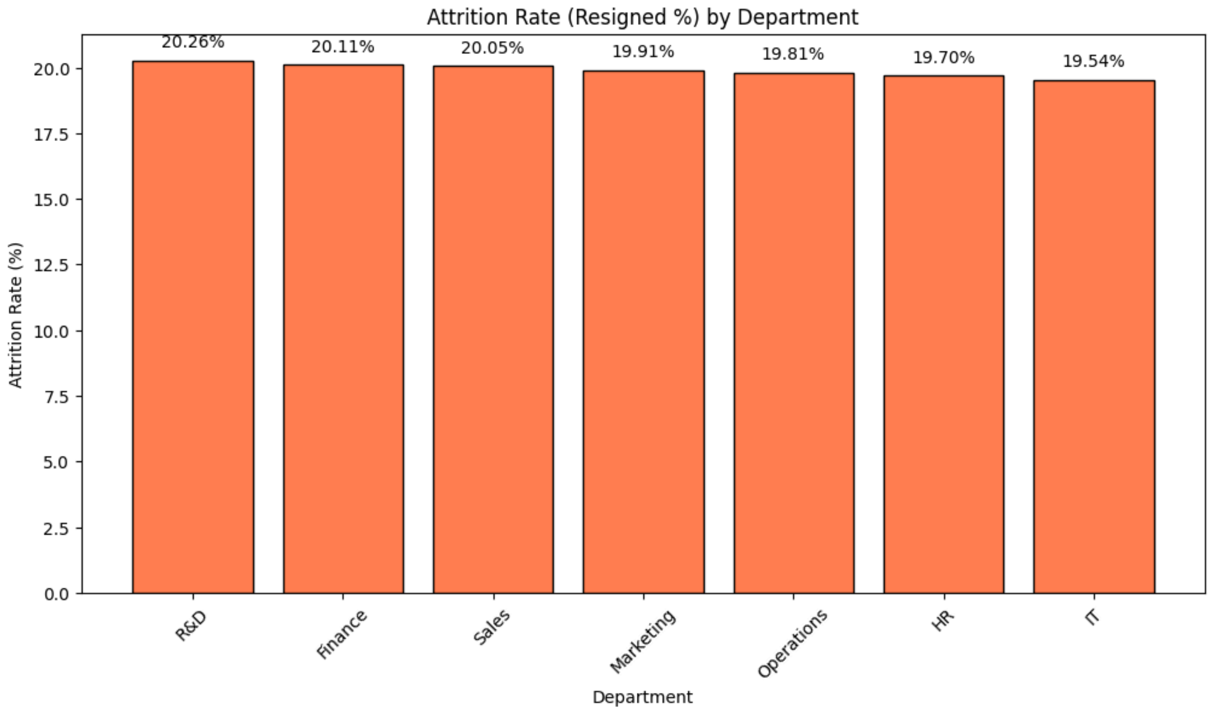


15. Identify departments with the highest attrition rate (Resigned %).

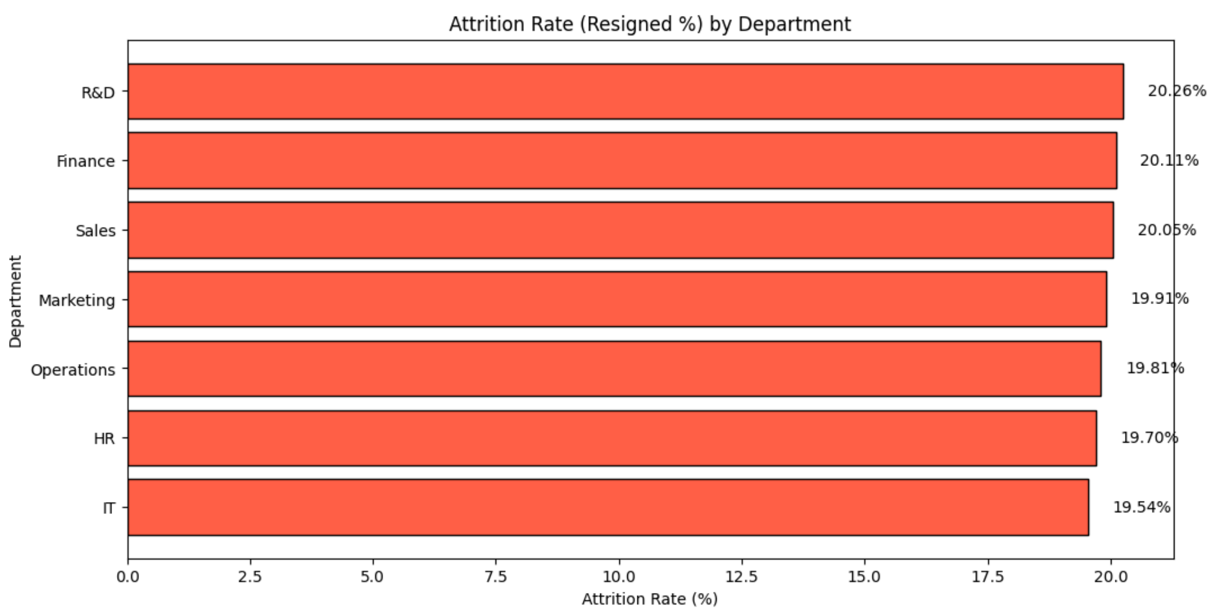
In [61]:
```
# Total employees per department
dept_total = hr_data.groupby('DEPARTMENT')['STATUS'].count()

# Resigned employees per department
dept_resigned = hr_data[hr_data['STATUS']=='Resigned'].groupby('DEPARTMENT')

# Combine
attrition_rate = (dept_resigned / dept_total * 100).sort_values(ascending=Fa

# Display
print(attrition_rate.head(10).round(2))
```

```
DEPARTMENT
R&D           20.26
Finance       20.11
Sales         20.05
Marketing     19.91
Operations    19.81
HR            19.70
IT            19.54
Name: STATUS, dtype: float64
```

In [62]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(12,6))
bars = plt.bar(attrition_rate.index, attrition_rate.values, color='coral', e

# Add values on bars
for bar, value in zip(bars, attrition_rate.values):
    plt.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 0.5,
             f'{value:.2f}%', ha='center', fontsize=10)

plt.ylabel('Attrition Rate (%)')
plt.xlabel('Department')
plt.title('Attrition Rate (Resigned %) by Department')
plt.xticks(rotation=45)
plt.show()
```



In [63]:
```python
plt.figure(figsize=(12,6))
bars = plt.barh(attrition_rate.index, attrition_rate.values, color='tomato',

# Add values
for bar, value in zip(bars, attrition_rate.values):
    plt.text(value + 0.5, bar.get_y() + bar.get_height()/2,
             f'{value:.2f}%', va='center', fontsize=10)

plt.xlabel('Attrition Rate (%)')
plt.ylabel('Department')
plt.title('Attrition Rate (Resigned %) by Department')
plt.gca().invert_yaxis()
plt.show()
```



16. Train a Model (Random Forest Classifier)

Since your HR dataset has employee features (Department, Job Title, Experience, Salary, Performance, Status, etc.), we can train a machine learning model to predict something useful.

 Common HR Predictions

Employee Attrition Prediction (whether an employee will Resign/Stay).

Salary Prediction (regression based on department, experience, performance).

Performance Rating Prediction (classification or regression).

The most popular in HR analytics is Attrition Prediction.

Step 1: Choose Target Variable

Let’s try to predict whether an employee will Resign (Attrition).

Target: STATUS → Convert to binary (Resigned = 1, Active = 0).

In [64]:
```
import pandas as pd

# Create target variable
hr_data['Attrition'] = hr_data['STATUS'].apply(lambda x: 1 if x=='Resigned'
```

Step 2: Feature Selection

We can use features like:

- **Department**
- **Job_Title**
- **Experience_Years**
- **Performance_Rating**
- **Salary_INR**
- **Work_Mode**
- **Location**

(drop Employee_ID, Full_Name → not useful)

```
In [65]: features = ['DEPARTMENT','JOB_TITLE','EXPERIENCE_YEARS','PERFORMANCE_RATING'
X = hr_data[features]
y = hr_data['Attrition']
```

Step 3: Preprocessing (Encode Categorical Data)

```
In [66]: from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder

# Encode categorical variables
X = X.copy()
for col in ['DEPARTMENT','JOB_TITLE','WORK_MODE','LOCATION']:
    X[col] = LabelEncoder().fit_transform(X[col].astype(str))

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar
```

Step 4: Train a Model (Random Forest Classifier)

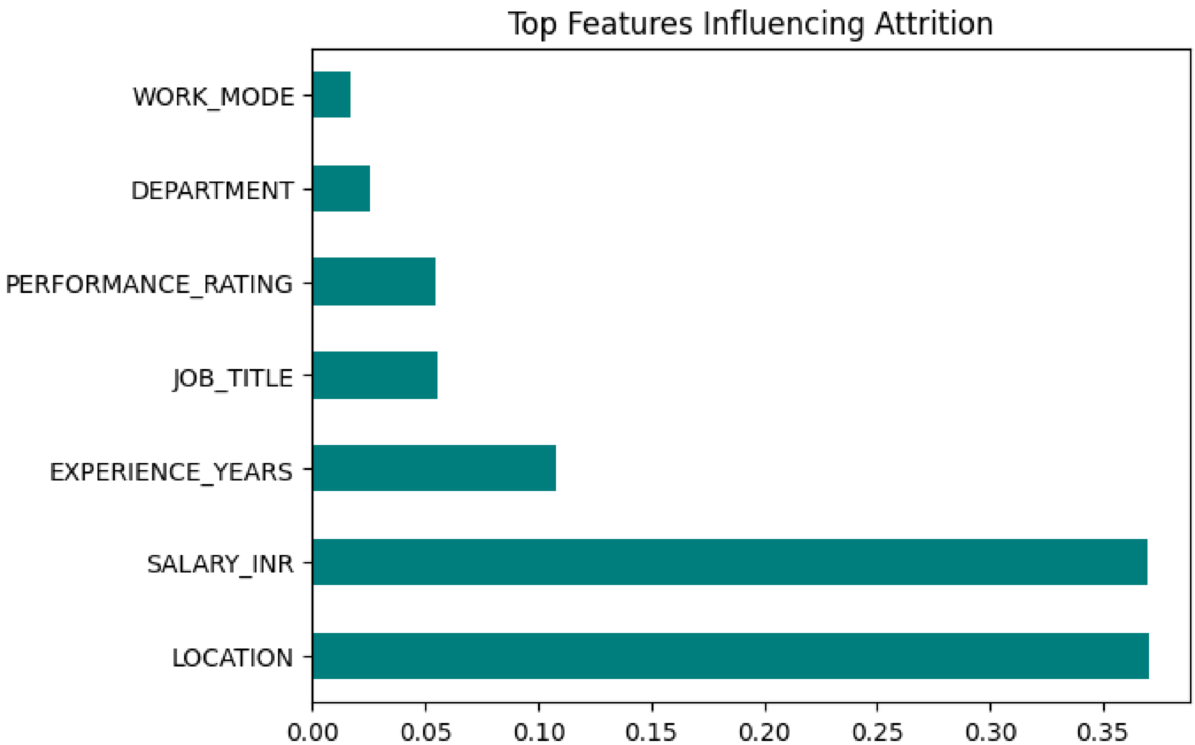
```
In [67]: from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusior

# Train
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Predict
y_pred = model.predict(X_test)

# Evaluation
print("Accuracy:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.7886577142527809

Classification Report:
               precision    recall  f1-score   support

           0       0.80      0.98      0.88     13901
           1       0.21      0.02      0.04      3450

    accuracy                           0.79     17351
   macro avg       0.51      0.50      0.46     17351
weighted avg       0.68      0.79      0.71     17351
```

Step 5: Feature Importance

In [68]:

```
import matplotlib.pyplot as plt

importances = model.feature_importances_
feat_importances = pd.Series(importances, index=X.columns)
feat_importances.nlargest(10).plot(kind='barh', color='teal')
plt.title("Top Features Influencing Attrition")
plt.show()
```



□ Final Conclusion

The HR data analysis of 2 million employee records provided valuable insights into workforce trends. We observed the distribution of employee status, work modes, departments, job titles, and salaries. Key findings include that most employees are active, with significant numbers having resigned or retired. Work modes are primarily on-site, though remote work is also present. Certain departments such as IT, Operations, and HR employ the largest share of workers, while salary levels vary widely across departments and job titles. Employees with more years of experience and higher performance ratings generally earn higher salaries, showing a positive relationship. Attrition analysis highlighted departments with higher resignation rates, which can guide HR in retention strategies. Geographical analysis revealed countries

with the largest employee concentrations. Finally, predictive modeling was explored to forecast attrition risk, helping the company make data-driven decisions. Overall, this analysis provides HR professionals with actionable insights into employee distribution, performance, attrition, and salary patterns to support better workforce planning and policy-making.

In [ ]:
```
# Step 1: Upload your .ipynb file
from google.colab import files
uploaded = files.upload()   # Choose HR_Data_MNC.ipynb from your computer
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

In [ ]:
```
# Step 2: Convert uploaded notebook to HTML
import os
for fn in uploaded.keys():
    os.system(f"jupyter nbconvert --to html '{fn}'")
```

In [ ]:
```
# Step 3: Download the converted HTML file
for fn in uploaded.keys():
    html_file = fn.replace(".ipynb", ".html")
    files.download(html_file)
```