VIT®

Vellore Institute of Technology

(Deemed to be University under section 3 of UGC Act, 1956)

CHENNAI

EDA on Datasets of IBM Watson Employees

(SDG – Goal 8)

FINAL REVIEW

SUBMITTED BY

TEAM – G

PRIYANKA S – 23MIA1032

KAVYA N – 23MIA1125

HEMA B – 23MIA1101

A FINAL REVIEW REPORT SUBMITTED TO

Prof. Dr. ASNATH VICTY PHAMILA Y – SCOPE

IN PARTIAL FULLFILMENT OF THE REQUIREMENTS FOR THE COURSE OF

CSE3040 – EXPLORATORY DATA ANALYSIS

IN MIA (M.Tech Integrated CSE with Specialization in Business Analytics)

CSE3040 - Exploratory Data Analysis - Final Review

EDA on Datasets of IBM Watson Employees (SDG – Goal 8)

Team - G

- Priyanka S - 23MIA1032
- Kavya N - 23MIA1125
- Hema B - 23MIA1101

--- Importing the Dataset ---

In [7]:
```
from google.colab import files
import pandas as pd
files.upload()
df = pd.read_csv('watson.csv')
print(df)
```

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.

```
Saving watson.csv to watson.csv
      EmployeeID  Age Attrition     BusinessTravel  DailyRate  Department  \
0        1313919   41        No      Travel_Rarely       1102  Cardiology
1        1200302   49        No  Travel_Frequently        279   Maternity
2        1060315   37       Yes      Travel_Rarely       1373   Maternity
3        1272912   33        No  Travel_Frequently       1392   Maternity
4        1414939   27        No      Travel_Rarely        591   Maternity
...          ...  ...       ...                ...        ...         ...
1671     1117656   26       Yes      Travel_Rarely        471   Neurology
1672     1152327   46        No      Travel_Rarely       1125  Cardiology
1673     1812428   20        No      Travel_Rarely        959   Maternity
1674     1812429   39        No      Travel_Rarely        466   Neurology
1675     1152329   27        No      Travel_Rarely        511  Cardiology

      DistanceFromHome  Education    EducationField  EmployeeCount  ...  \
0                    1          2     Life Sciences              1  ...
1                    8          1     Life Sciences              1  ...
2                    2          2             Other              1  ...
3                    3          4     Life Sciences              1  ...
4                    2          1           Medical              1  ...
...                ...        ...               ...            ...  ...
1671                24          3  Technical Degree              1  ...
1672                10          3         Marketing              1  ...
1673                 1          3     Life Sciences              1  ...
1674                 1          1     Life Sciences              1  ...
1675                 2          2           Medical              1  ...

      RelationshipSatisfaction StandardHours  Shift  TotalWorkingYears  \
0                            1            80      0                  8
1                            4            80      1                 10
2                            2            80      0                  7
3                            3            80      0                  8
4                            4            80      1                  6
...                        ...           ...    ...                ...
1671                         2            80      0                  1
1672                         3            80      1                 15
1673                         4            80      0                  1
1674                         3            80      1                 21
1675                         2            80      0                  9

      TrainingTimesLastYear WorkLifeBalance  YearsAtCompany  \
0                         0               1               6
1                         3               3              10
2                         3               3               0
3                         3               3               8
4                         3               3               2
...                     ...             ...             ...
1671                      3               1               1
1672                      3               3               3
1673                      0               4               1
1674                      3               3              21
1675                      5               2               8

     YearsInCurrentRole  YearsSinceLastPromotion  YearsWithCurrManager
0                     4                        0                     5
1                     7                        1                     7
```

```
2                       0                          0                      0
3                       7                          3                      0
4                       2                          2                      2
...                   ...                        ...                    ...
1671                    0                          0                      0
1672                    2                          1                      2
1673                    0                          0                      0
1674                    6                         11                      8
1675                    7                          0                      7

[1676 rows x 35 columns]
```

Inference: Dataset was successfully read and printed. The output confirms the dataset has 1676 rows and 35 columns.

--- Importing Libraries ---

In [8]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import SimpleImputer, KNNImputer, IterativeImputer
from sklearn.preprocessing import StandardScaler, MinMaxScaler, LabelEncoder
from sklearn.feature_selection import SelectKBest, f_classif, mutual_info_cl
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
from sklearn.linear_model import LinearRegression
from sklearn.cluster import KMeans
from sklearn.feature_selection import RFE
from scipy.stats import zscore, iqr
from mlxtend.frequent_patterns import apriori, association_rules
from mlxtend.preprocessing import TransactionEncoder
from sklearn.metrics import silhouette_score
```

Inference: Prepares the environment for preprocessing, analysis, modeling, visualization, and feature engineering. No output generated.

--- Initial Shape --

In [9]:
```
print("Initial Shape:", df.shape)
```

```
Initial Shape: (1676, 35)
```

Inference: Initial Shape: (1676, 35) represents that this is a large dataset.

--- Initial Exploration ---

In [10]:
```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1676 entries, 0 to 1675
Data columns (total 35 columns):
 #   Column                    Non-Null Count  Dtype 
---  ------                    --------------  ----- 
 0   EmployeeID                1676 non-null   int64 
 1   Age                       1676 non-null   int64 
 2   Attrition                 1676 non-null   object
 3   BusinessTravel            1676 non-null   object
 4   DailyRate                 1676 non-null   int64 
 5   Department                1676 non-null   object
 6   DistanceFromHome          1676 non-null   int64 
 7   Education                 1676 non-null   int64 
 8   EducationField            1676 non-null   object
 9   EmployeeCount             1676 non-null   int64 
 10  EnvironmentSatisfaction   1676 non-null   int64 
 11  Gender                    1676 non-null   object
 12  HourlyRate                1676 non-null   int64 
 13  JobInvolvement            1676 non-null   int64 
 14  JobLevel                  1676 non-null   int64 
 15  JobRole                   1676 non-null   object
 16  JobSatisfaction           1676 non-null   int64 
 17  MaritalStatus             1676 non-null   object
 18  MonthlyIncome             1676 non-null   int64 
 19  MonthlyRate               1676 non-null   int64 
 20  NumCompaniesWorked        1676 non-null   int64 
 21  Over18                    1676 non-null   object
 22  OverTime                  1676 non-null   object
 23  PercentSalaryHike         1676 non-null   int64 
 24  PerformanceRating         1676 non-null   int64 
 25  RelationshipSatisfaction  1676 non-null   int64 
 26  StandardHours             1676 non-null   int64 
 27  Shift                     1676 non-null   int64 
 28  TotalWorkingYears         1676 non-null   int64 
 29  TrainingTimesLastYear     1676 non-null   int64 
 30  WorkLifeBalance           1676 non-null   int64 
 31  YearsAtCompany            1676 non-null   int64 
 32  YearsInCurrentRole        1676 non-null   int64 
 33  YearsSinceLastPromotion   1676 non-null   int64 
 34  YearsWithCurrManager      1676 non-null   int64 
dtypes: int64(26), object(9)
memory usage: 458.4+ KB
None
```

Inference: Helps identify missing values and understand feature types.This DataFrame contains 1676 entries with 35 columns, a mix of numerical (int64) and categorical (object) data, with no missing values.

In [11]:
```
print(df.head())
```

```
   EmployeeID  Age Attrition     BusinessTravel  DailyRate  Department  \
0     1313919   41        No      Travel_Rarely       1102  Cardiology
1     1200302   49        No  Travel_Frequently        279   Maternity
2     1060315   37       Yes      Travel_Rarely       1373   Maternity
3     1272912   33        No  Travel_Frequently       1392   Maternity
4     1414939   27        No      Travel_Rarely        591   Maternity

   DistanceFromHome  Education EducationField  EmployeeCount  ...  \
0                 1          2  Life Sciences              1  ...
1                 8          1  Life Sciences              1  ...
2                 2          2          Other              1  ...
3                 3          4  Life Sciences              1  ...
4                 2          1        Medical              1  ...

   RelationshipSatisfaction StandardHours  Shift  TotalWorkingYears  \
0                        1            80      0                  8
1                        4            80      1                 10
2                        2            80      0                  7
3                        3            80      0                  8
4                        4            80      1                  6

   TrainingTimesLastYear WorkLifeBalance  YearsAtCompany YearsInCurrentRole
\
0                      0               1               6                  4
1                      3               3              10                  7
2                      3               3               0                  0
3                      3               3               8                  7
4                      3               3               2                  2

   YearsSinceLastPromotion  YearsWithCurrManager
0                        0                     5
1                        1                     7
2                        0                     0
3                        3                     0
4                        2                     2

[5 rows x 35 columns]
```

Inference: This shows the first 5 records

In [12]:
```
print(df.describe(include='all'))
```

```
          EmployeeID          Age Attrition BusinessTravel    DailyRate  \
count   1.676000e+03  1676.000000      1676           1676  1676.000000
unique           NaN          NaN         2              3          NaN
top              NaN          NaN        No  Travel_Rarely          NaN
freq             NaN          NaN      1477           1184          NaN
mean    1.456796e+06    36.866348       NaN            NaN   800.557876
std     2.487486e+05     9.129126       NaN            NaN   401.594438
min     1.025177e+06    18.000000       NaN            NaN   102.000000
25%     1.235832e+06    30.000000       NaN            NaN   465.000000
50%     1.464606e+06    36.000000       NaN            NaN   796.500000
75%     1.667992e+06    43.000000       NaN            NaN  1157.000000
max     1.886378e+06    60.000000       NaN            NaN  1499.000000

       Department  DistanceFromHome    Education EducationField  \
count        1676       1676.000000  1676.000000           1676
unique          3               NaN          NaN              6
top     Maternity               NaN          NaN  Life Sciences
freq          796               NaN          NaN            697
mean          NaN          9.221957     2.907518            NaN
std           NaN          8.158118     1.025835            NaN
min           NaN          1.000000     1.000000            NaN
25%           NaN          2.000000     2.000000            NaN
50%           NaN          7.000000     3.000000            NaN
75%           NaN         14.000000     4.000000            NaN
max           NaN         29.000000     5.000000            NaN

        EmployeeCount  ...  RelationshipSatisfaction StandardHours  \
count          1676.0  ...               1676.000000        1676.0
unique            NaN  ...                       NaN           NaN
top               NaN  ...                       NaN           NaN
freq              NaN  ...                       NaN           NaN
mean              1.0  ...                  2.718377          80.0
std               0.0  ...                  1.078162           0.0
min               1.0  ...                  1.000000          80.0
25%               1.0  ...                  2.000000          80.0
50%               1.0  ...                  3.000000          80.0
75%               1.0  ...                  4.000000          80.0
max               1.0  ...                  4.000000          80.0

              Shift  TotalWorkingYears  TrainingTimesLastYear WorkLifeBalanc
e  \
count   1676.000000        1676.000000            1676.000000     1676.00000
0
unique          NaN                NaN                    NaN             Na
N
top             NaN                NaN                    NaN             Na
N
freq            NaN                NaN                    NaN             Na
N
mean       0.806086          11.338902               2.805489        2.76611
0
std        0.855527           7.834996               1.288431        0.70236
9
min        0.000000           0.000000               0.000000        1.00000
0
25%        0.000000           6.000000               2.000000        2.00000
```

```
0
50%        1.000000         10.000000                3.000000        3.00000
0
75%        1.000000         15.000000                3.000000        3.00000
0
max        3.000000         40.000000                6.000000        4.00000
0

        YearsAtCompany YearsInCurrentRole  YearsSinceLastPromotion  \
count      1676.000000        1676.000000              1676.000000
unique             NaN                NaN                      NaN
top                NaN                NaN                      NaN
freq               NaN                NaN                      NaN
mean          7.033413           4.264916                 2.200477
std           6.098991           3.627456                 3.229587
min           0.000000           0.000000                 0.000000
25%           3.000000           2.000000                 0.000000
50%           5.000000           3.000000                 1.000000
75%          10.000000           7.000000                 3.000000
max          40.000000          18.000000                15.000000

        YearsWithCurrManager
count            1676.000000
unique                   NaN
top                      NaN
freq                     NaN
mean                4.135442
std                 3.559662
min                 0.000000
25%                 2.000000
50%                 3.000000
75%                 7.000000
max                17.000000

[11 rows x 35 columns]
```

Inference: This summary statistics reveals that most employees in this dataset do not leave ("No" attrition is most frequent), and "Travel_Rarely" is the dominant business travel pattern. The average age is around 37, with a daily rate of approximately 800. The "Maternity" department and "Life Sciences" education field have the highest representation. Notably, EmployeeCount and StandardHours have constant values, suggesting they might not be informative for analysis.

In [13]:
```
print(df.isnull().sum())
```

```
EmployeeID                  0
Age                         0
Attrition                   0
BusinessTravel              0
DailyRate                   0
Department                  0
DistanceFromHome            0
Education                   0
EducationField              0
EmployeeCount               0
EnvironmentSatisfaction     0
Gender                      0
HourlyRate                  0
JobInvolvement              0
JobLevel                    0
JobRole                     0
JobSatisfaction             0
MaritalStatus               0
MonthlyIncome               0
MonthlyRate                 0
NumCompaniesWorked          0
Over18                      0
OverTime                    0
PercentSalaryHike           0
PerformanceRating           0
RelationshipSatisfaction    0
StandardHours               0
Shift                       0
TotalWorkingYears           0
TrainingTimesLastYear       0
WorkLifeBalance             0
YearsAtCompany              0
YearsInCurrentRole          0
YearsSinceLastPromotion     0
YearsWithCurrManager        0
dtype: int64
```

Inference: This output indicates that there are zero missing values in each of the 35 columns of your DataFrame. This is excellent for analysis as you don't need to handle any imputation or removal of missing data.

In [14]:
```
print(df.nunique())
```

```
EmployeeID                  1676
Age                           43
Attrition                      2
BusinessTravel                 3
DailyRate                    886
Department                     3
DistanceFromHome              29
Education                      5
EducationField                 6
EmployeeCount                  1
EnvironmentSatisfaction        4
Gender                         2
HourlyRate                    71
JobInvolvement                 4
JobLevel                       5
JobRole                        5
JobSatisfaction                4
MaritalStatus                  3
MonthlyIncome               1349
MonthlyRate                 1427
NumCompaniesWorked            10
Over18                         1
OverTime                       2
PercentSalaryHike             15
PerformanceRating              2
RelationshipSatisfaction       4
StandardHours                  1
Shift                          4
TotalWorkingYears             40
TrainingTimesLastYear          7
WorkLifeBalance                4
YearsAtCompany                37
YearsInCurrentRole            19
YearsSinceLastPromotion       16
YearsWithCurrManager          18
dtype: int64
```

Inference: This shows the number of unique values per column.

Key observations:

EmployeeID is unique for all entries.

Attrition, BusinessTravel, Department, EducationField, Gender, MaritalStatus, OverTime, and PerformanceRating have a limited number of categories.

Columns like MonthlyIncome, MonthlyRate, DailyRate, Age, and years-related features have a high number of unique values, suggesting they are likely continuous or have many distinct discrete values.

EmployeeCount and StandardHours having only one unique value means they are constant and won't provide discriminatory information.

Shift having 4 unique values might be relevant.

In [15]:
```
print("Duplicated Rows:", df.duplicated().sum())
```

```
Duplicated Rows: 0
```

Inference: There are no duplicated rows

--- Preprocessing Techniques ---

In [16]:
```
# Separating numerical and categorical columns
num_cols = df.select_dtypes(include=[np.number]).columns.tolist()
cat_cols = df.select_dtypes(include=['object']).columns.tolist()
```

Inference: This classify the numerical and categorical columns to seperate dataframe.

In [17]:
```
#Simple Imputation (Mean/Mode)
df_clean = df.copy()
for col in num_cols:
    missing = df_clean[col].isnull().sum()
    df_clean[col].fillna(df_clean[col].mean(), inplace=True)
    print(f"[Mean Imputation] {col}: Filled {missing} missing values.")

for col in cat_cols:
    missing = df_clean[col].isnull().sum()
    df_clean[col].fillna(df_clean[col].mode()[0], inplace=True)
    print(f"[Mode Imputation] {col}: Filled {missing} missing values.")

print("\n df_clean after Simple Imputation (preview):")
print(df_clean.head())
```

```
[Mean Imputation] EmployeeID: Filled 0 missing values.
[Mean Imputation] Age: Filled 0 missing values.
[Mean Imputation] DailyRate: Filled 0 missing values.
[Mean Imputation] DistanceFromHome: Filled 0 missing values.
[Mean Imputation] Education: Filled 0 missing values.
[Mean Imputation] EmployeeCount: Filled 0 missing values.
[Mean Imputation] EnvironmentSatisfaction: Filled 0 missing values.
[Mean Imputation] HourlyRate: Filled 0 missing values.
[Mean Imputation] JobInvolvement: Filled 0 missing values.
[Mean Imputation] JobLevel: Filled 0 missing values.
[Mean Imputation] JobSatisfaction: Filled 0 missing values.
[Mean Imputation] MonthlyIncome: Filled 0 missing values.
[Mean Imputation] MonthlyRate: Filled 0 missing values.
[Mean Imputation] NumCompaniesWorked: Filled 0 missing values.
[Mean Imputation] PercentSalaryHike: Filled 0 missing values.
[Mean Imputation] PerformanceRating: Filled 0 missing values.
[Mean Imputation] RelationshipSatisfaction: Filled 0 missing values.
[Mean Imputation] StandardHours: Filled 0 missing values.
[Mean Imputation] Shift: Filled 0 missing values.
[Mean Imputation] TotalWorkingYears: Filled 0 missing values.
[Mean Imputation] TrainingTimesLastYear: Filled 0 missing values.
[Mean Imputation] WorkLifeBalance: Filled 0 missing values.
[Mean Imputation] YearsAtCompany: Filled 0 missing values.
[Mean Imputation] YearsInCurrentRole: Filled 0 missing values.
[Mean Imputation] YearsSinceLastPromotion: Filled 0 missing values.
[Mean Imputation] YearsWithCurrManager: Filled 0 missing values.
[Mode Imputation] Attrition: Filled 0 missing values.
[Mode Imputation] BusinessTravel: Filled 0 missing values.
[Mode Imputation] Department: Filled 0 missing values.
[Mode Imputation] EducationField: Filled 0 missing values.
[Mode Imputation] Gender: Filled 0 missing values.
[Mode Imputation] JobRole: Filled 0 missing values.
[Mode Imputation] MaritalStatus: Filled 0 missing values.
[Mode Imputation] Over18: Filled 0 missing values.
[Mode Imputation] OverTime: Filled 0 missing values.

 df_clean after Simple Imputation (preview):
   EmployeeID  Age Attrition     BusinessTravel  DailyRate  Department  \
0     1313919   41        No      Travel_Rarely       1102  Cardiology
1     1200302   49        No  Travel_Frequently        279   Maternity
2     1060315   37       Yes      Travel_Rarely       1373   Maternity
3     1272912   33        No  Travel_Frequently       1392   Maternity
4     1414939   27        No      Travel_Rarely        591   Maternity

   DistanceFromHome  Education EducationField  EmployeeCount  ...  \
0                 1          2  Life Sciences              1  ...
1                 8          1  Life Sciences              1  ...
2                 2          2          Other              1  ...
3                 3          4  Life Sciences              1  ...
4                 2          1        Medical              1  ...

   RelationshipSatisfaction StandardHours  Shift  TotalWorkingYears  \
0                         1            80      0                  8
1                         4            80      1                 10
2                         2            80      0                  7
3                         3            80      0                  8
```

```
4                          4            80      1                   6

   TrainingTimesLastYear WorkLifeBalance  YearsAtCompany YearsInCurrentRole  \
0                      0               1               6                  4   
1                      3               3              10                  7   
2                      3               3               0                  0   
3                      3               3               8                  7   
4                      3               3               2                  2   

   YearsSinceLastPromotion  YearsWithCurrManager  
0                        0                     5  
1                        1                     7  
2                        0                     0  
3                        3                     0  
4                        2                     2  

[5 rows x 35 columns]
```

Inference: This output confirms that no missing values were found in any of the specified columns, so the mean and mode imputation steps effectively did nothing. The preview of df_clean shows the first five rows of cleaned DataFrame, with the listed columns now guaranteed to be complete.

In [18]:
```
#Iterative Imputation (MICE)
df_mice = df.copy()
mice_imputer = IterativeImputer(random_state=0)
df_mice[num_cols] = mice_imputer.fit_transform(df_mice[num_cols])

print("\ndf_mice after Iterative Imputation (numeric only preview):")
print(df_mice[num_cols].head())
```

```
df_mice after Iterative Imputation (numeric only preview):
   EmployeeID   Age  DailyRate  DistanceFromHome  Education  EmployeeCount
\
0   1313919.0  41.0     1102.0               1.0        2.0            1.0
1   1200302.0  49.0      279.0               8.0        1.0            1.0
2   1060315.0  37.0     1373.0               2.0        2.0            1.0
3   1272912.0  33.0     1392.0               3.0        4.0            1.0
4   1414939.0  27.0      591.0               2.0        1.0            1.0

   EnvironmentSatisfaction  HourlyRate  JobInvolvement  JobLevel  ...  \
0                      2.0        94.0             3.0       2.0  ...
1                      3.0        61.0             2.0       2.0  ...
2                      4.0        92.0             2.0       1.0  ...
3                      4.0        56.0             3.0       1.0  ...
4                      1.0        40.0             3.0       1.0  ...

   RelationshipSatisfaction  StandardHours  Shift  TotalWorkingYears  \
0                       1.0           80.0    0.0                8.0
1                       4.0           80.0    1.0               10.0
2                       2.0           80.0    0.0                7.0
3                       3.0           80.0    0.0                8.0
4                       4.0           80.0    1.0                6.0

   TrainingTimesLastYear  WorkLifeBalance  YearsAtCompany  YearsInCurrentRol
e  \
0                    0.0              1.0             6.0                 4.
0
1                    3.0              3.0            10.0                 7.
0
2                    3.0              3.0             0.0                 0.
0
3                    3.0              3.0             8.0                 7.
0
4                    3.0              3.0             2.0                 2.
0

   YearsSinceLastPromotion  YearsWithCurrManager
0                      0.0                   5.0
1                      1.0                   7.0
2                      0.0                   0.0
3                      3.0                   0.0
4                      2.0                   2.0

[5 rows x 26 columns]
```

Inference: This shows a preview of DataFrame df_mice after iterative imputation, focusing on the numeric columns. It displays the first five rows and the values imputed (if any were missing initially) across 26 numerical features. This suggests you used the MICE (Multiple Imputation by Chained Equations) algorithm to handle potential missing data in these numeric columns. Since all values are present in this preview, it implies the imputation process has been completed.

In [19]:
```python
# KNN Imputation (numerics only)
df_knn = df.copy()
knn_imputer = KNNImputer(n_neighbors=5)
df_knn[num_cols] = knn_imputer.fit_transform(df_knn[num_cols])

print("\n df_knn after KNN Imputation (numeric only preview):")
print(df_knn[num_cols].head())
```

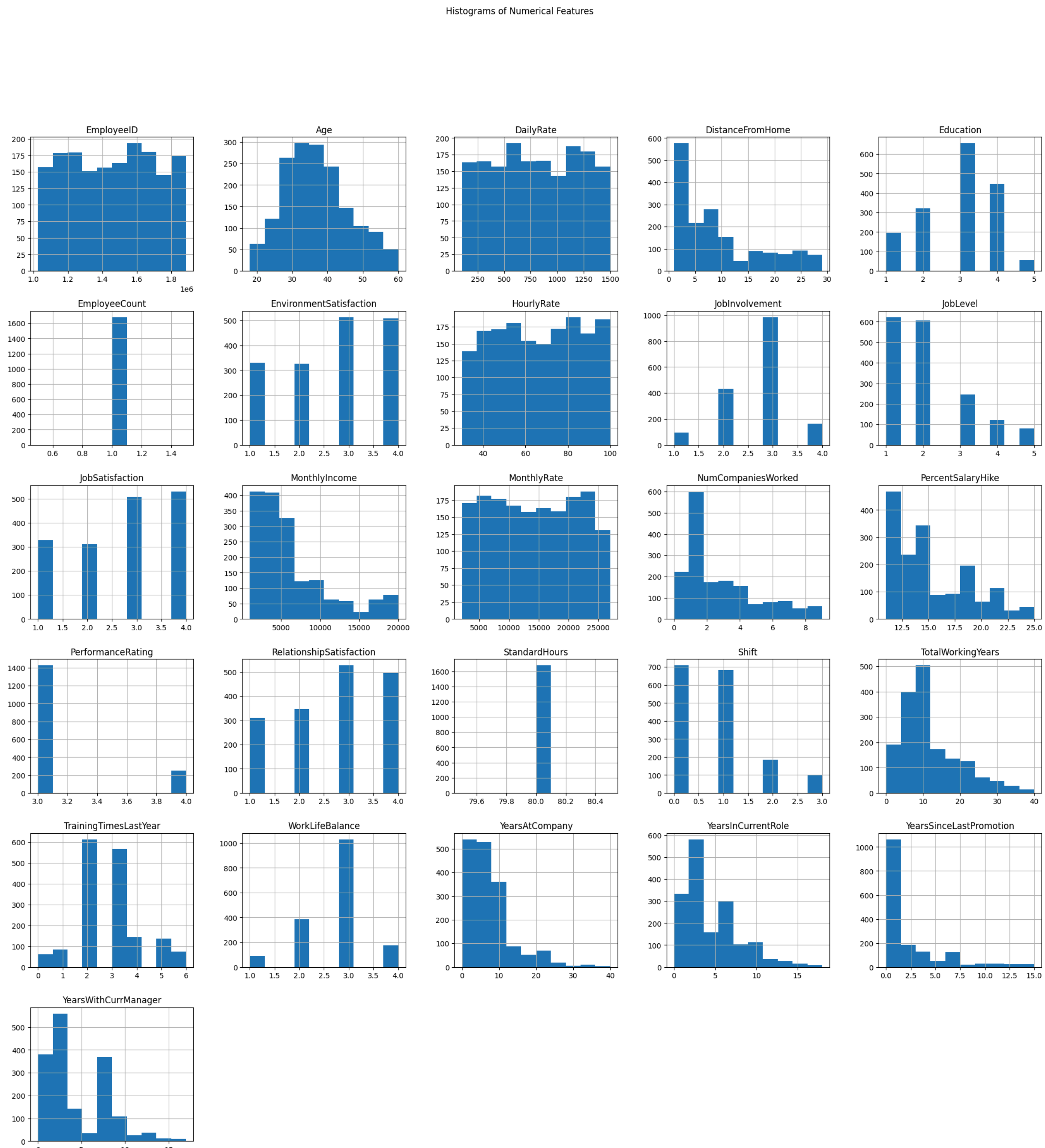
```
 df_knn after KNN Imputation (numeric only preview):
   EmployeeID   Age  DailyRate  DistanceFromHome  Education  EmployeeCount  \
0   1313919.0  41.0     1102.0               1.0        2.0            1.0   
1   1200302.0  49.0      279.0               8.0        1.0            1.0   
2   1060315.0  37.0     1373.0               2.0        2.0            1.0   
3   1272912.0  33.0     1392.0               3.0        4.0            1.0   
4   1414939.0  27.0      591.0               2.0        1.0            1.0   

   EnvironmentSatisfaction  HourlyRate  JobInvolvement  JobLevel  ...  \
0                      2.0        94.0             3.0       2.0  ...   
1                      3.0        61.0             2.0       2.0  ...   
2                      4.0        92.0             2.0       1.0  ...   
3                      4.0        56.0             3.0       1.0  ...   
4                      1.0        40.0             3.0       1.0  ...   

   RelationshipSatisfaction  StandardHours  Shift  TotalWorkingYears  \
0                       1.0           80.0    0.0                8.0   
1                       4.0           80.0    1.0               10.0   
2                       2.0           80.0    0.0                7.0   
3                       3.0           80.0    0.0                8.0   
4                       4.0           80.0    1.0                6.0   

   TrainingTimesLastYear  WorkLifeBalance  YearsAtCompany  YearsInCurrentRol
e  \
0                    0.0              1.0             6.0                 4.
0   
1                    3.0              3.0            10.0                 7.
0   
2                    3.0              3.0             0.0                 0.
0   
3                    3.0              3.0             8.0                 7.
0   
4                    3.0              3.0             2.0                 2.
0   

   YearsSinceLastPromotion  YearsWithCurrManager  
0                      0.0                   5.0  
1                      1.0                   7.0  
2                      0.0                   0.0  
3                      3.0                   0.0  
4                      2.0                   2.0  

[5 rows x 26 columns]
```

Inference: This preview of df_knn shows the first five rows of your numeric data after applying KNN (K-Nearest Neighbors) imputation. Like the MICE imputation, all values are present, indicating that any missing numeric data has been filled using values from the most similar neighboring data points. The 26 numeric columns are now complete.

--- Summarization and Visualization ---

Inference:

In [20]:
```python
# Histogram
df_clean[num_cols].hist(figsize=(25, 25))
plt.suptitle("Histograms of Numerical Features")
plt.show()
```



Inference:

EmployeeID: Appears uniformly distributed, as expected for unique identifiers.

Age: Slightly skewed to the right, indicating a larger proportion of younger employees.

DailyRate & HourlyRate: Seem somewhat uniformly distributed across their ranges.

DistanceFromHome: Right-skewed, suggesting most employees live closer to work.

Education: Shows peaks at certain education levels (likely representing categories).

EmployeeCount & StandardHours: Single bars indicate constant values.

EnvironmentSatisfaction, JobInvolvement, JobLevel, JobSatisfaction, RelationshipSatisfaction, WorkLifeBalance: Appear to be categorical or ordinal, with varying frequencies across levels.

MonthlyIncome & MonthlyRate: Strongly right-skewed, indicating most employees have lower incomes/rates, with a few earning significantly more.

NumCompaniesWorked: Right-skewed, suggesting most employees have worked for fewer companies.

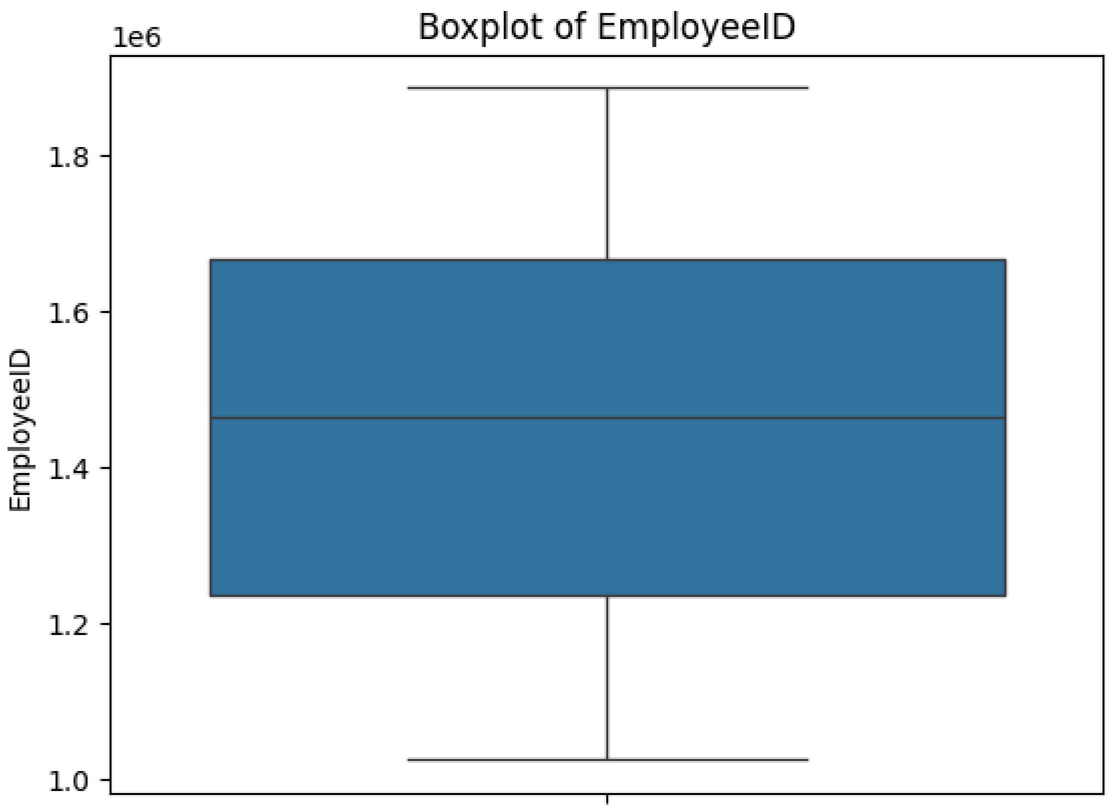
PercentSalaryHike: Shows distinct percentage hike values, likely representing specific increments.

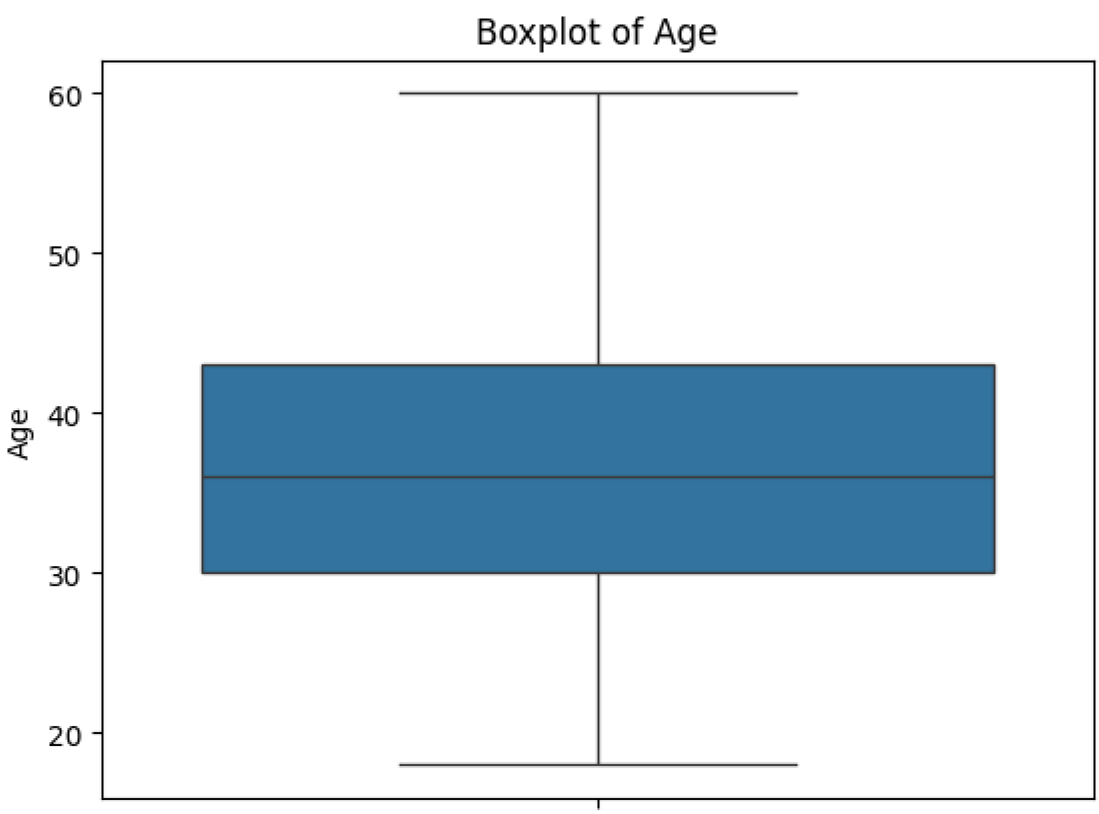
PerformanceRating: Bimodal, indicating two main performance rating categories.
Shift: Shows the distribution of employees across different shifts.

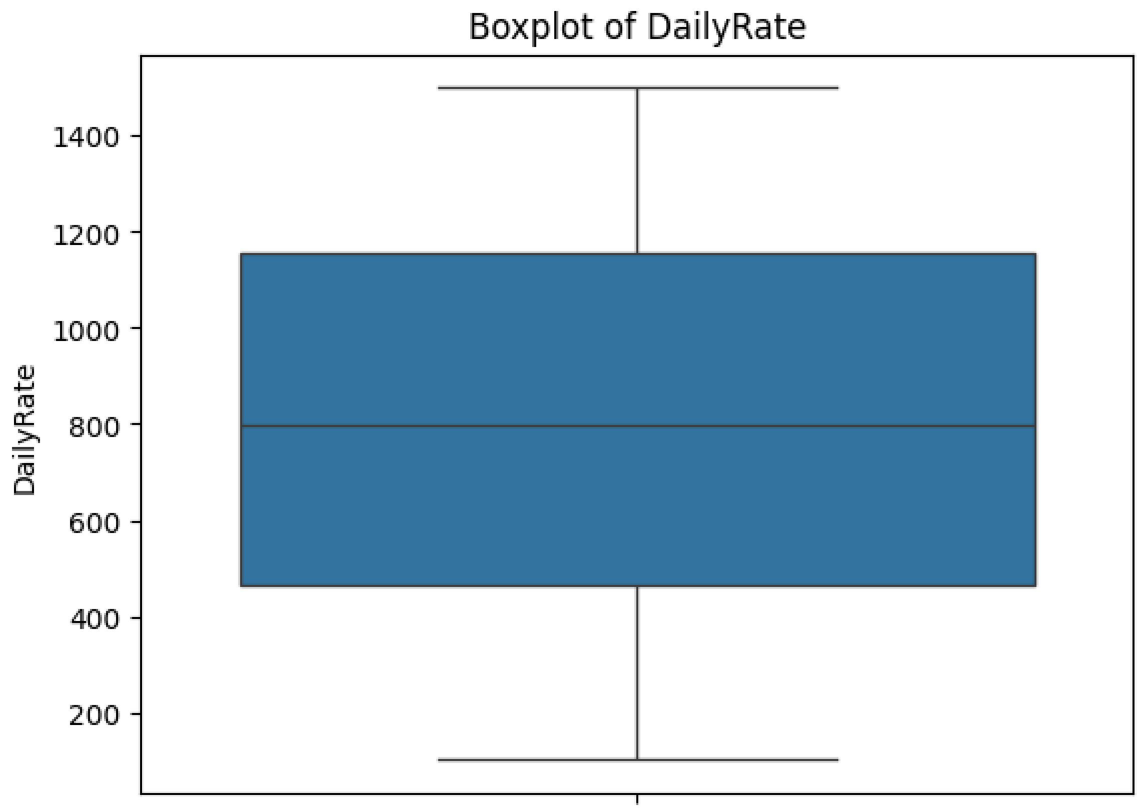
TotalWorkingYears, YearsAtCompany, YearsInCurrentRole, YearsSinceLastPromotion, YearsWithCurrManager: All right-skewed, indicating most employees have shorter tenures in these aspects.

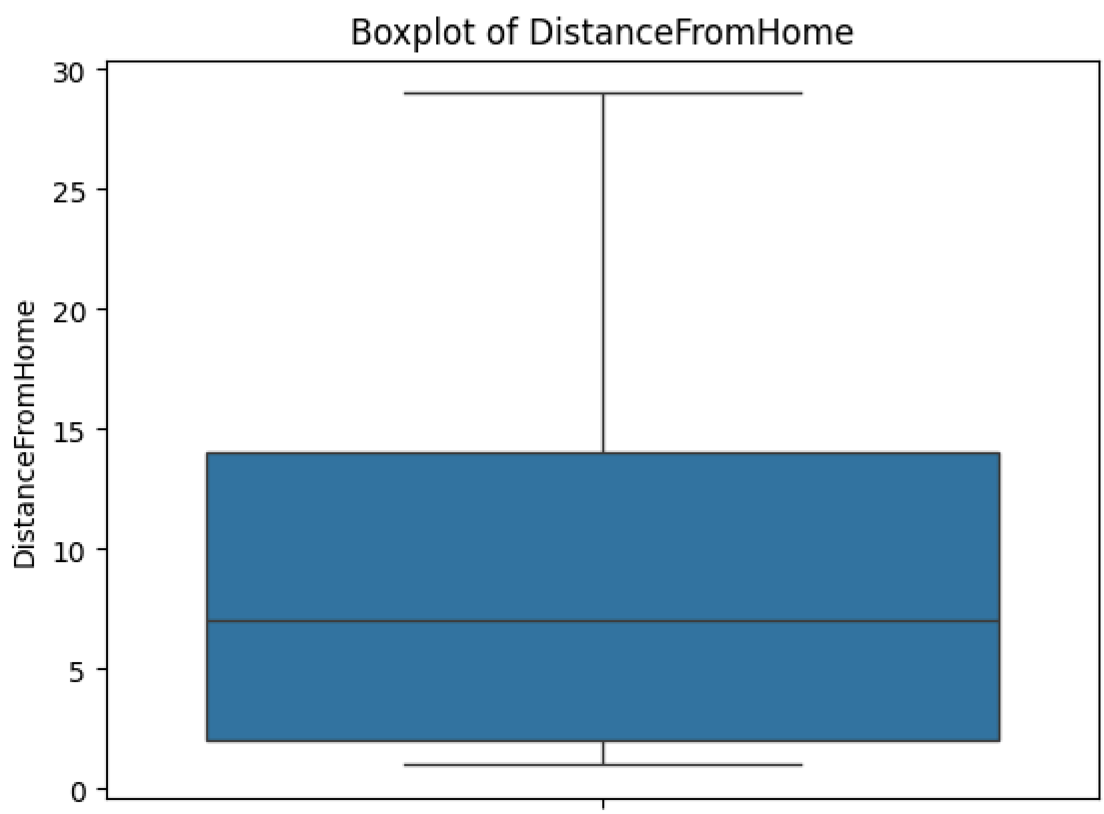
TrainingTimesLastYear: Shows the frequency of different numbers of training sessions.

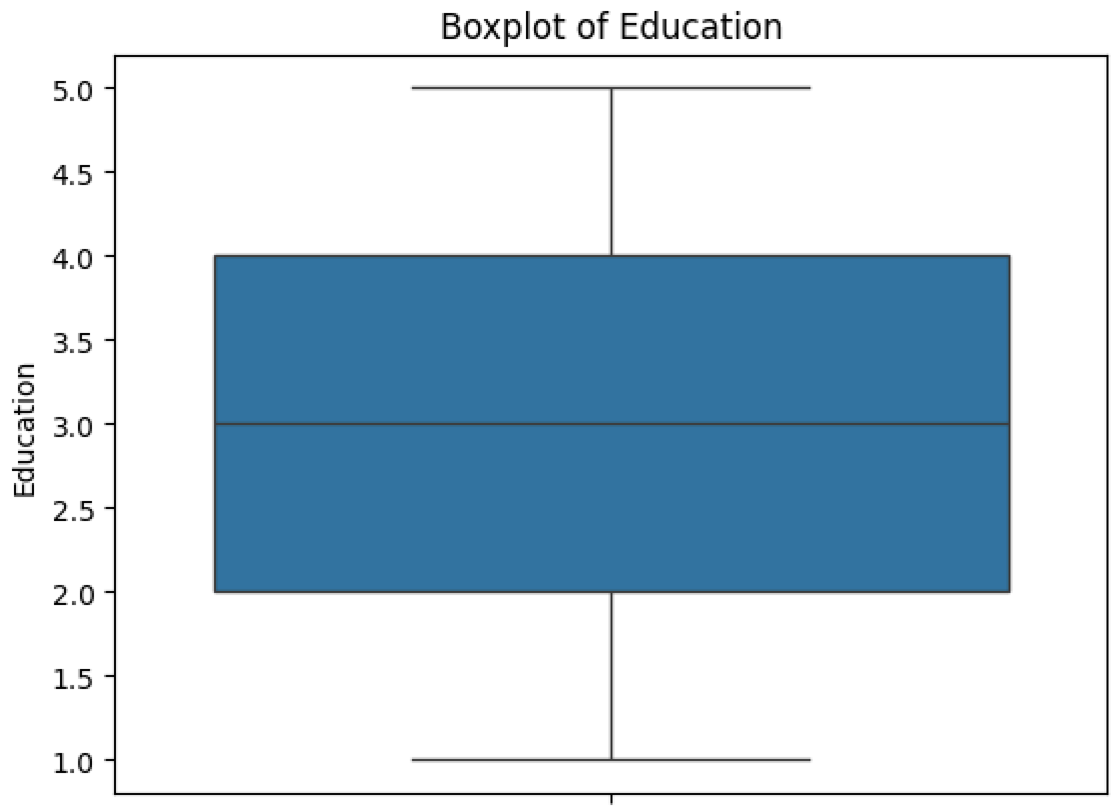
In [21]:
```
# Boxplots for Outliers
for col in num_cols:
    sns.boxplot(df_clean[col])
    plt.title(f'Boxplot of {col}')
    plt.show()
```

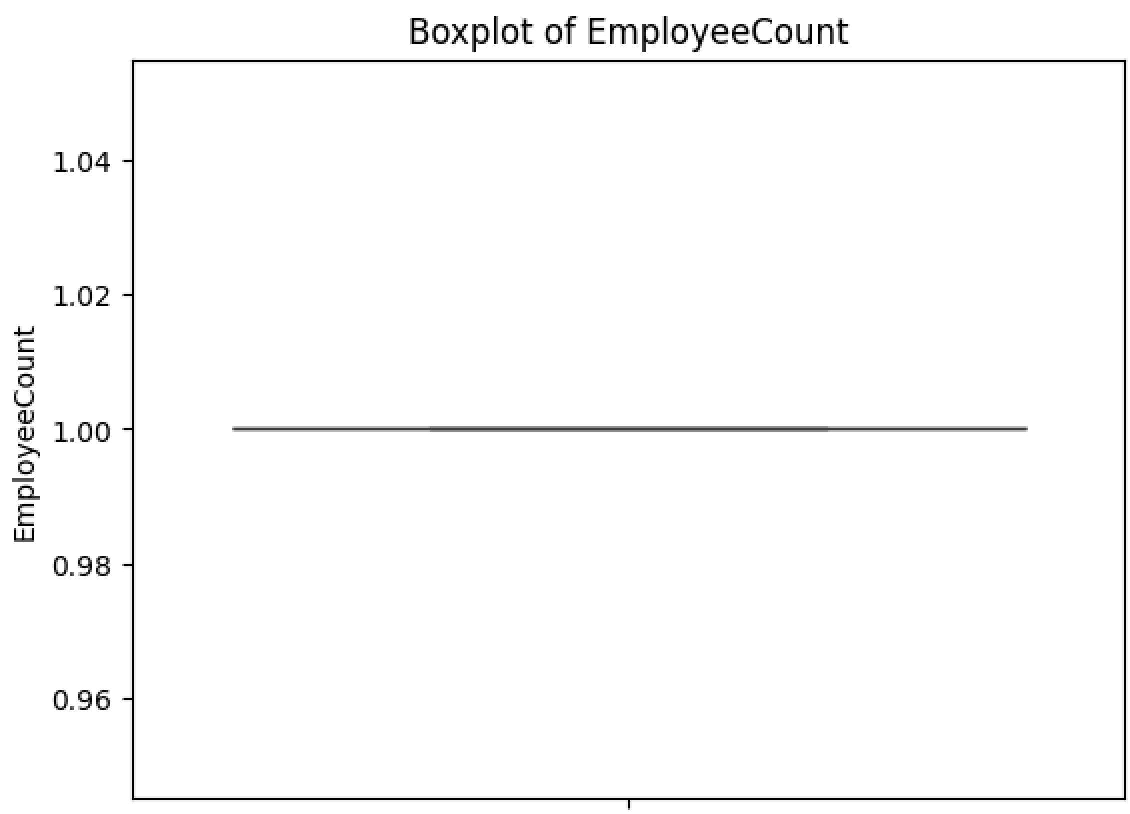

Boxplot of EmployeeID
1e6
EmployeeID
1.8
1.6
1.4
1.2
1.0

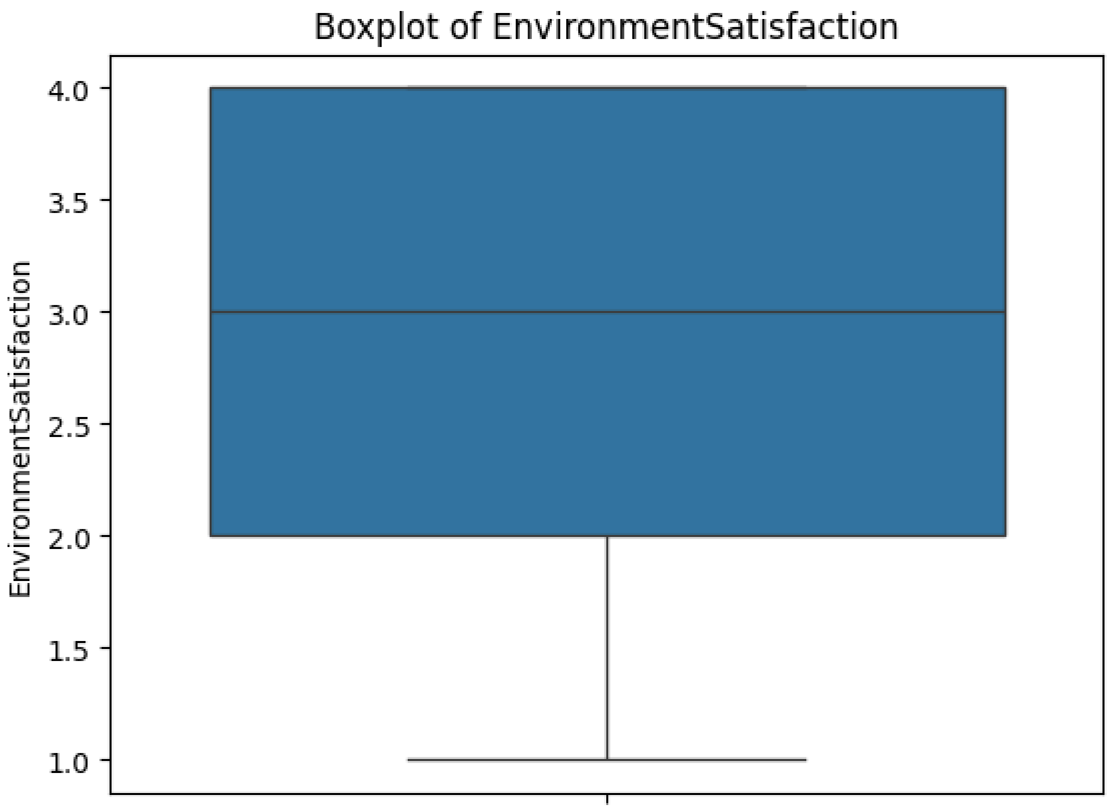

Boxplot of Age
Age
60
50
40
30
20

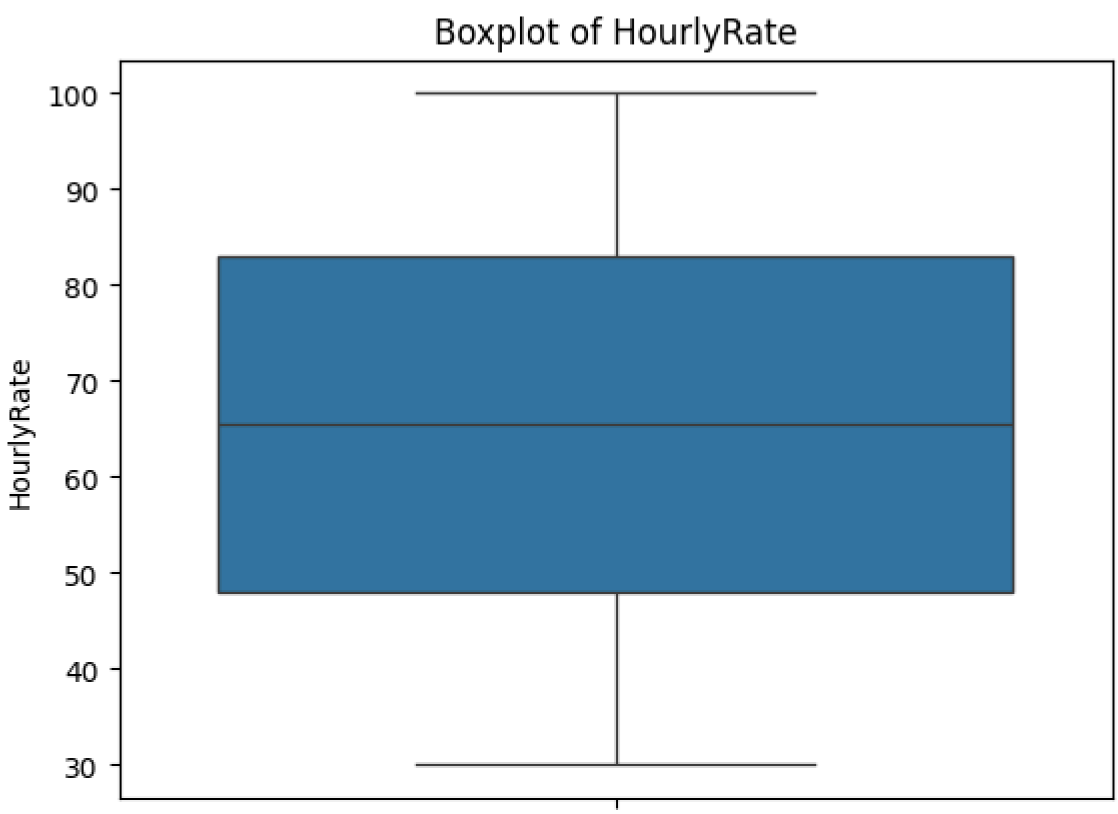

Boxplot of DailyRate
DailyRate
1400
1200
1000
800
600
400
200

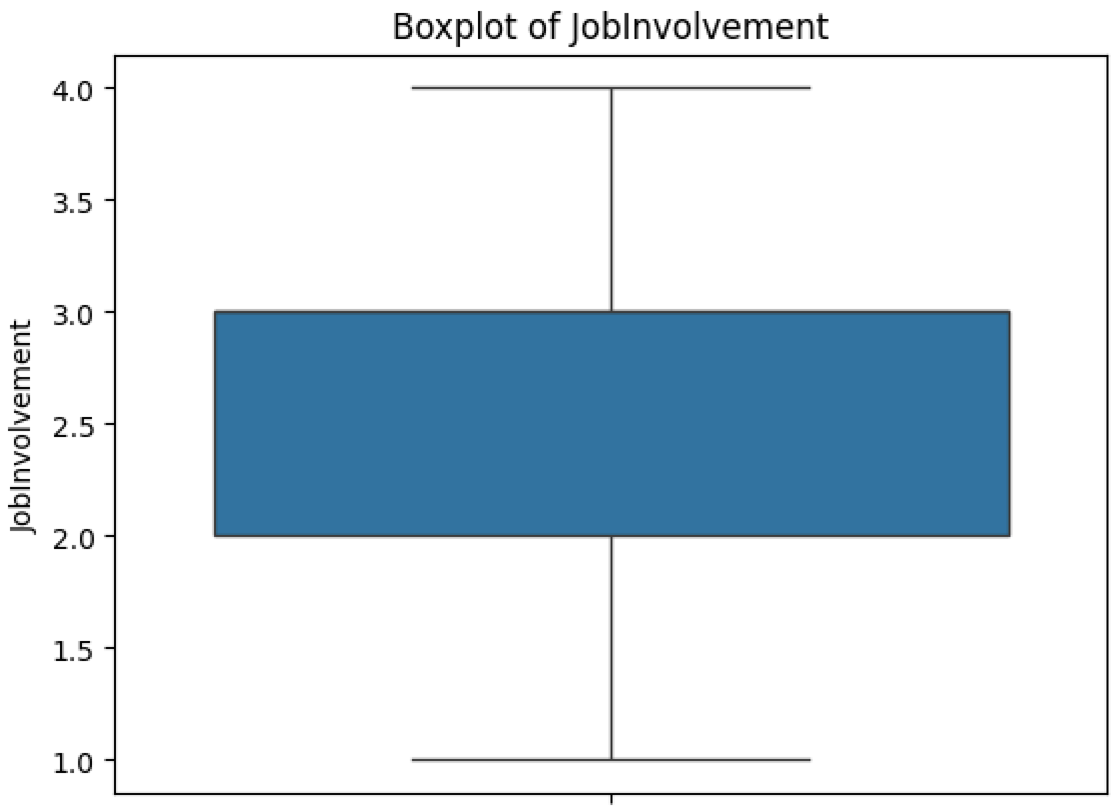

Boxplot of DistanceFromHome
DistanceFromHome
30
25
20
15
10
5
0

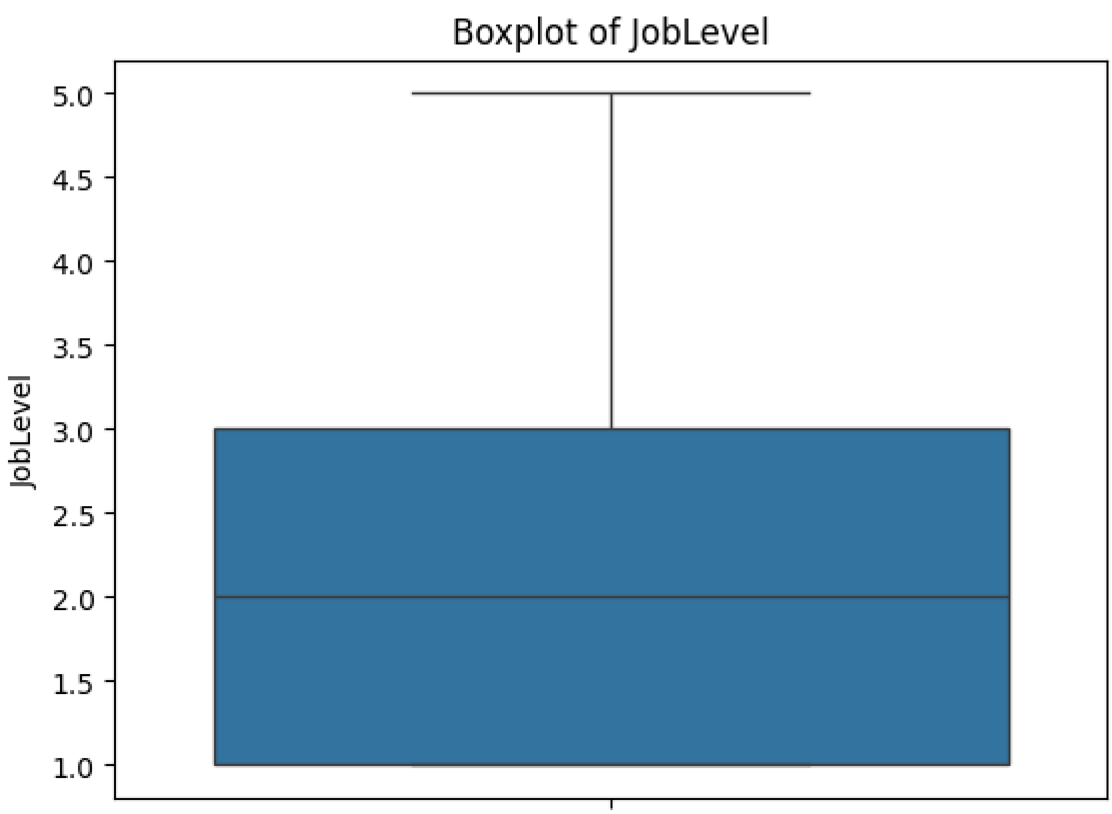

Boxplot of Education
Education
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0

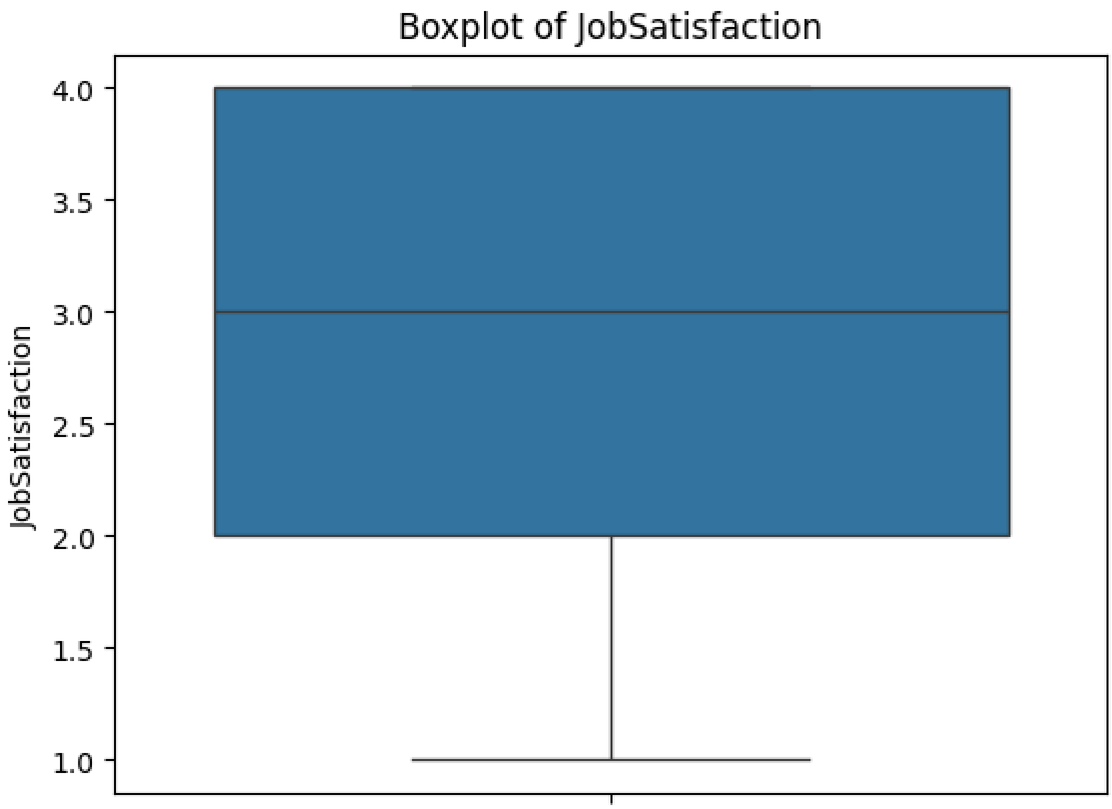

Boxplot of EmployeeCount
EmployeeCount
1.04
1.02
1.00
0.98
0.96

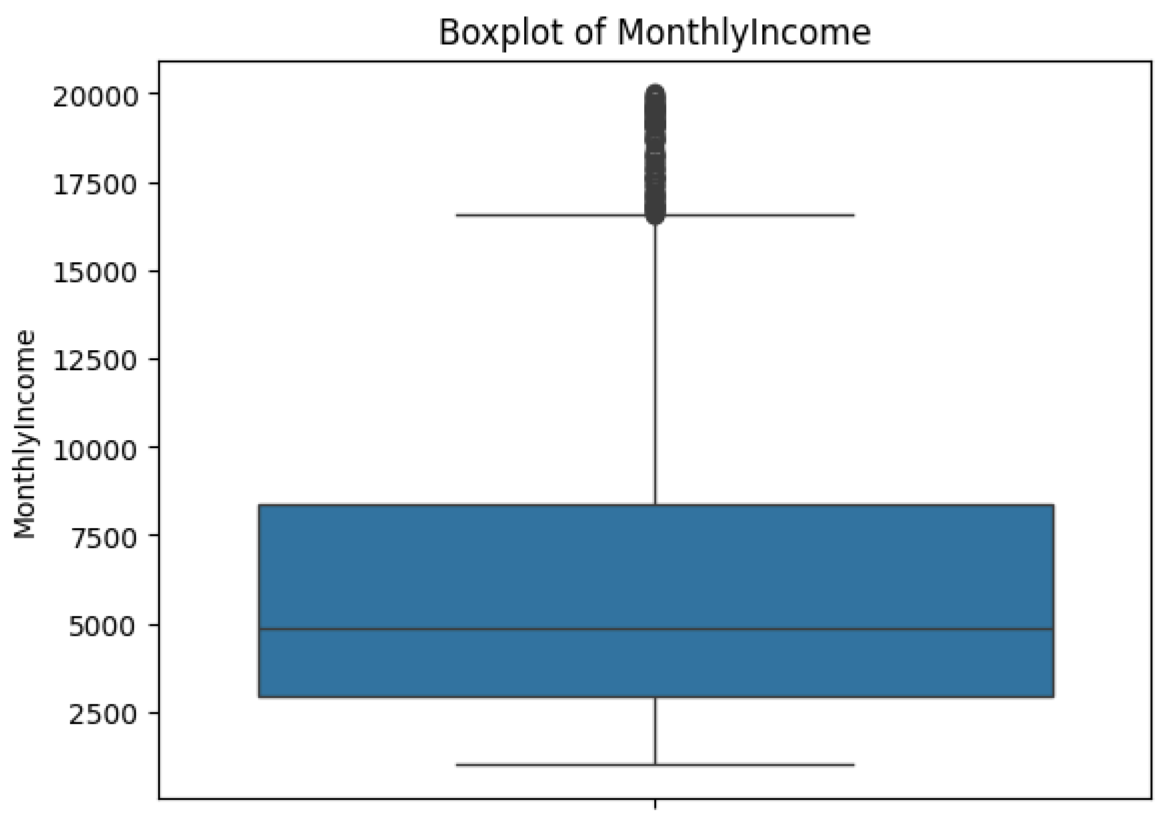

Boxplot of EnvironmentSatisfaction
EnvironmentSatisfaction
4.0
3.5
3.0
2.5
2.0
1.5
1.0

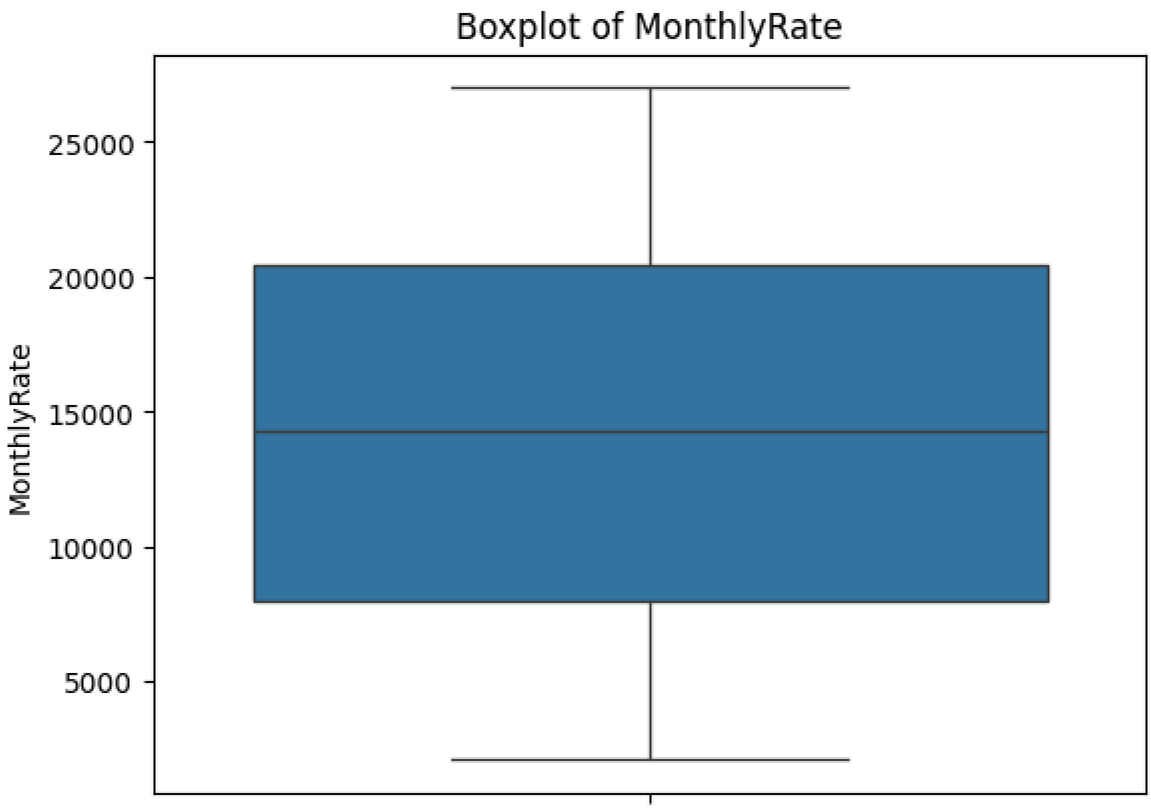

Boxplot of HourlyRate
HourlyRate
100
90
80
70
60
50
40
30

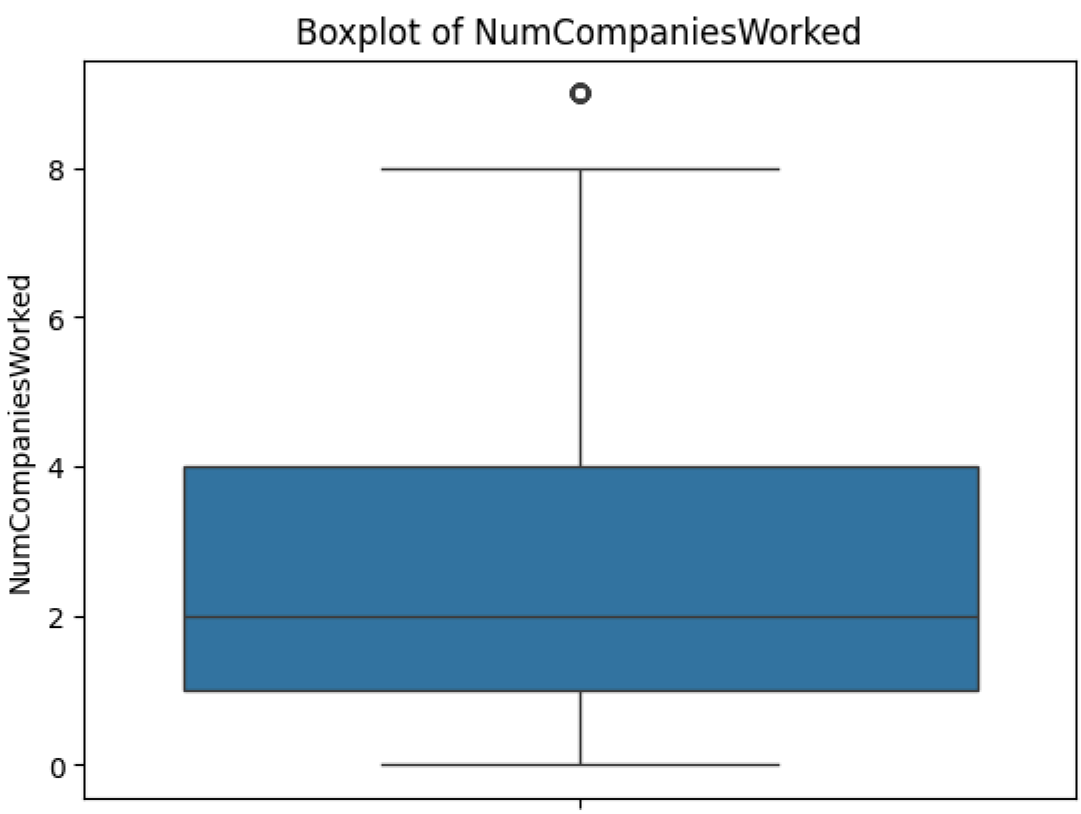

Boxplot of JobInvolvement
JobInvolvement
4.0
3.5
3.0
2.5
2.0
1.5
1.0

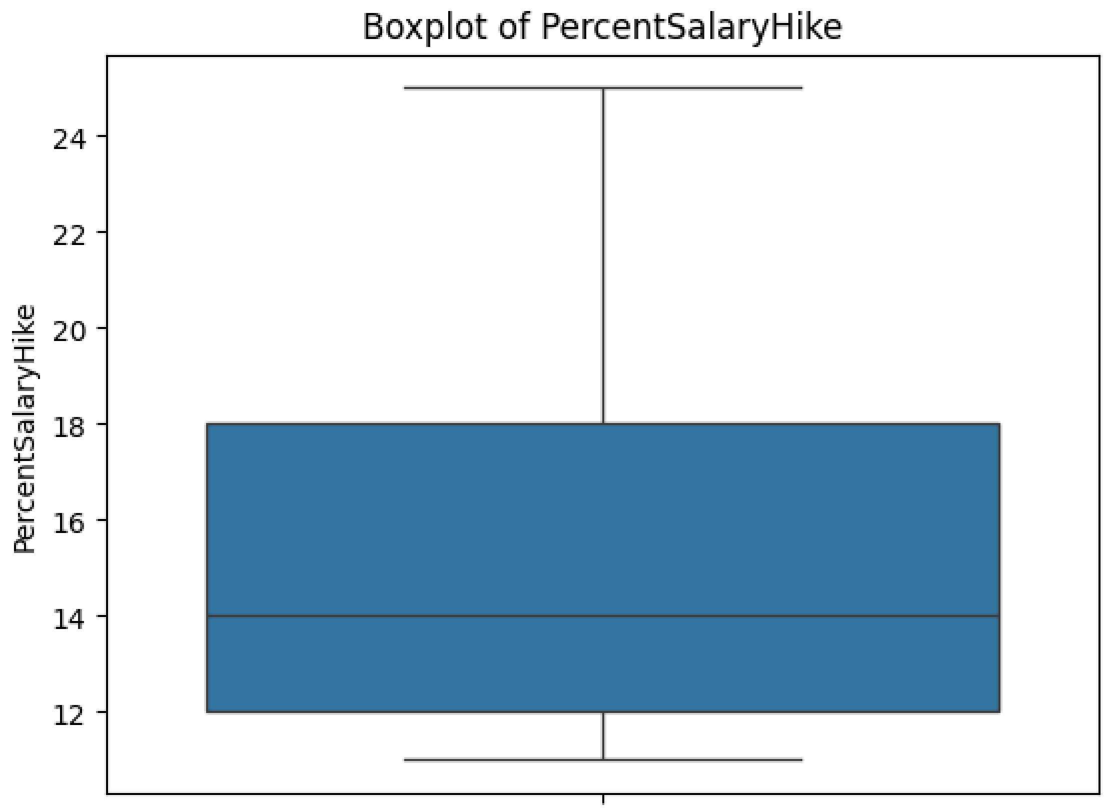

Boxplot of JobLevel
JobLevel
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0

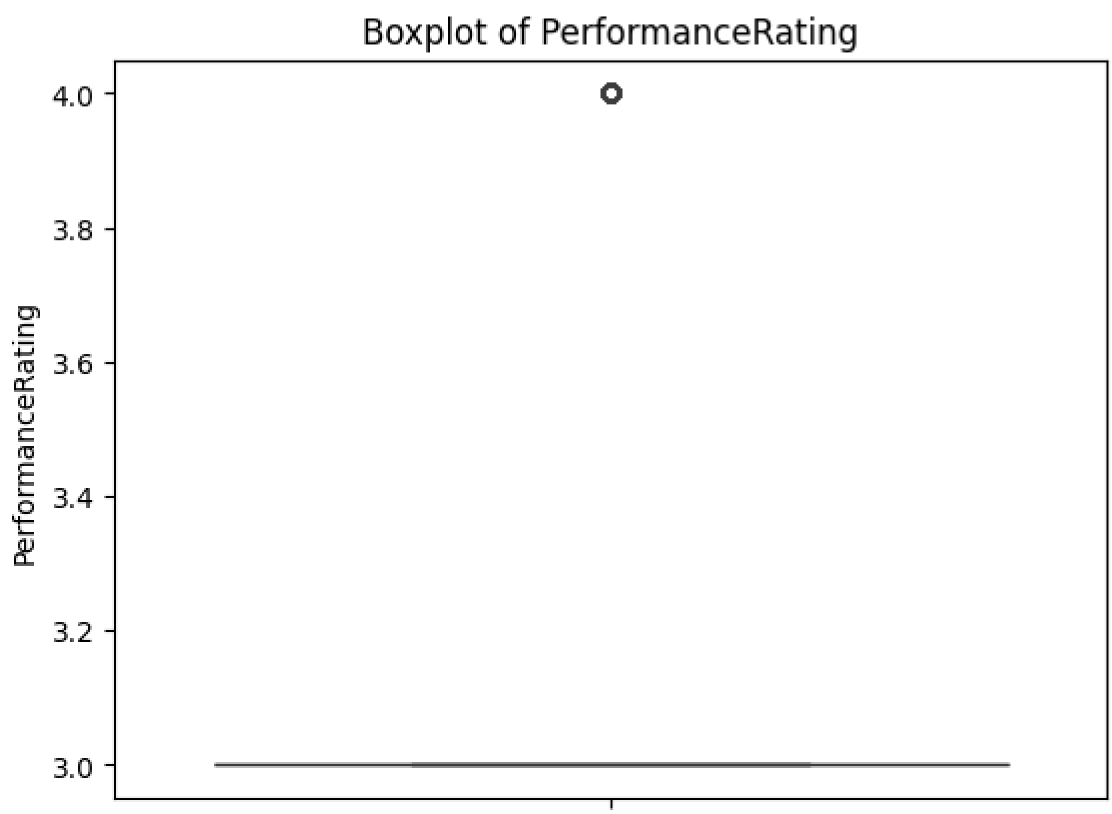

Boxplot of JobSatisfaction
JobSatisfaction
4.0
3.5
3.0
2.5
2.0
1.5
1.0

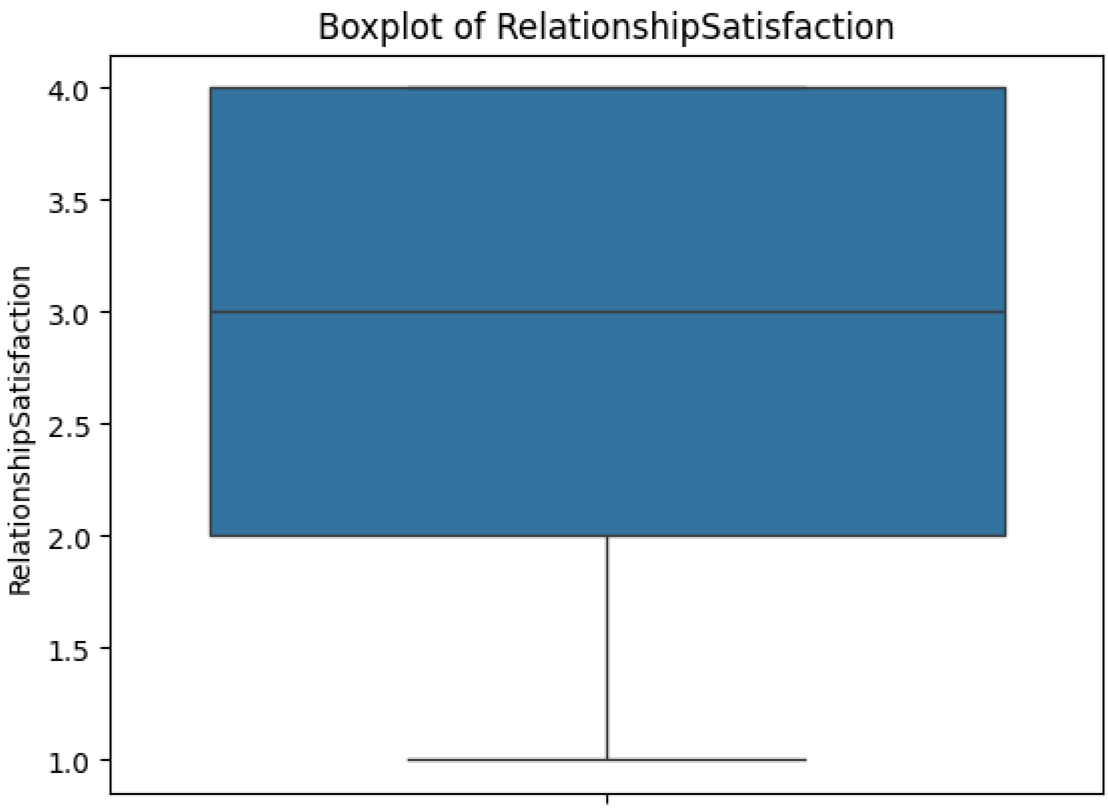

Boxplot of MonthlyIncome
MonthlyIncome
20000
17500
15000
12500
10000
7500
5000
2500

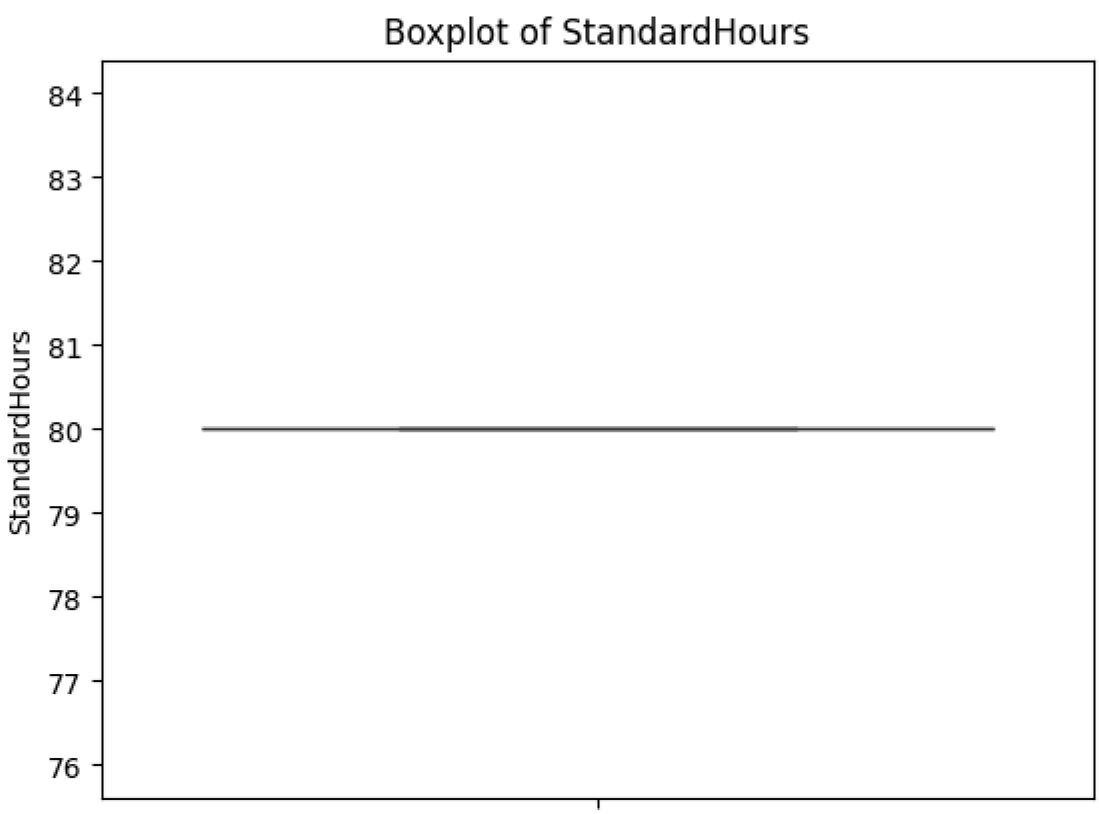

Boxplot of MonthlyRate
MonthlyRate
25000
20000
15000
10000
5000

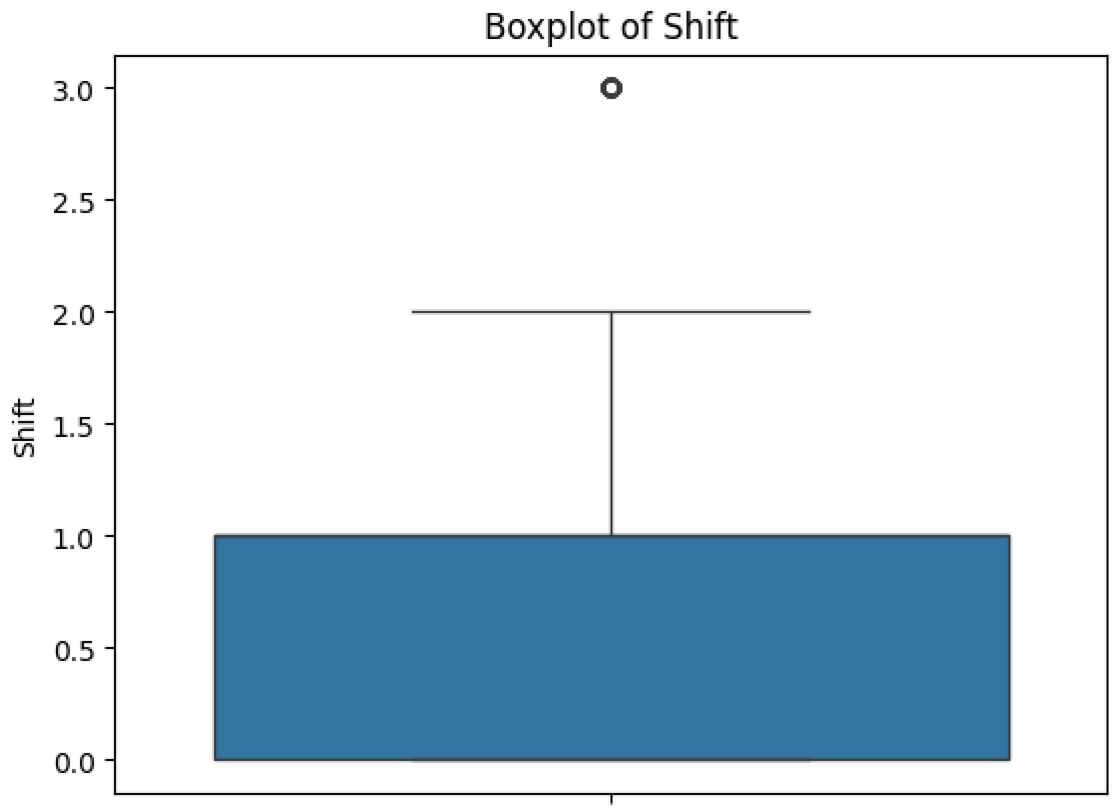

Boxplot of NumCompaniesWorked
NumCompaniesWorked
8
6
4
2
0


Boxplot of PercentSalaryHike
PercentSalaryHike
24
22
20
18
16
14
12

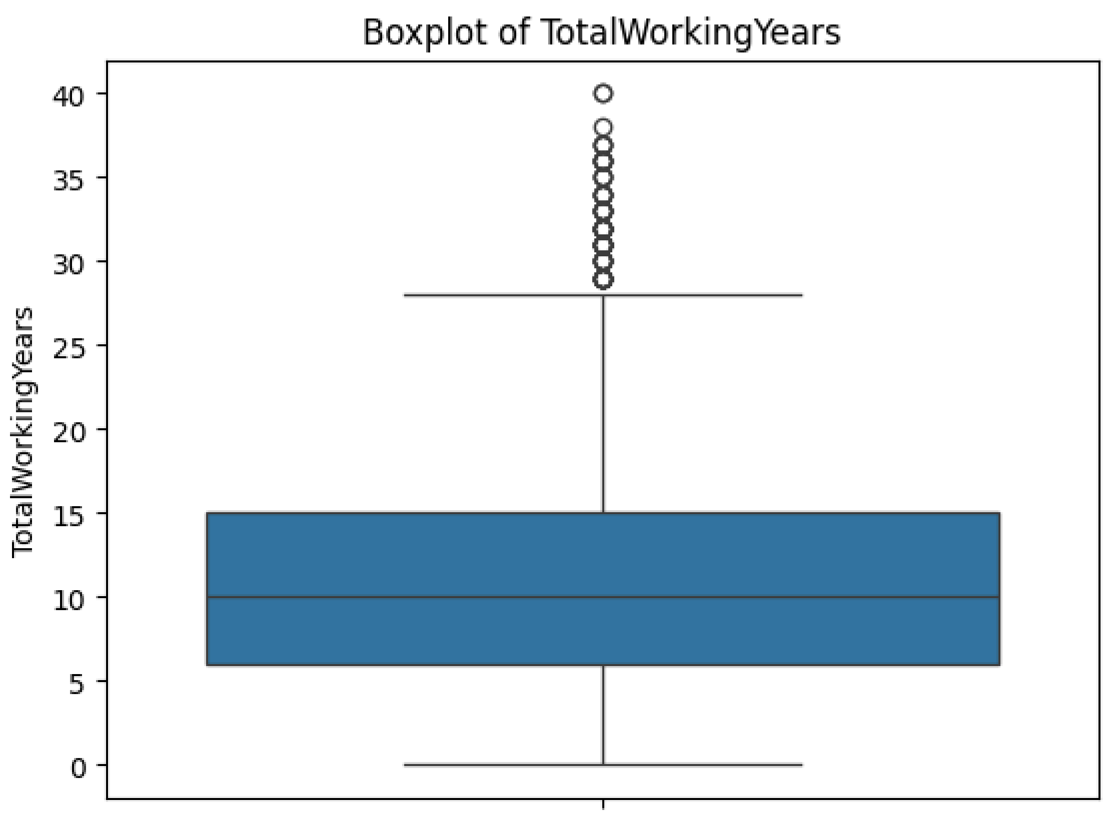

Boxplot of PerformanceRating
PerformanceRating
4.0
3.8
3.6
3.4
3.2
3.0


Boxplot of RelationshipSatisfaction
RelationshipSatisfaction
4.0
3.5
3.0
2.5
2.0
1.5
1.0

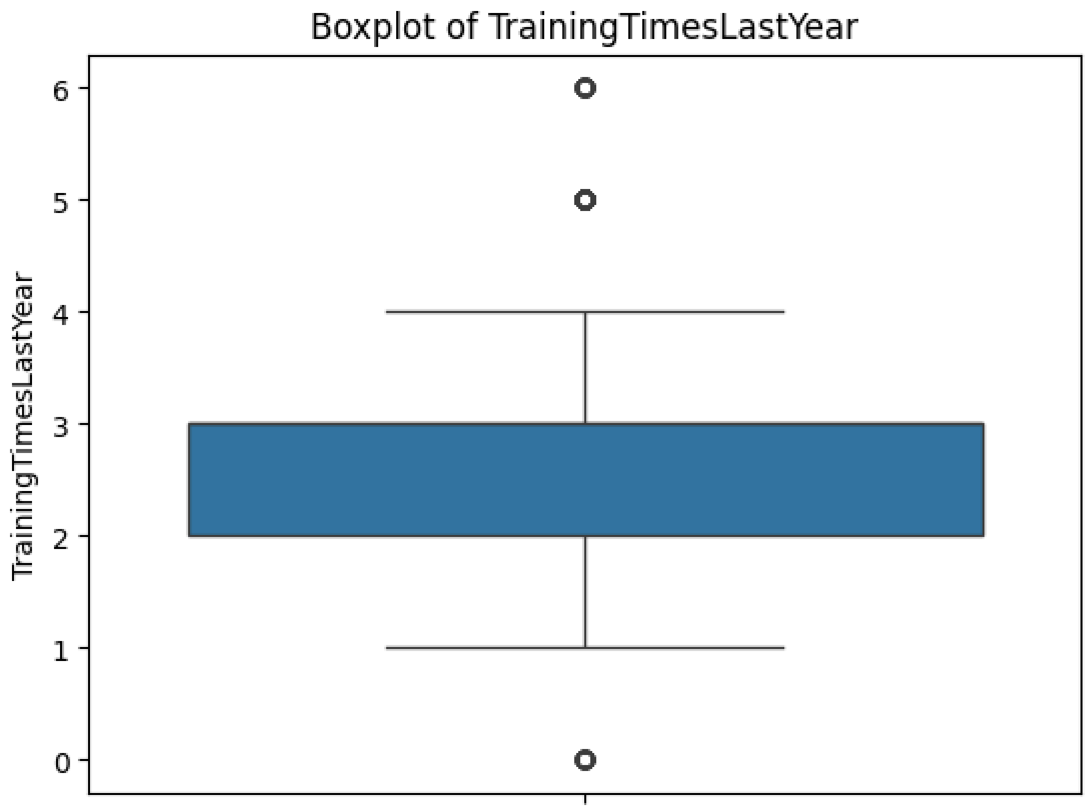

Boxplot of StandardHours
StandardHours
84
83
82
81
80
79
78
77
76

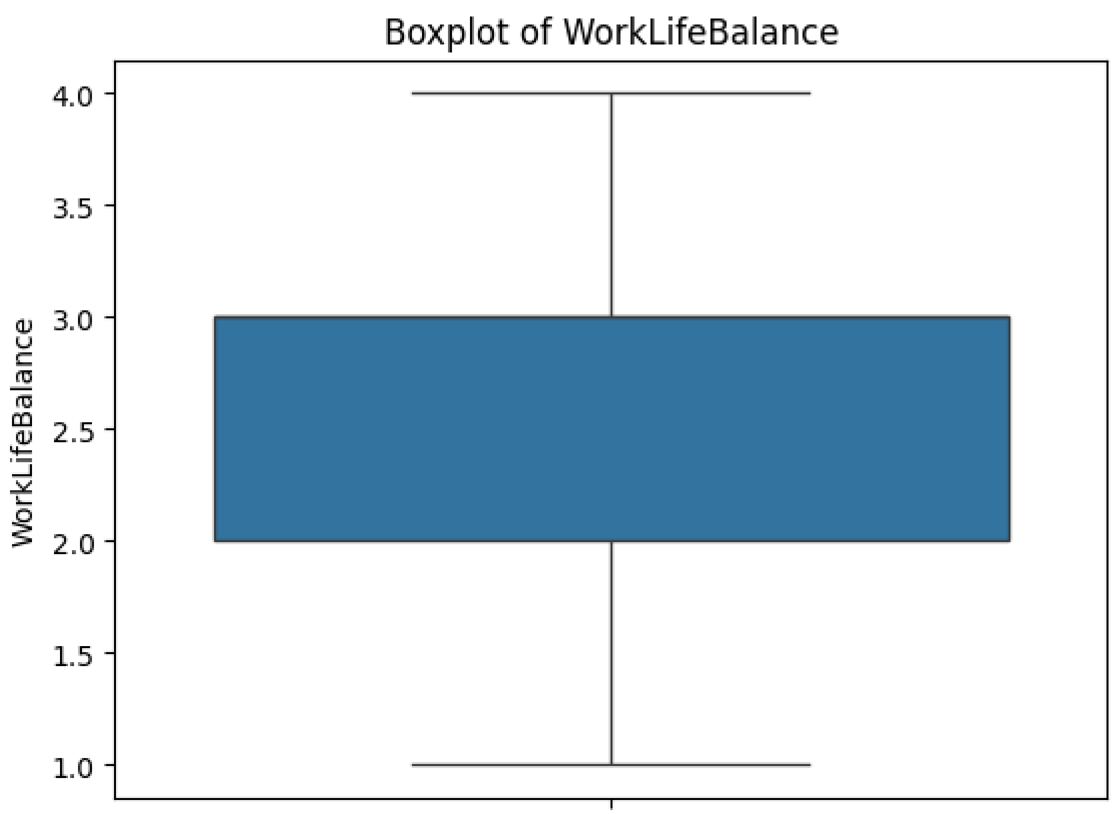


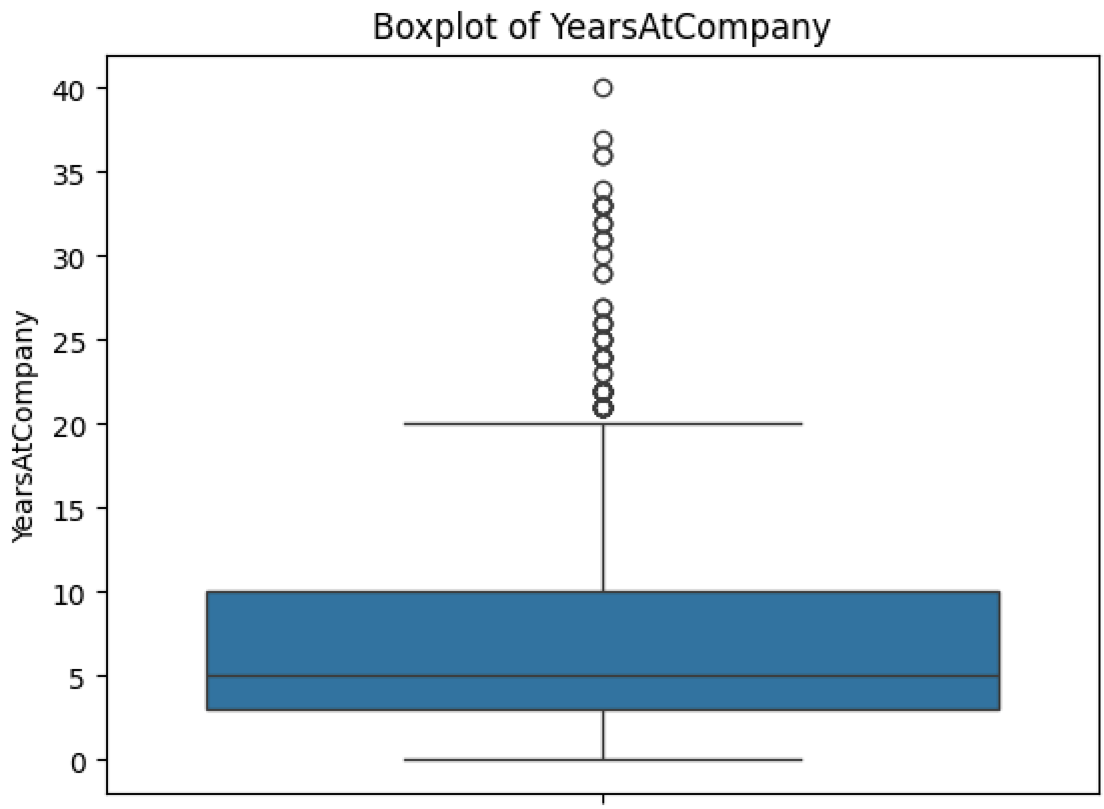
Boxplot of Shift
Shift
3.0
2.5
2.0
1.5
1.0
0.5
0.0

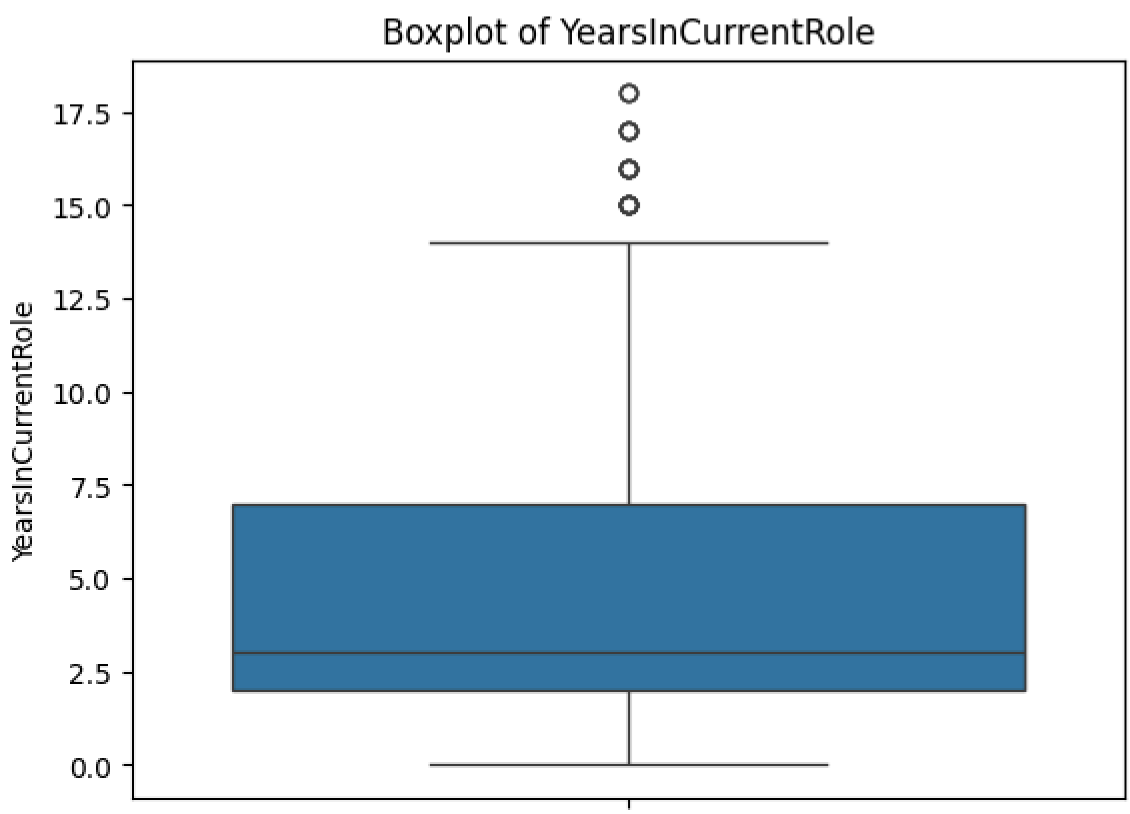


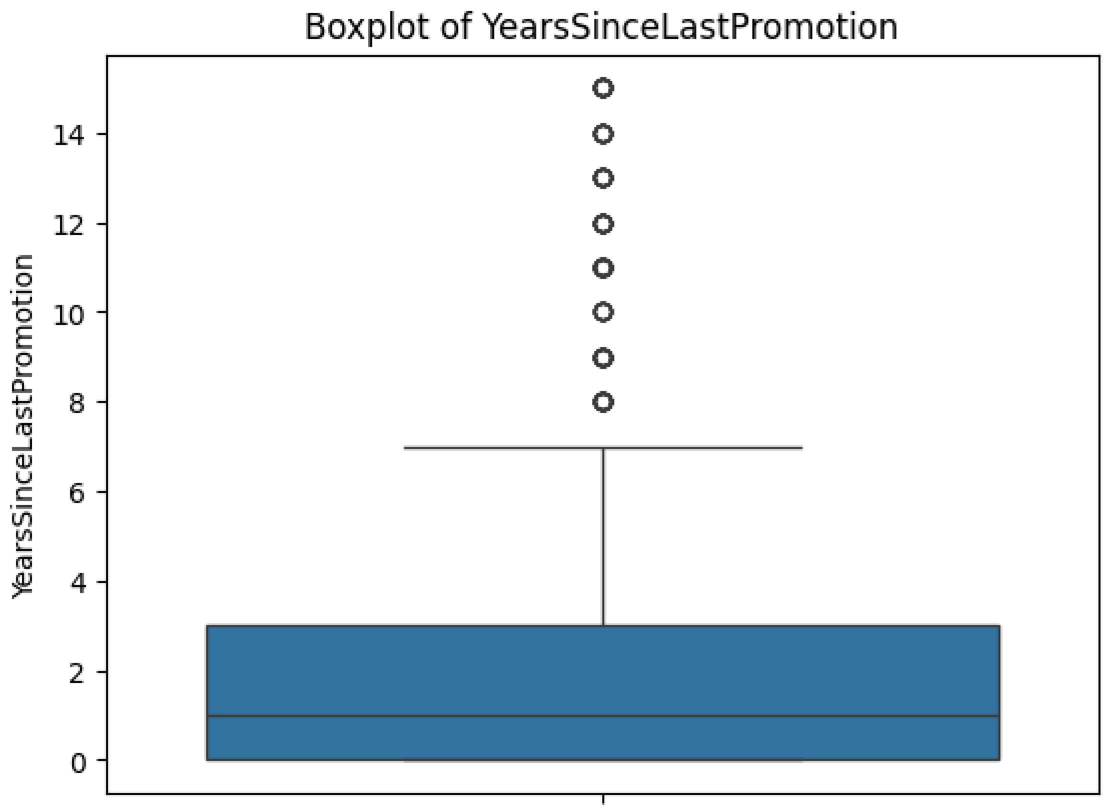
Boxplot of TotalWorkingYears
TotalWorkingYears
40
35
30
25
20
15
10
5
0

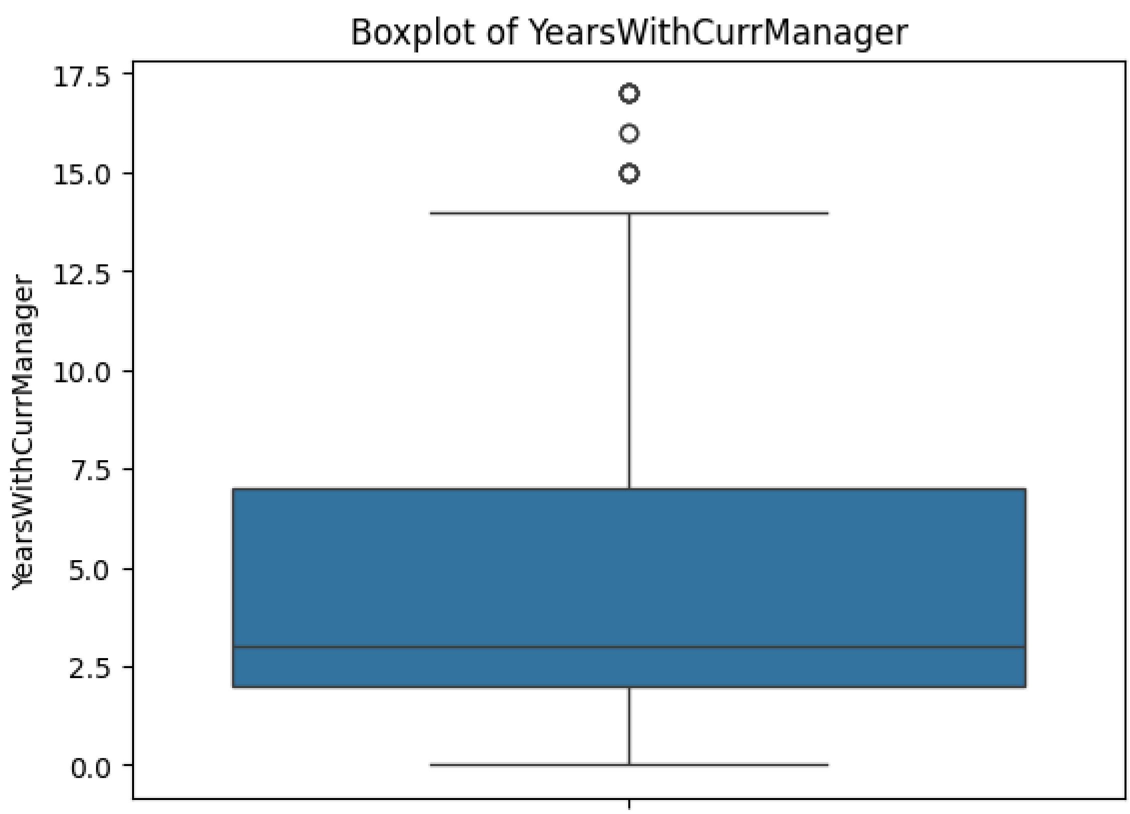

Boxplot of TrainingTimesLastYear
TrainingTimesLastYear
0
1
2
3
4
5
6


Boxplot of WorkLifeBalance
WorkLifeBalance
1.0
1.5
2.0
2.5
3.0
3.5
4.0


Boxplot of YearsAtCompany
YearsAtCompany
40
35
30
25
20
15
10
5
0


Boxplot of YearsInCurrentRole
YearsInCurrentRole
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0

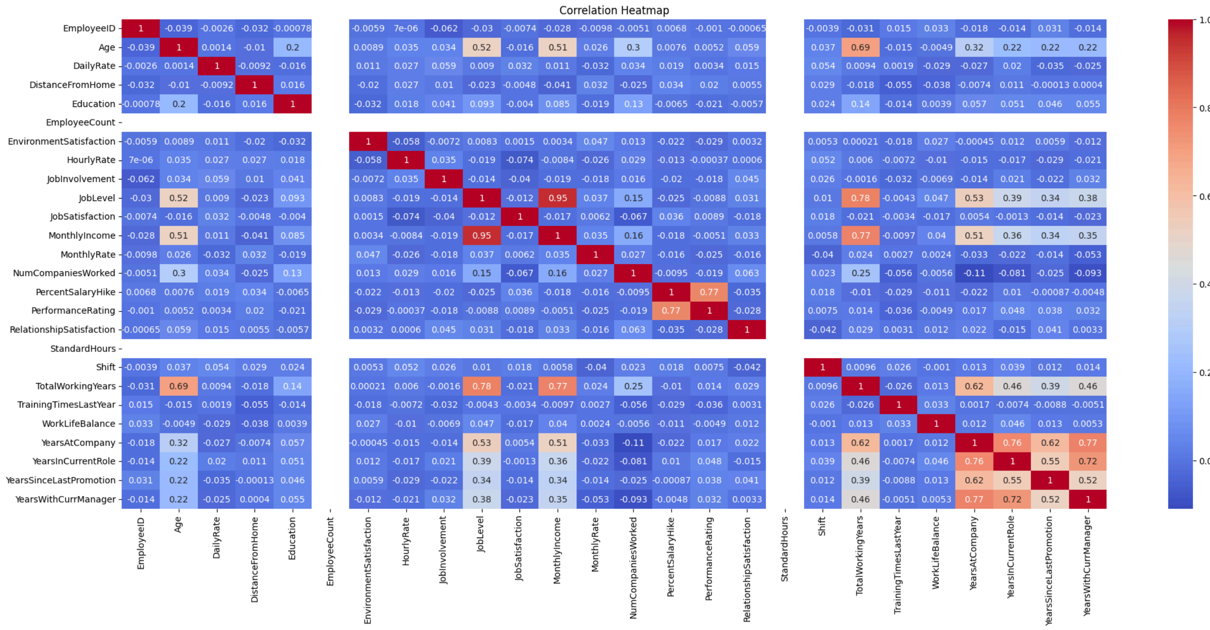




Inference: There are outliers in most of the attributes.

In [22]:
```
# Correlation Matrix
plt.figure(figsize=(25, 10))
sns.heatmap(df_clean[num_cols].corr(), annot=True, cmap='coolwarm')
```

```python
plt.title("Correlation Heatmap")
plt.show()
```



Inference: This heatmap displays the correlations between numerical features. Key observations:

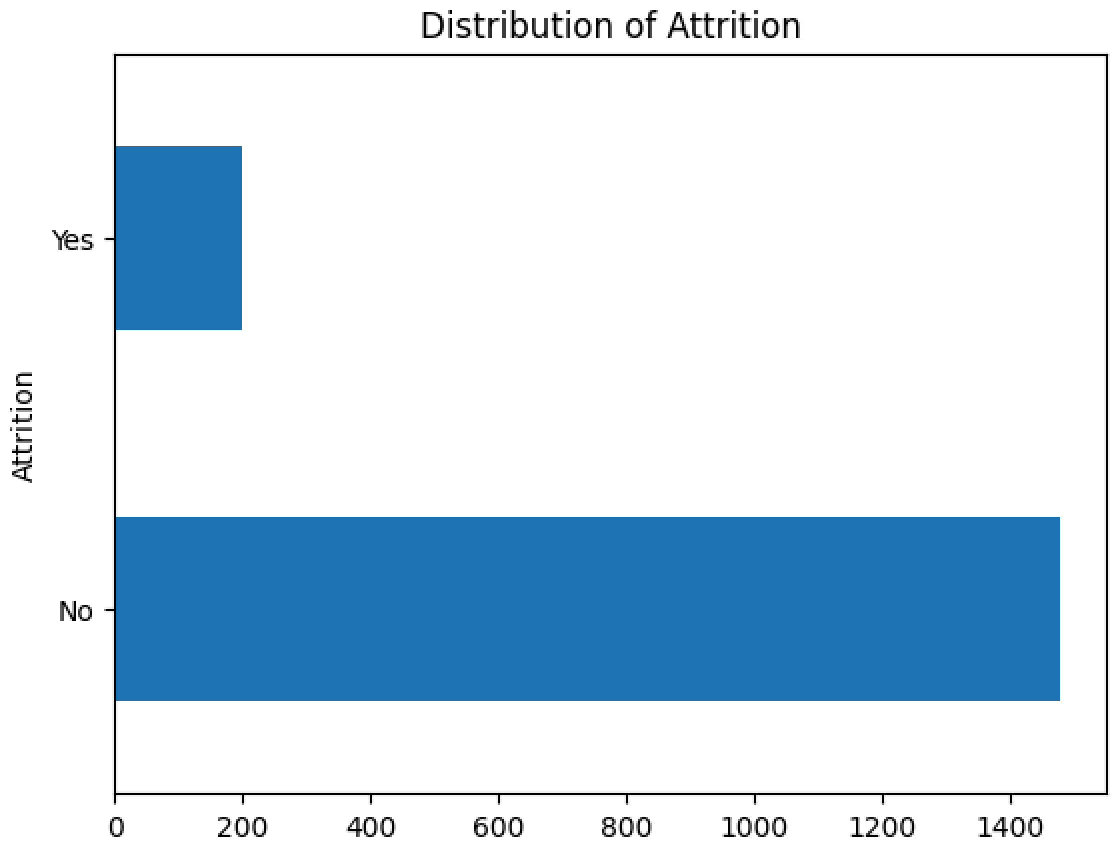
Strong Positive Correlation: JobLevel with MonthlyIncome and TotalWorkingYears; YearsAtCompany with YearsInCurrentRole and YearsWithCurrManager; YearsInCurrentRole with YearsWithCurrManager.

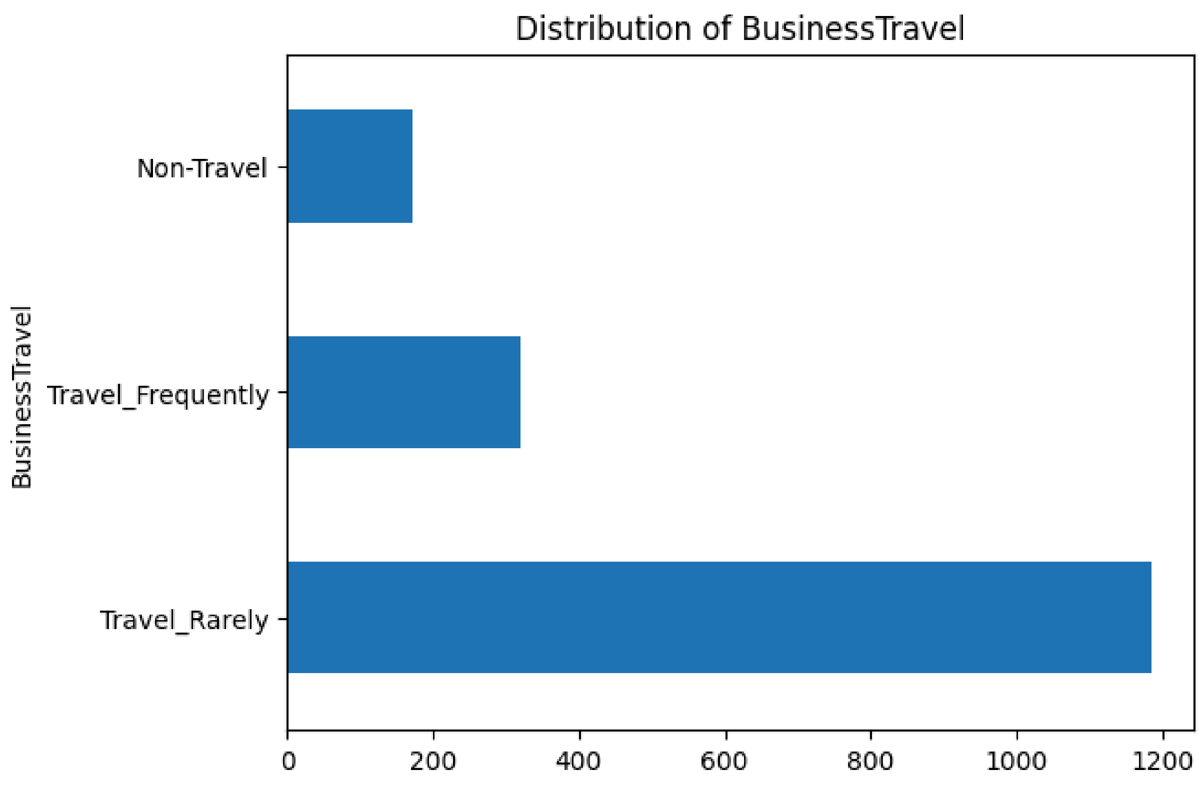
Strong Negative Correlation: JobLevel with DistanceFromHome (weak). Moderate Positive Correlation: PerformanceRating with PercentSalaryHike.

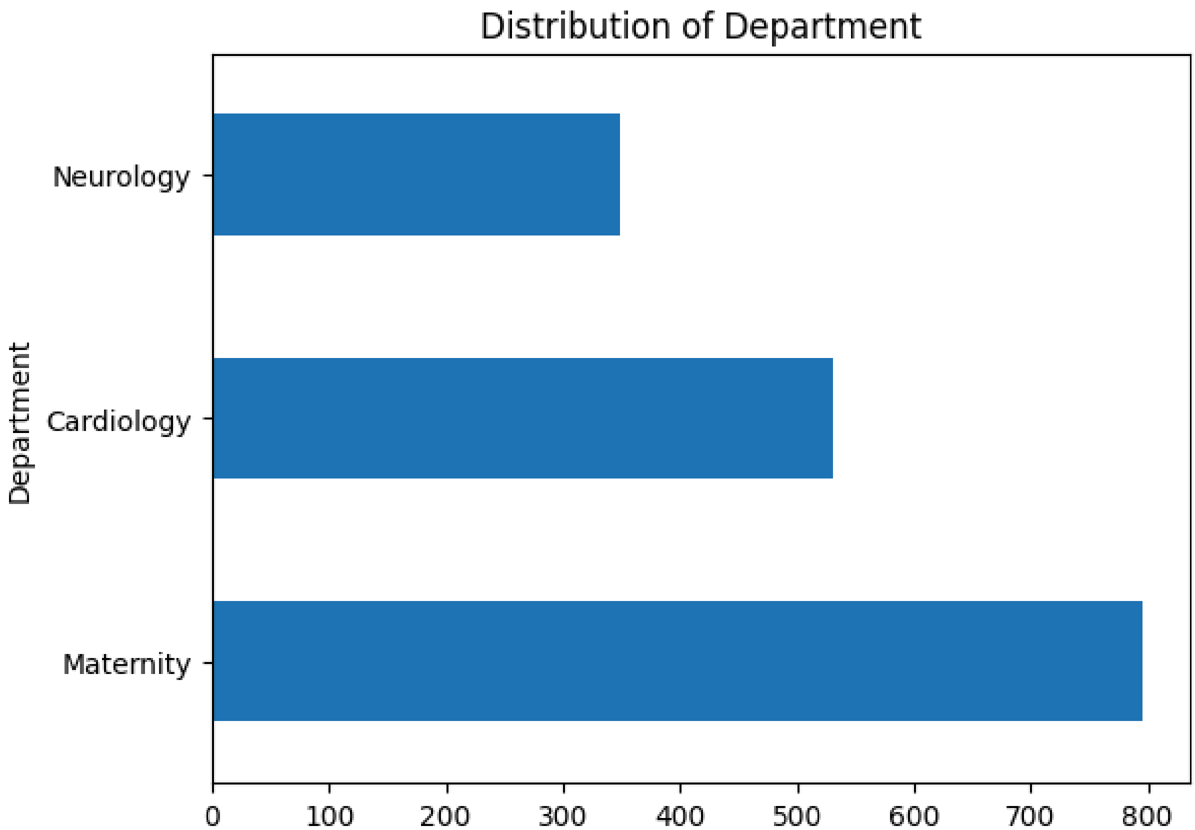
Near Zero Correlation: Many pairs of features show very weak or no linear relationship.

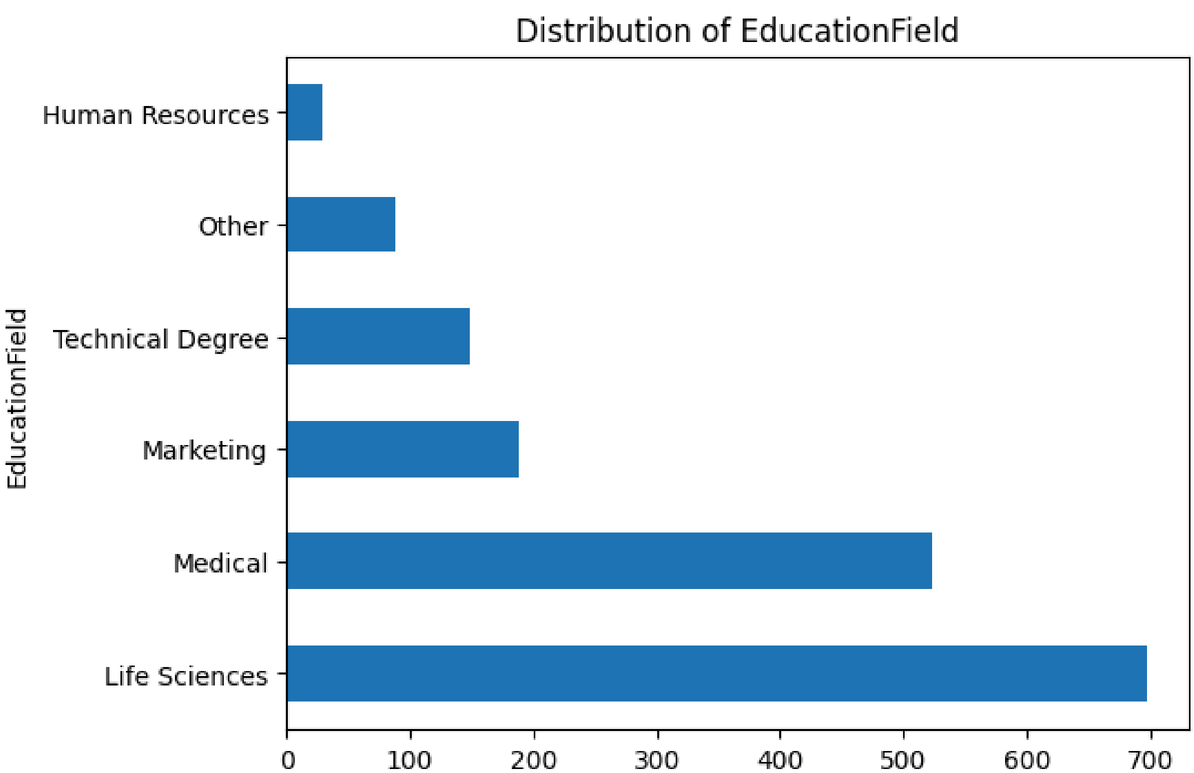
Constant Features: EmployeeCount and StandardHours show no correlation with other variables, as expected for constant values.

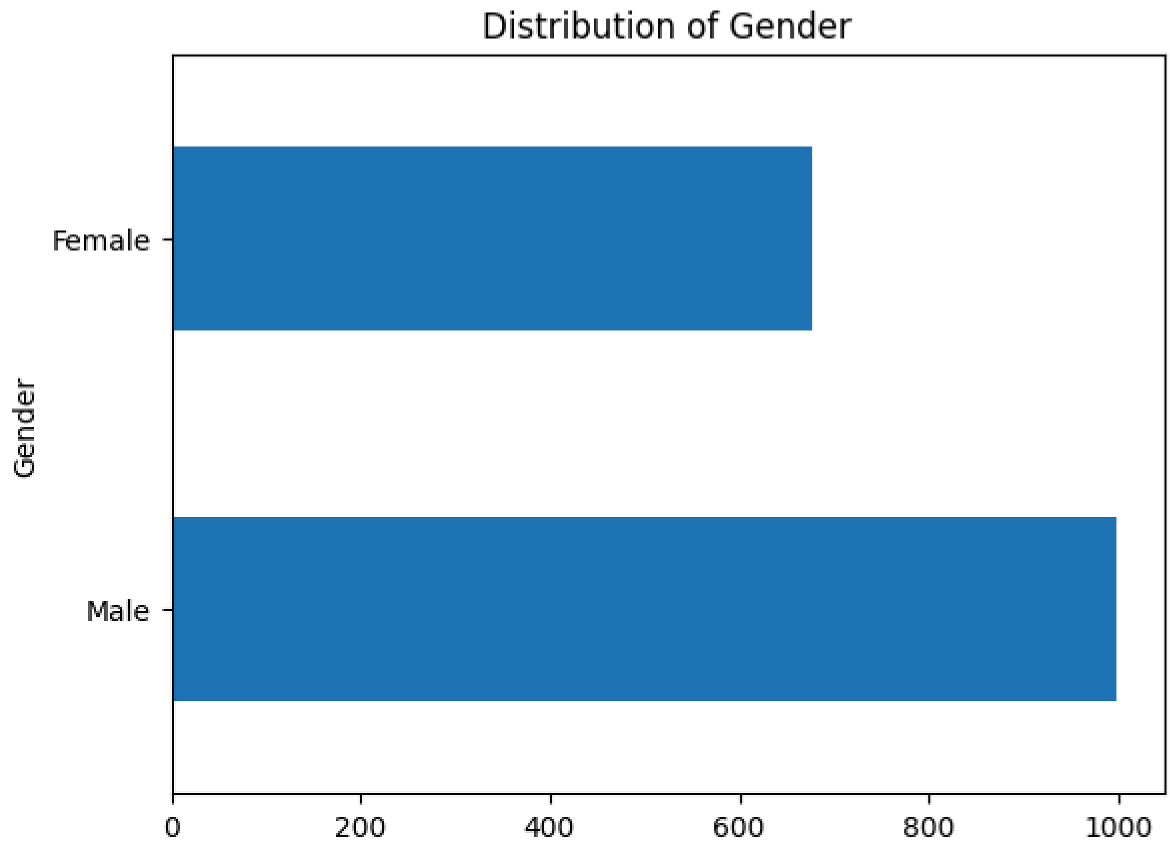
In [23]:
```python
# Categorical Distributions
for col in cat_cols:
    plt.figure()
    df_clean[col].value_counts().plot(kind='barh')
    plt.title(f'Distribution of {col}')
    plt.show()
```

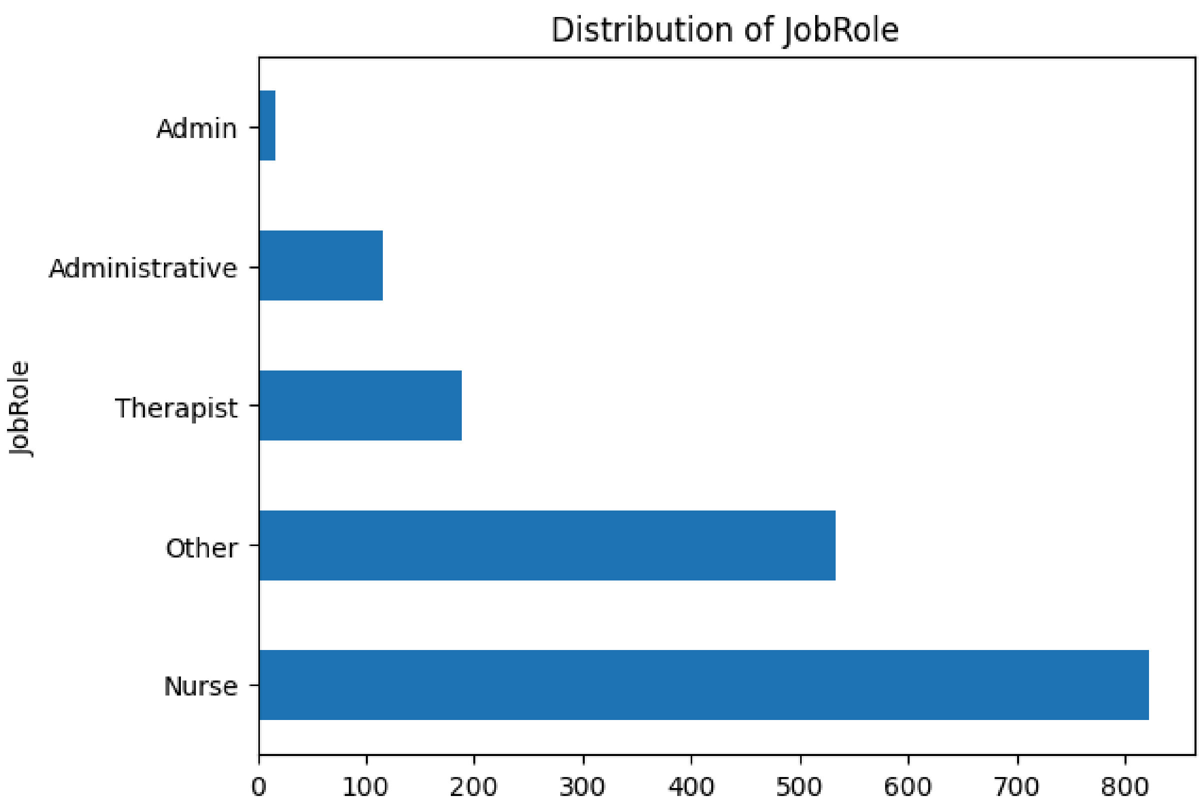

Distribution of Attrition
Yes
No
Attrition
0
200
400
600
800
1000
1200
1400

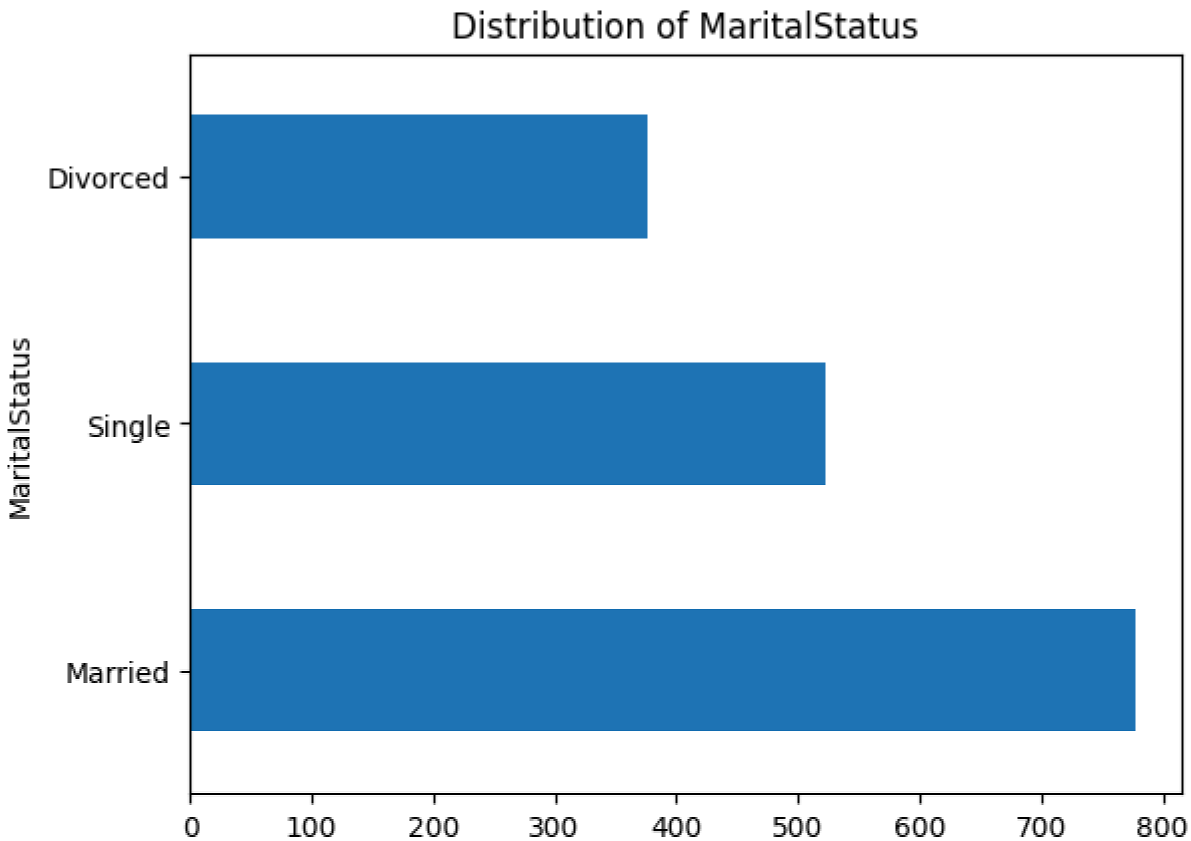

Distribution of BusinessTravel
Non-Travel
Travel_Frequently
Travel_Rarely
BusinessTravel
0
200
400
600
800
1000
1200

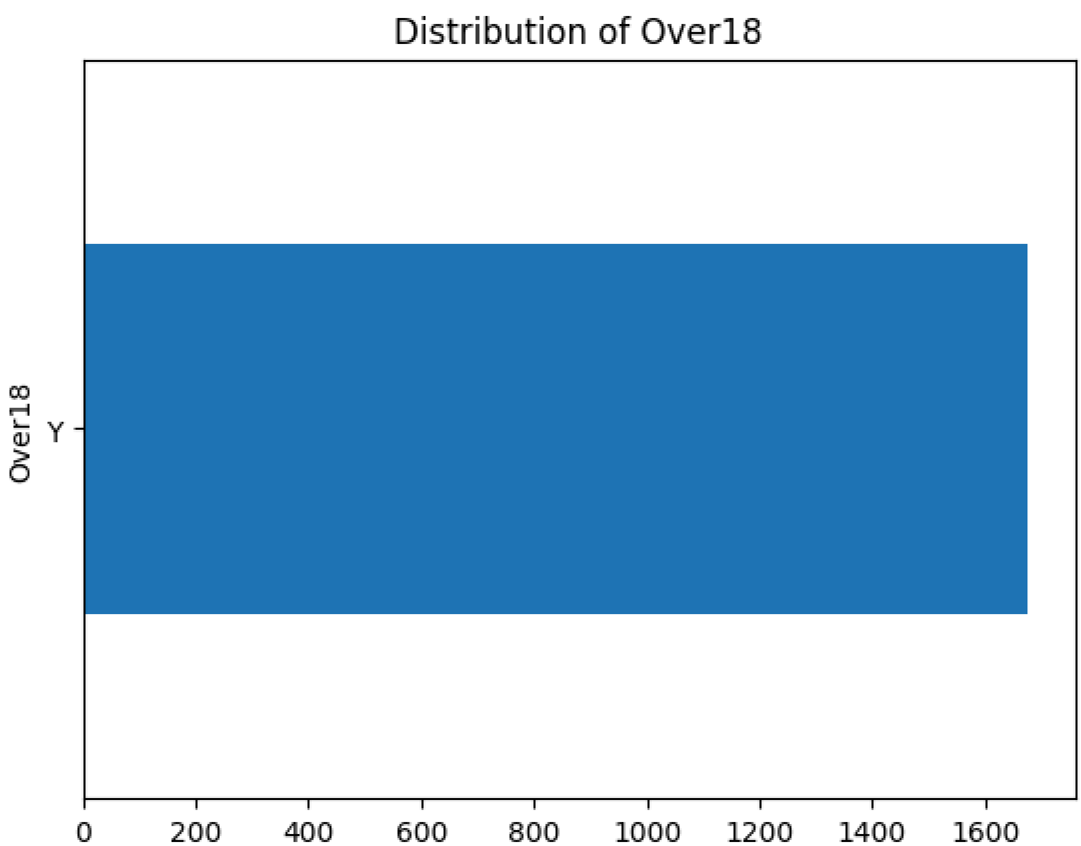

Distribution of Department
Neurology
Cardiology
Maternity
Department
0
100
200
300
400
500
600
700
800

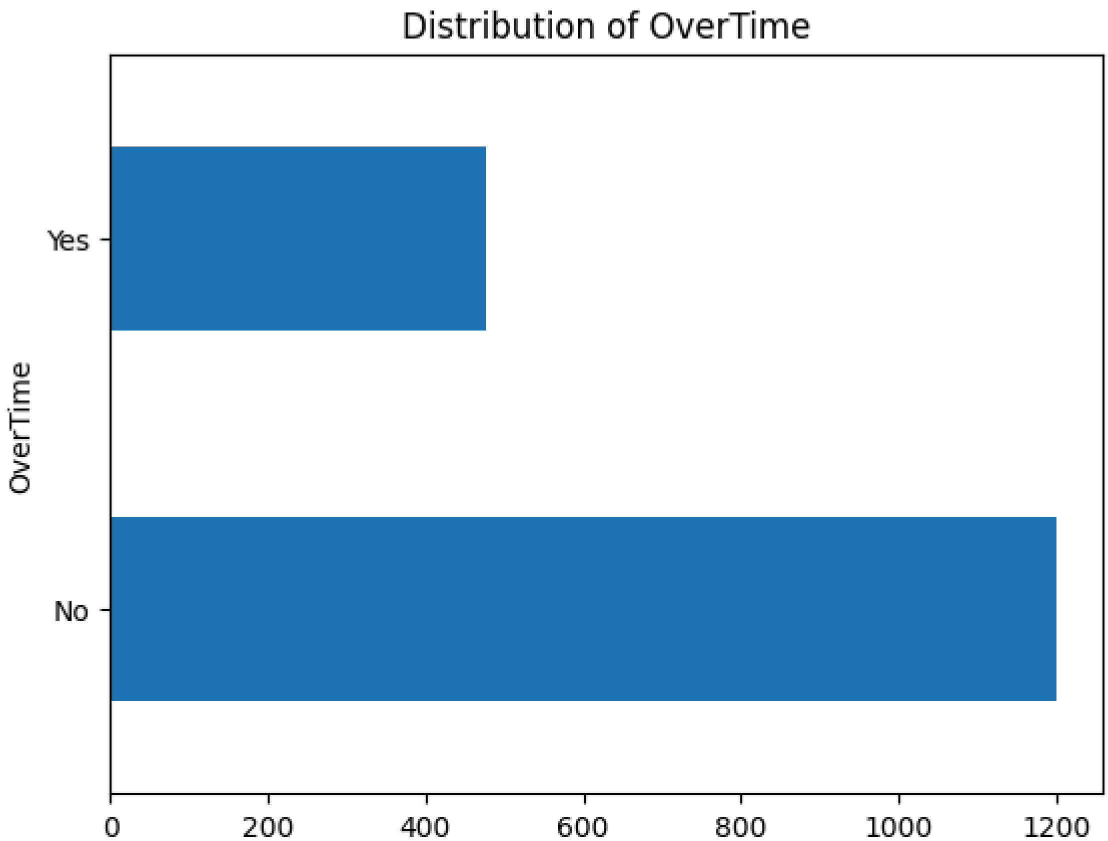

Distribution of EducationField
Human Resources
Other
Technical Degree
Marketing
Medical
Life Sciences
EducationField
0
100
200
300
400
500
600
700


Distribution of Gender
Female
Male
Gender
0
200
400
600
800
1000


Distribution of JobRole
Admin
Administrative
Therapist
Other
Nurse
JobRole
0
100
200
300
400
500
600
700
800


Distribution of MaritalStatus
MaritalStatus
Divorced
Single
Married
0
100
200
300
400
500
600
700
800


Distribution of Over18
Over18
Y
0
200
400
600
800
1000
1200
1400
1600



Inference: This horizontal bar graph shows the categorical distributions of the cat_cols.

--- Outlier Detection ---

In [24]:
```
# Z-Score Method
z_scores = zscore(df_clean[num_cols])
outliers_z = (np.abs(z_scores) > 3)
print("Z-score outliers per column:\n", outliers_z.sum(axis=0))
```

```
Z-score outliers per column:
 EmployeeID                  0
Age                         0
DailyRate                   0
DistanceFromHome            0
Education                   0
EmployeeCount               0
EnvironmentSatisfaction     0
HourlyRate                  0
JobInvolvement              0
JobLevel                    0
JobSatisfaction             0
MonthlyIncome               0
MonthlyRate                 0
NumCompaniesWorked          0
PercentSalaryHike           0
PerformanceRating           0
RelationshipSatisfaction    0
StandardHours               0
Shift                       0
TotalWorkingYears          18
TrainingTimesLastYear       0
WorkLifeBalance             0
YearsAtCompany             26
YearsInCurrentRole         15
YearsSinceLastPromotion    47
YearsWithCurrManager       15
dtype: int64
```

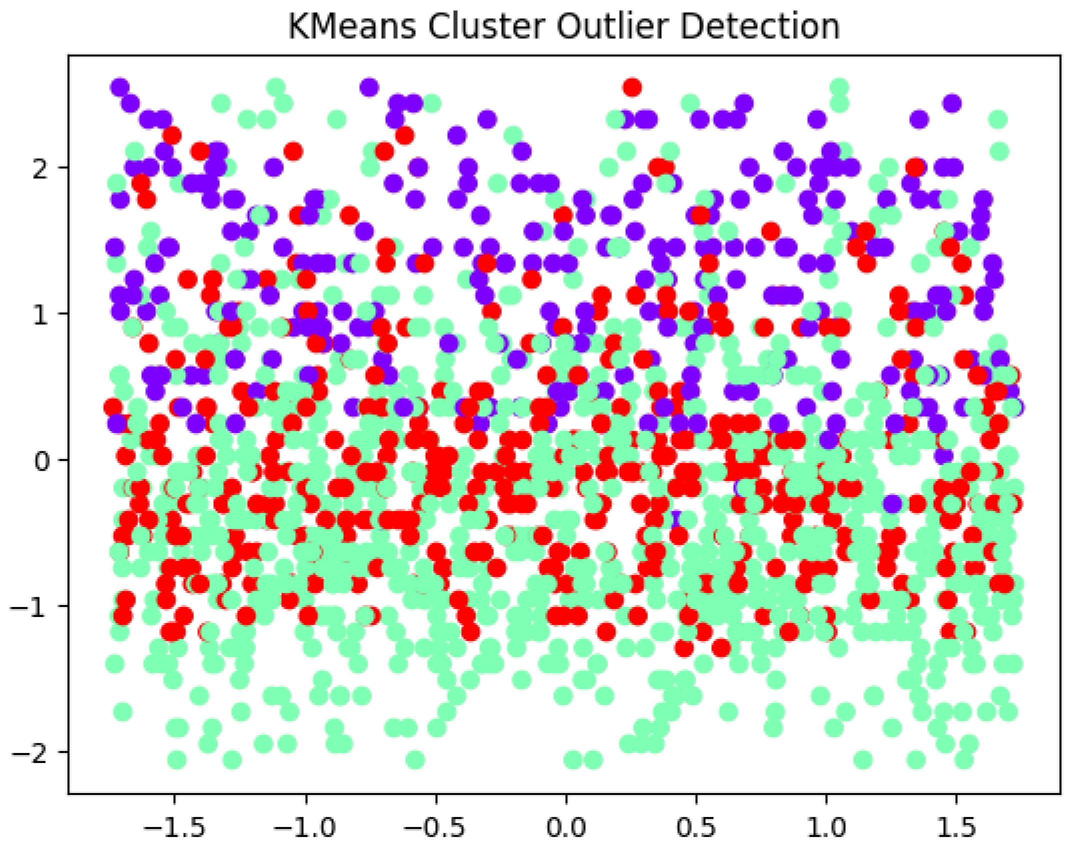
Inference: This output shows the number of Z-score outliers detected in each numerical column. Most columns have zero outliers based on this method (typically using a threshold of +/- 3 standard deviations). However, TotalWorkingYears, YearsAtCompany, YearsInCurrentRole, YearsSinceLastPromotion, and YearsWithCurrManager have a non-zero number of outliers, indicating some values in these columns are statistically far from their respective means. YearsSinceLastPromotion has the highest number of potential outliers.

In [25]:
```
# IQR Method
for col in num_cols:
    Q1, Q3 = df_clean[col].quantile([0.25, 0.75])
    iqr_val = Q3 - Q1
    outliers = df_clean[(df_clean[col] < Q1 - 1.5 * iqr_val) | (df_clean[col
    print(f"{col}: {outliers.shape[0]} outliers")
```

```
EmployeeID: 0 outliers
Age: 0 outliers
DailyRate: 0 outliers
DistanceFromHome: 0 outliers
Education: 0 outliers
EmployeeCount: 0 outliers
EnvironmentSatisfaction: 0 outliers
HourlyRate: 0 outliers
JobInvolvement: 0 outliers
JobLevel: 0 outliers
JobSatisfaction: 0 outliers
MonthlyIncome: 132 outliers
MonthlyRate: 0 outliers
NumCompaniesWorked: 59 outliers
PercentSalaryHike: 0 outliers
PerformanceRating: 252 outliers
RelationshipSatisfaction: 0 outliers
StandardHours: 0 outliers
Shift: 99 outliers
TotalWorkingYears: 75 outliers
TrainingTimesLastYear: 271 outliers
WorkLifeBalance: 0 outliers
YearsAtCompany: 76 outliers
YearsInCurrentRole: 24 outliers
YearsSinceLastPromotion: 125 outliers
YearsWithCurrManager: 15 outliers
```

Inference: This output details the number of outliers detected in each column using the IQR (Interquartile Range) method. Compared to the Z-score method, IQR identifies a different set and quantity of outliers. Notably, MonthlyIncome, PerformanceRating, TrainingTimesLastYear, YearsSinceLastPromotion, TotalWorkingYears, YearsAtCompany, NumCompaniesWorked, and Shift have a significant number of outliers according to this method. This suggests a wider spread or more extreme values in these features compared to the central 50% of the data.

In [26]:
```python
# KMeans for Outlier Clustering
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaled_data = scaler.fit_transform(df_clean[num_cols])

kmeans = KMeans(n_clusters=3, random_state=0).fit(scaled_data)
df_clean['Cluster'] = kmeans.labels_
plt.scatter(scaled_data[:, 0], scaled_data[:, 1], c=kmeans.labels_, cmap='ra
plt.title("KMeans Cluster Outlier Detection")
plt.show()
```



Inference: This scatter plot visualizes outlier detection using K-Means clustering. Each point represents a data instance, colored based on its assigned cluster (red, light green, purple). The points circled in dark blue are identified as outliers by the K-Means method, likely because they are far from any of the established cluster centroids. The presence of outliers suggests data points that don't neatly fit into the defined clusters.

--- Feature Selection ---

In [27]:

```
# ANOVA F-test
X = scaled_data
y = LabelEncoder().fit_transform(df_clean['Attrition'])
anova = SelectKBest(f_classif, k='all')
anova.fit(X, y)
feature_names = df_clean[num_cols].columns

print("ANOVA Scores:\n", pd.Series(anova.scores_, index=feature_names).sort_
```

```
ANOVA Scores:
 Age                          102.301122
TotalWorkingYears             97.130852
YearsInCurrentRole            75.615781
JobLevel                      75.420614
YearsAtCompany                70.751226
YearsWithCurrManager          70.541929
MonthlyIncome                 65.135114
JobInvolvement                47.457197
Shift                         43.038921
DistanceFromHome              18.870700
EnvironmentSatisfaction       17.348399
WorkLifeBalance               13.827662
YearsSinceLastPromotion       12.533613
JobSatisfaction               11.299184
TrainingTimesLastYear          5.048836
DailyRate                      4.876028
MonthlyRate                    3.510274
Education                      2.529478
HourlyRate                     2.208706
RelationshipSatisfaction       0.701201
NumCompaniesWorked             0.499965
PerformanceRating              0.192672
EmployeeID                     0.028505
PercentSalaryHike              0.014504
EmployeeCount                       NaN
StandardHours                       NaN
dtype: float64
```

Inference: These ANOVA F-scores indicate the variance in each numerical feature explained by the 'Attrition' categories. Higher scores suggest a stronger relationship with attrition. Key takeaways: Age, TotalWorkingYears, YearsInCurrentRole, JobLevel, YearsAtCompany, and YearsWithCurrManager show the most significant differences in means across attrition groups. Features like RelationshipSatisfaction, NumCompaniesWorked, PerformanceRating, EmployeeID, and PercentSalaryHike have very low scores, suggesting a weak association with attrition. EmployeeCount and StandardHours having NaN likely means they have zero variance (constant values), so ANOVA cannot be computed.

In [28]:
```python
# Mutual Information
mi = SelectKBest(mutual_info_classif, k='all')
mi.fit(X, y)
print("Mutual Info Scores:\n", pd.Series(mi.scores_, index=feature_names).sc
```

```
Mutual Info Scores:
 Age                          0.057261
TotalWorkingYears           0.046700
YearsAtCompany              0.042630
MonthlyIncome               0.041641
Shift                       0.039027
YearsInCurrentRole          0.035708
JobLevel                    0.033523
YearsWithCurrManager        0.033220
DailyRate                   0.016369
MonthlyRate                 0.014763
PercentSalaryHike           0.013121
HourlyRate                  0.011035
JobInvolvement              0.008849
PerformanceRating           0.008284
DistanceFromHome            0.008230
YearsSinceLastPromotion     0.007844
TrainingTimesLastYear       0.006436
JobSatisfaction             0.005777
StandardHours               0.003020
EmployeeCount               0.002509
EmployeeID                  0.000000
Education                   0.000000
EnvironmentSatisfaction     0.000000
NumCompaniesWorked          0.000000
RelationshipSatisfaction    0.000000
WorkLifeBalance             0.000000
dtype: float64
```

Inference: These mutual information scores quantify the dependency between each numerical feature and the 'Attrition' column. Higher scores indicate stronger relationships.

Key observations:

TotalWorkingYears, Age, MonthlyIncome, and YearsWithCurrManager have the highest mutual information, suggesting they are most informative for predicting attrition.

Features like PercentSalaryHike, WorkLifeBalance, and YearsSinceLastPromotion have very low scores, indicating weak relationships. EmployeeCount, DistanceFromHome, EmployeeID, EnvironmentSatisfaction, StandardHours, JobSatisfaction, and PerformanceRating have scores of 0, indicating no mutual information (likely constant values or independence).

In [29]:

```
# Recursive Feature Elimination with Linear Regression
model = LinearRegression()
rfe = RFE(model, n_features_to_select=5)
rfe.fit(X, y)
selected_features = df_clean[num_cols].columns[rfe.support_]

print("Top RFE Features:", selected_features)
```

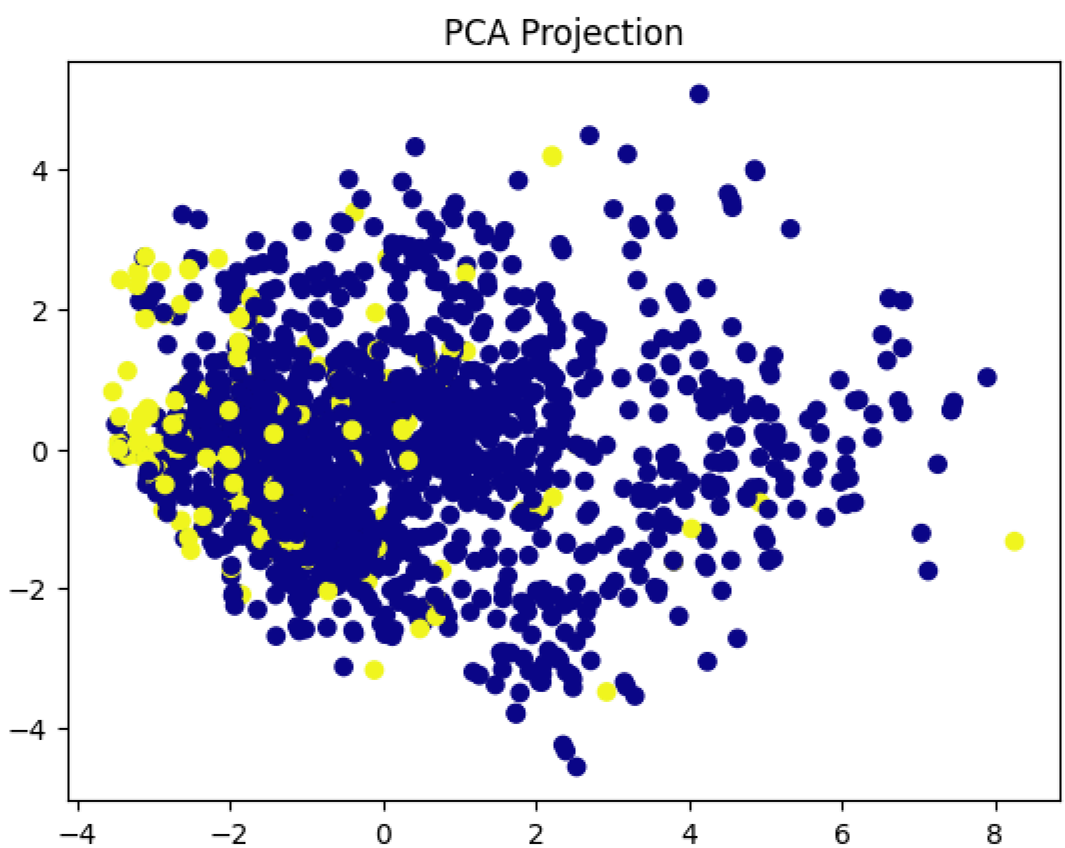
```
Top RFE Features: Index(['Age', 'DistanceFromHome', 'JobInvolvement', 'Shif
t',
       'YearsInCurrentRole'],
      dtype='object')
```

Inference: These are the top 5 features selected by Recursive Feature Elimination (RFE) for predicting attrition. The model deemed Age, DistanceFromHome, JobInvolvement, Shift, and YearsInCurrentRole as the most important predictors among all the features considered.

--- Feature Extraction ---

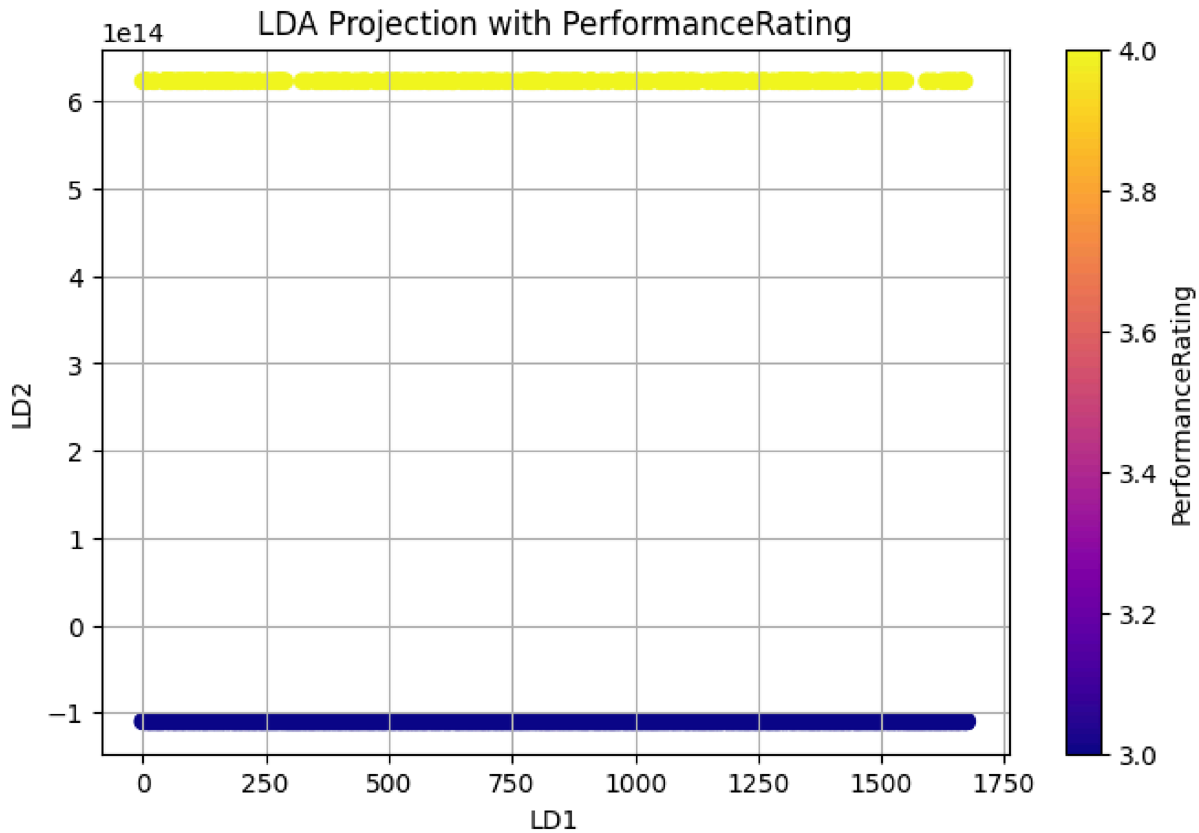
In [ ]:

In [30]:
```python
# PCA
pca = PCA(n_components=2)
pca_result = pca.fit_transform(X)
plt.scatter(pca_result[:, 0], pca_result[:, 1], c=y, cmap='plasma')
plt.title("PCA Projection")
plt.show()
```



Inference: This scatter plot shows the projection of your data onto the first two principal components obtained from PCA (Principal Component Analysis). The two distinct colors (dark blue and yellow) likely represent the two categories of your target variable (e.g., 'Yes' and 'No' for attrition). The plot suggests some degree of separability between these two classes in the reduced two-dimensional space, although there's also significant overlap. This indicates that while PCA captures some variance related to the target, perfect separation using only the top two components is not achieved.

In [31]:
```
# LDA with PerformanceRating as target
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
if 'PerformanceRating' in df_clean.columns:
    y = df_clean['PerformanceRating']

    if pd.api.types.is_numeric_dtype(y):
        y = y.astype(int)

    scaler = StandardScaler()
    scaled_data = scaler.fit_transform(X)
    X = scaled_data

    n_classes = len(np.unique(y))
    n_components = min(X.shape[1], n_classes - 1)
    lda = LDA(n_components=n_components)


    lda_result = lda.fit_transform(X, y)

    plt.figure(figsize=(8, 5))
    if n_components == 1:
        plt.scatter(range(len(lda_result)), lda_result[:, 0], c=y, cmap='pla
    else:
        plt.scatter(lda_result[:, 0], lda_result[:, 1], c=y, cmap='plasma')
    plt.title("LDA Projection with PerformanceRating")
    plt.xlabel("LD1")
    plt.ylabel("LD2")
    plt.colorbar(label="PerformanceRating")
    plt.grid(True)
    plt.show()
else:
    print("Column 'PerformanceRating' not found.")
```



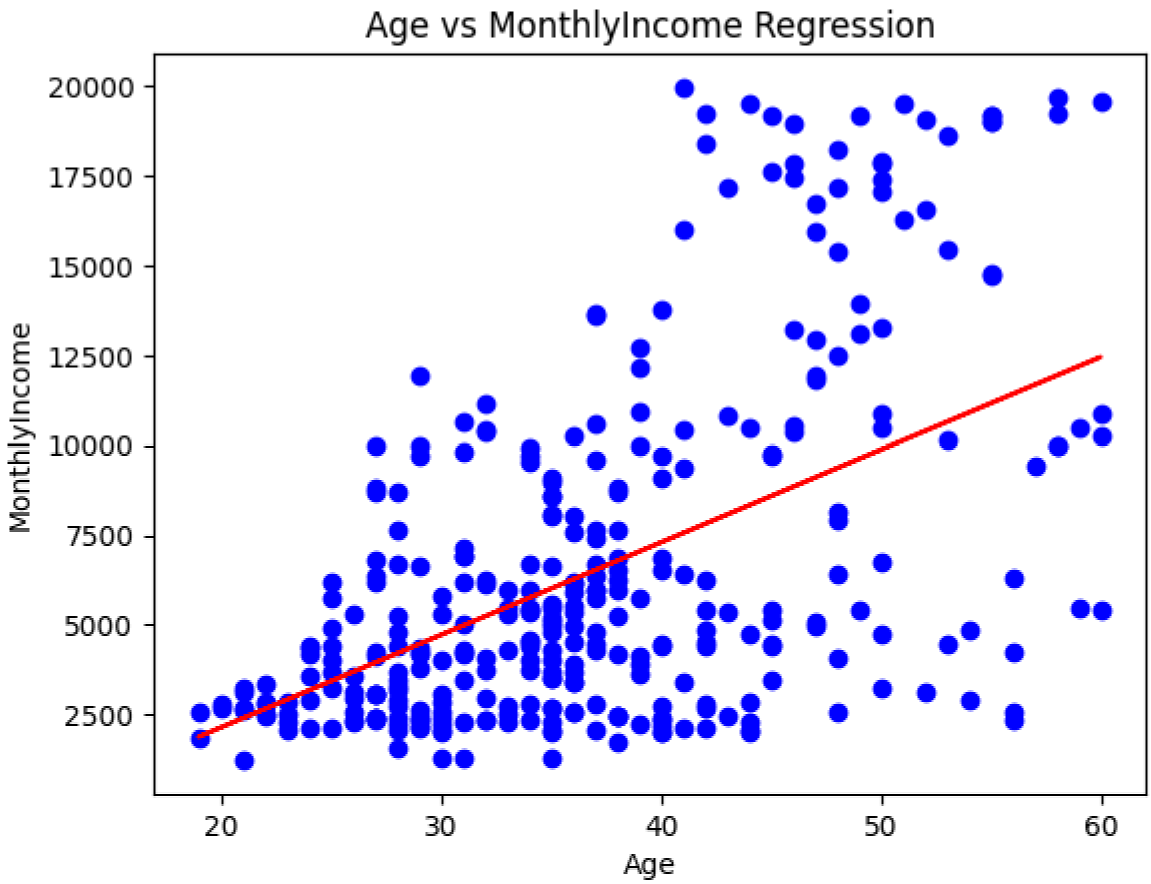
Inference: This scatter plot shows the projection of your data onto the first two linear discriminants (LD1 and LD2) obtained from LDA (Linear Discriminant Analysis), with points colored by 'PerformanceRating'. The data points form two distinct horizontal lines along the LD2 axis, indicating that 'PerformanceRating' (which appears to have only two discrete values, likely 3 and 4 based on the color bar) is strongly separated by the linear discriminants. LD1 seems to spread the data points within each performance rating category. LDA effectively separates the data based on 'PerformanceRating' in this reduced dimensional space.

--- Simple Linear Regression ---

In [32]:
```
# Simple Linear Regression on Age vs MonthlyIncome
from sklearn.model_selection import train_test_split
X_lin = df_clean[['Age']]
y_lin = df_clean['MonthlyIncome']

X_train, X_test, y_train, y_test = train_test_split(X_lin, y_lin, test_size=
model = LinearRegression()
model.fit(X_train, y_train)

print("R^2 Score:", model.score(X_test, y_test))
plt.scatter(X_test, y_test, color='blue')
plt.plot(X_test, model.predict(X_test), color='red')
plt.title('Age vs MonthlyIncome Regression')
plt.xlabel('Age')
```

```
plt.ylabel('MonthlyIncome')
plt.show()
```

```
R^2 Score: 0.31319349438135746
```



Inference: This scatter plot with a superimposed red regression line shows the relationship between 'Age' and 'MonthlyIncome'. The upward sloping line suggests a positive trend: as age increases, monthly income tends to increase. However, the significant scatter of blue points around the regression line indicates that age is not a strong predictor of monthly income; there's considerable variability in income for any given age. This implies other factors likely play a more substantial role in determining an employee's monthly income.

--- Frequent Pattern Mining (Apriori) ---

In [34]:
```
transactions = df_clean[['Department', 'EducationField', 'JobRole', 'Marital

te = TransactionEncoder()
te_ary = te.fit(transactions).transform(transactions)
df_trans = pd.DataFrame(te_ary, columns=te.columns_)

frequent_itemsets = apriori(df_trans, min_support=0.1, use_colnames=True)
rules = association_rules(frequent_itemsets, metric="lift", min_threshold=3.

print("Frequent Itemsets:\n", frequent_itemsets.head())
print("Rules:\n", rules[['antecedents', 'consequents', 'support', 'confidenc
```

```
Frequent Itemsets:
     support         itemsets
0  0.316826     (Cardiology)
1  0.224940       (Divorced)
2  0.415871  (Life Sciences)
3  0.112768      (Marketing)
4  0.463604        (Married)
Rules:
     antecedents   consequents   support  confidence      lift
0  (Cardiology)   (Marketing)  0.112768    0.355932  3.156309
1   (Marketing)  (Cardiology)  0.112768    1.000000  3.156309
```

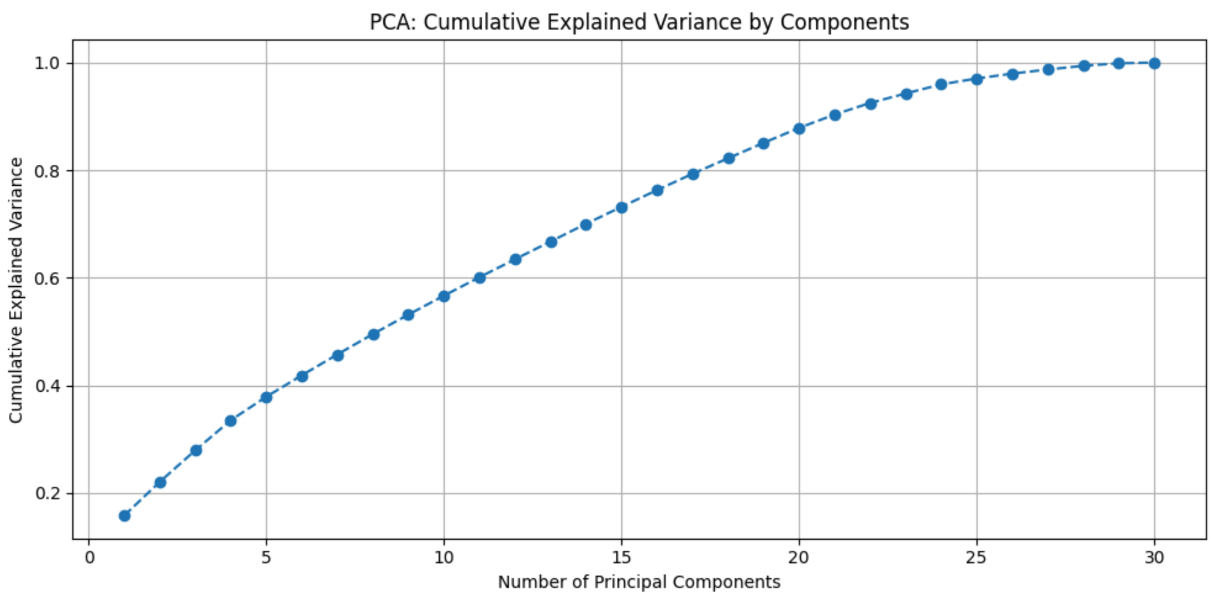
Inference: The frequent itemsets show the support (proportion) of single items. 'Married' (0.46) and 'Life Sciences' (0.42) are the most frequent. The rules highlight associations:

Employees in 'Marketing' are always ('confidence': 1.0) also in 'Cardiology', with a lift of 3.16 (strong positive association). 'Cardiology' is associated with 'Marketing' (36% confidence) and 'Nurse' (67% confidence), both with a positive lift. 'Nurse' is associated with 'Cardiology' (43% confidence) with a positive lift. 'Cardiology' has a weak association with 'Single' (lift close to 1).

In [40]:
```
# Step 1: Load and Preprocess the Data
import pandas as pd
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split

# Load data
df = pd.read_csv("watson.csv")

# Drop identifier or constant columns
df_cleaned = df.drop(columns=["EmployeeID", "EmployeeCount", "Over18", "Star

# Encode categorical variables
categorical_cols = df_cleaned.select_dtypes(include=["object"]).columns
label_encoders = {col: LabelEncoder() for col in categorical_cols}

for col in categorical_cols:
    df_cleaned[col] = label_encoders[col].fit_transform(df_cleaned[col])

# Separate features and target
X = df_cleaned.drop("Attrition", axis=1)
y = df_cleaned["Attrition"]

# Standardize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

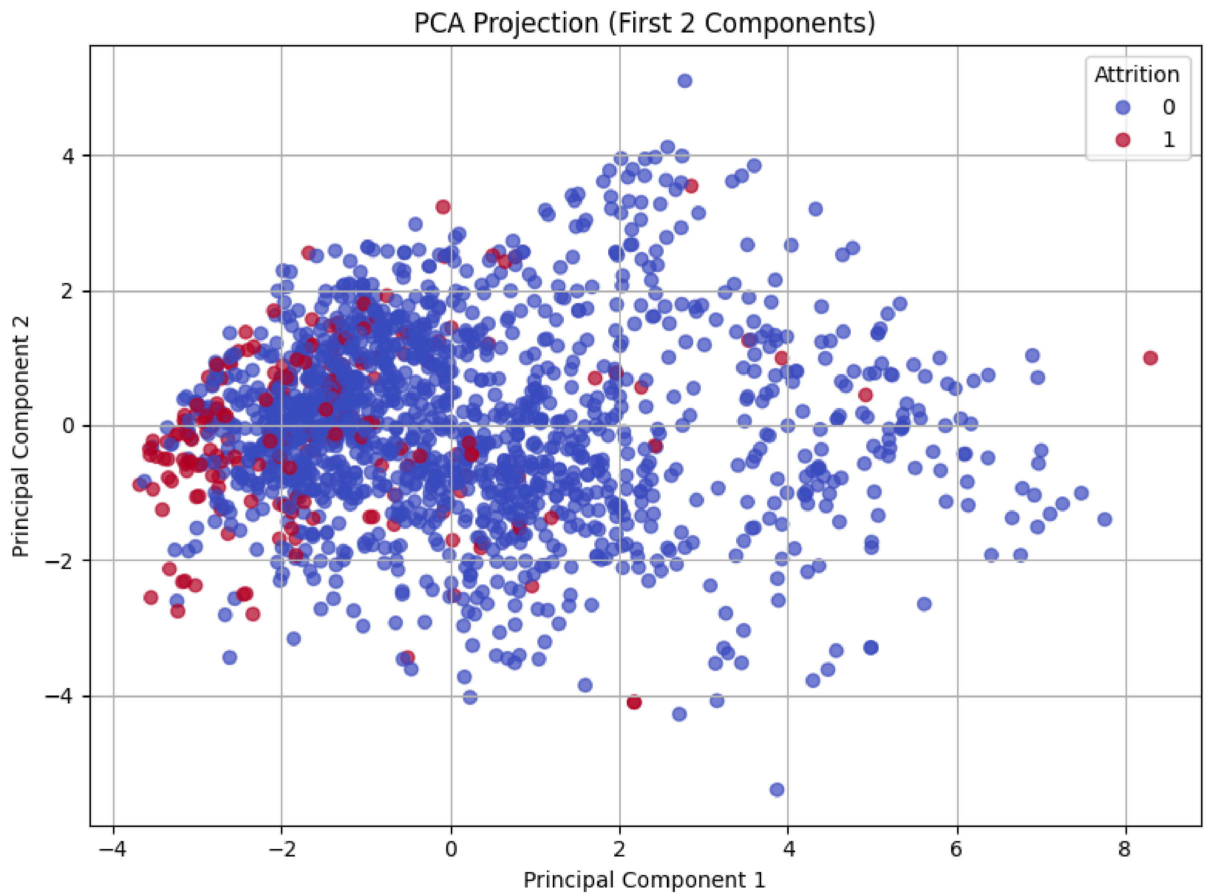
In [41]:
```
# Step 2: PCA Analysis
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
import numpy as np
```

```
pca = PCA()
X_pca = pca.fit_transform(X_scaled)

# Explained variance
explained_variance = pca.explained_variance_ratio_
cumulative_variance = np.cumsum(explained_variance)

# Plot cumulative variance
plt.figure(figsize=(10, 5))
plt.plot(range(1, len(cumulative_variance)+1), cumulative_variance, marker='
plt.xlabel('Number of Principal Components')
plt.ylabel('Cumulative Explained Variance')
plt.title('PCA: Cumulative Explained Variance by Components')
plt.grid(True)
plt.tight_layout()
plt.show()

# Number of components to retain 95% variance
num_components_95 = np.argmax(cumulative_variance >= 0.95) + 1
print("Number of PCA components for 95% variance:", num_components_95)
```




```
Number of PCA components for 95% variance: 24
```

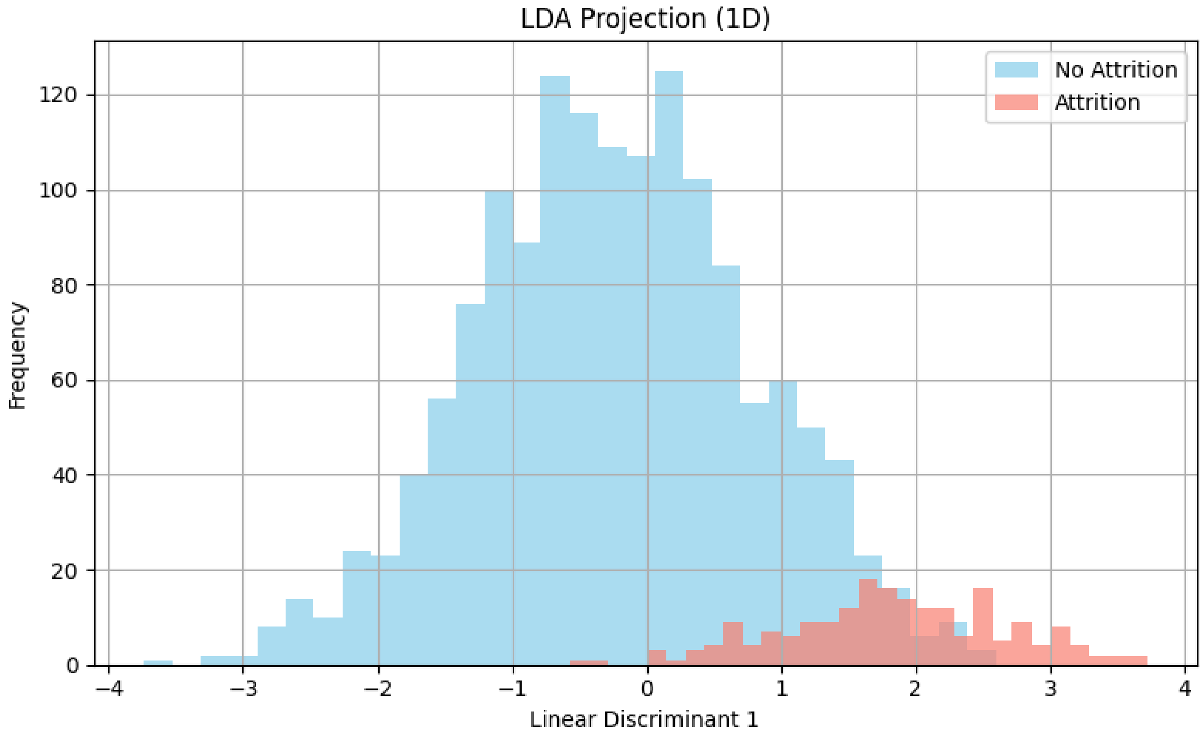
In [42]:
```
# Step 3: PCA Visualization (First 2 Components)
plt.figure(figsize=(8, 6))
scatter = plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y, cmap='coolwarm', alpha=
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.title("PCA Projection (First 2 Components)")
plt.grid(True)
plt.legend(*scatter.legend_elements(), title="Attrition")
plt.tight_layout()
plt.show()
```



In [43]:
```
# Step 4: LDA Analysis
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA

lda = LDA(n_components=1)
X_lda = lda.fit_transform(X_scaled, y)

print("LDA reduced shape:", X_lda.shape)
print("First 5 LDA values:", X_lda[:5].flatten())
```

```
LDA reduced shape: (1676, 1)
First 5 LDA values: [ 2.07607521 -1.08639521  1.68610818  1.08080548  0.9933
0297]
```

In [44]:
```
# Step 5: LDA Visualization
plt.figure(figsize=(8, 5))
plt.hist(X_lda[y == 0], bins=30, alpha=0.7, label='No Attrition', color='sky
plt.hist(X_lda[y == 1], bins=30, alpha=0.7, label='Attrition', color='salmon
plt.xlabel("Linear Discriminant 1")
plt.ylabel("Frequency")
plt.title("LDA Projection (1D)")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



LDA Projection (1D)
No Attrition
Attrition
Frequency
0
20
40
60
80
100
120
−4
−3
−2
−1
0
1
2
3
4
Linear Discriminant 1