MGT 6203 Group Project Progress Report (Team 50)

***Analysis of Factors that Affect Employee Attrition Rates***

**TEAM MEMBERS**

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**INTRODUCTION & PROJECT OBJECTIVE**

**Background Information on chosen project topic:**

Employee attrition creates a host of issues, ranging from hidden costs such as employee burnout and lost industry knowledge, to more quantifiable ones like lost productivity and recruitment costs. Concerning hard costs alone, some studies have shown that replacing a single employee can incur a hard cost of three to four times that of the position’s salary (Navarra, 2023) while other estimates place this cost even higher (Santovec, 2010).

It’s in most companies’ interest to increase employee retention and therefore reduce both the hidden and hard costs of rehiring. In order to do this, employers must be able to identify and understand the factors that might affect employee attrition including, and not limited to: commute times, frequency of business trips, salary, percentage of salary increases, work-life balance, and job satisfaction.

Once the factors affecting employee attrition are identified, employers can better understand the extent of impact of these factors so that companies may enact employee retention strategies or change their recruitment criteria to filter for employees that are more likely to remain with the company for extended periods of time.

**Problem Statement:**

This analysis seeks to identify the key factors and the extent of these factors that lead to employee attrition so that companies can retain employees for longer to reduce personnel costs.

**Research Questions:**

1. Understand the key underlying factors resulting in employee attrition.
2. Classify and group factors that are related to employee retention
3. Identify departments or teams that needs intervention
4. Optimize relevant predictors to minimize employee attrition

**Business Justification:**   
As mentioned previously, hiring replacement employees to compensate for attrition can be quite costly. These costs (hidden and hard costs) can be broken down into additional categories:

1. **Employee Burnout**

* Company operations must continue with reduced staff and the consequential understaffing adds additional stress to the remaining employees who have increased workload and responsibility.
* Employee burnout and attrition usually has an adverse impact on company morale, productivity, and motivation that is difficult to quantify (Zavgorodnii et al., 2020).

1. **Lost industry knowledge**

* Company business practices and undocumented best business practices can be lost with the leaving employee.

1. **High cost of retraining new hires**

* Loss in productivity during the gap of a leaving employee and retraining of new hire
* New hires take time to fully integrate into their new role, prompting further loss of productivity
* The costs for HR and team managers to find a suitable replacement

New hires always have a risk of a mishire which incur fees much higher than lost productivity (Erling, 2011).

**DATASET**

This is a fictional dataset ([click here to assess the dataset](https://www.kaggle.com/datasets/pavansubhasht/ibm-hr-analytics-attrition-dataset/data)) created by IBM data scientists, and contains information about employee attrition. The data includes 35 columns, including Age, DistanceFromHome, Education, EnvironmentSatisfaction, JobInvolvement, JobSatisfaction, PerformanceRating, RelationshipSatisfaction, WorkLifeBalance, etc. For more details on the dataset, refer to Appendix A.

Dependent Variables: Attrition (Yes/ No)

Independent: As the dataset contains many different variables, the team carried out exploratory data analysis (“EDA”) to pick out the most relevant variables, and categorised them into groups to address the identified research questions. This will be further elaborated upon in the “Exploratory Data Analysis” section.

**METHODOLOGY**

Our planned approach can be broken down into four main parts, and more details are found in the subsequent sections:

* + - 1. **Data Cleaning & Transformation**
      2. **Exploratory Data Analysis**
      3. **Model Training & Optimization**
      4. **Results Validation**

**DATA CLEANING & TRANSFORMATION**

The dataset is relatively clean, hence there are no missing or duplicate values to address. However, 3 key actions were taken:

|  |  |  |
| --- | --- | --- |
| **No.** | **Step** | **Impact** |
| 1 | Remove columns with only 1 unique value | Removal of: “EmployeeCount”, “Over18”, “StandardHours” |
| 2 | Convert categorical response variable into binary form to enable modelling | In the “Attribution” column, “Yes” values is transformed into “1”, and “No” values into “0” |
| 3 | Convert categorical independent variables into:   * Binary form * Dummy variables * Grouping into relevant range | Conversion of variables such as “BusinessTravel”, Gender”, “JobRole” into binary or dummary variables  Grouping of “Age” into relevant age groups |

**EXPLORATORY DATA ANALYSIS**

The key objectives of this step include:

1. Identification of high level patterns, trends and correlations
2. Selection of variables for modelling
3. Detection of outliers and anomalies

To achieve the above, the team explored visualizations that include correlation matrix and charts. The following discussion shows the key observations and steps taken in selecting variables for modelling. Other variable reduction not discussed below are achieved during model validation and testing.

## **Correlation Matrix**

As a first step, in the correlation matrix in Figure 1, several variables with high correlation are observed, as noted by the pairs in dark blue. If highly correlated variables are included into the models, it could introduce **multicollinearity,** which can destabilize the estimation of coefficients in regression models, and make it difficult to determine the effect of individual predictors on the response variable.

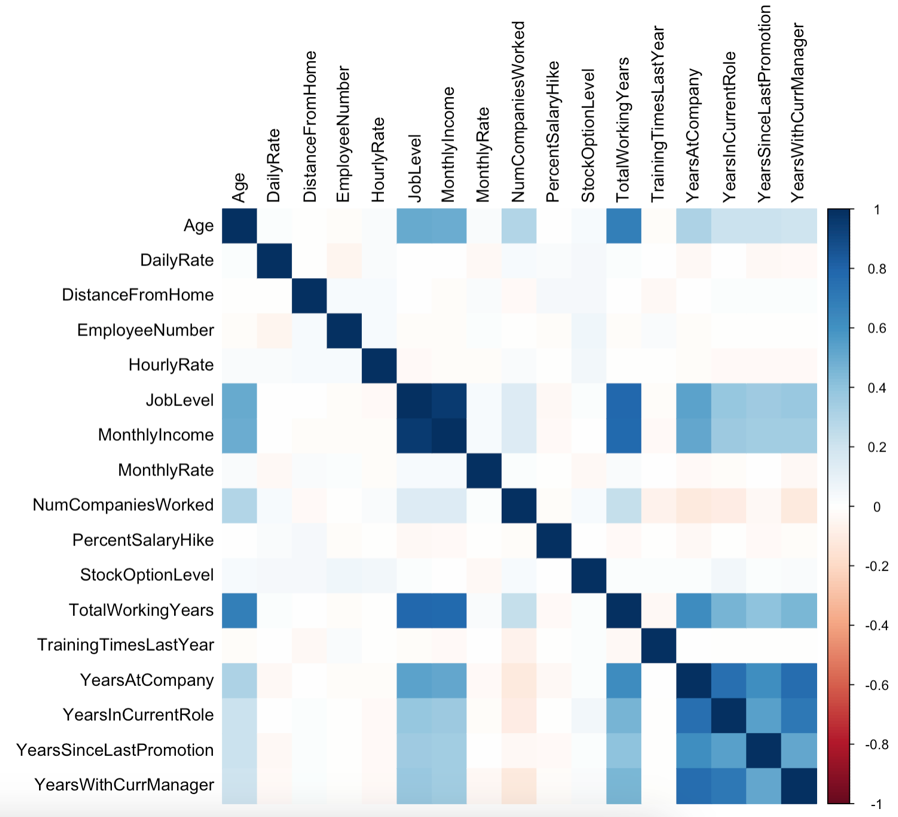


Figure 1: Correlation Matrix

Some of the pairings showing high correlation include the bottom right hand corner, which are related to the number of years worked, including factors such as “TotalWorkingYears”, “YearsAtCompany”, “YearsInCurrentRole”, “YearsSinceLastPromotion”, “YearsWithCurrentManager”, “JobLevel”, and “MonthlyIncome”.

Based on personal experience, the high correlation in these pairings makes sense, given that higher working experience results in higher ranks and income, as well as the number of years in the role and with current manager. When combined with other methods, “TotalWorkingYears” was selected out of this grouping for modeling.

## **Charts**

The team also plotted charts for different variables against the response variable. The following charts show a sample of the attributes that show clear indication of trends related to attrition, and which are ultimately used in the modelling.

**Age Groups:** Grouping ages into different age groups, we observed a trend of younger individuals 18-25 followed by those aged 26-35 having a higher attrition rate compared to other age groups (Figure 2).

**Work Life Balance:** A notable trend emerged, showing higher attrition among individuals with lower scores for work-life balance (Figure 3).

**No. of Companies Worked:** A higher attrition rate among individuals at their 2nd job was observed, followed by a plateau before seeing higher attrition among “serial job movers” (Figure 4).

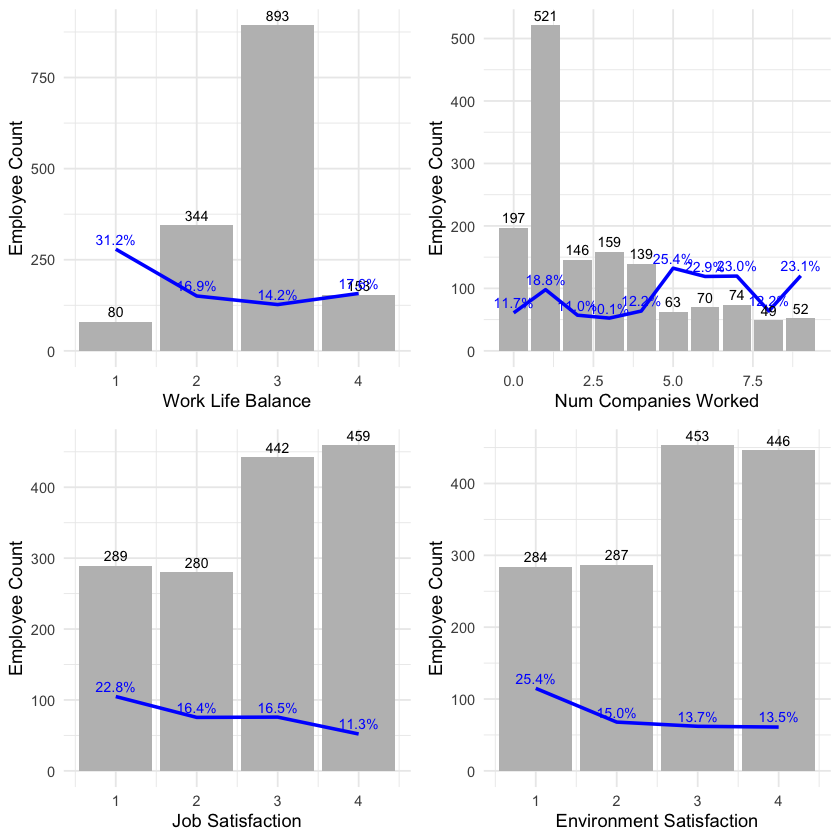


Figure 4: No. of Companies Worked

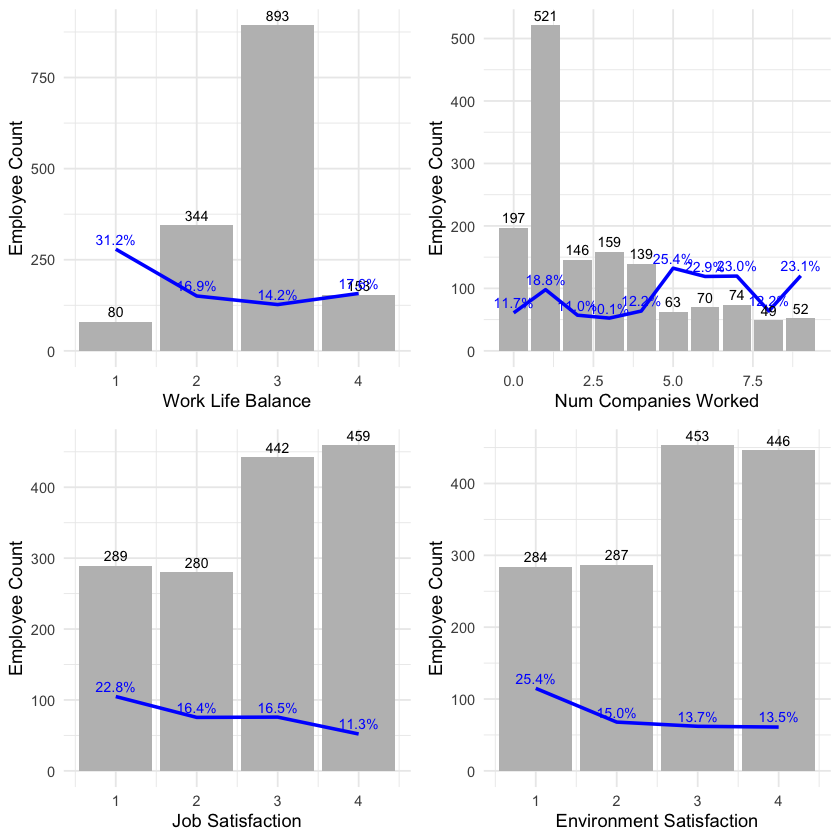


Figure 3: Work Life Balance

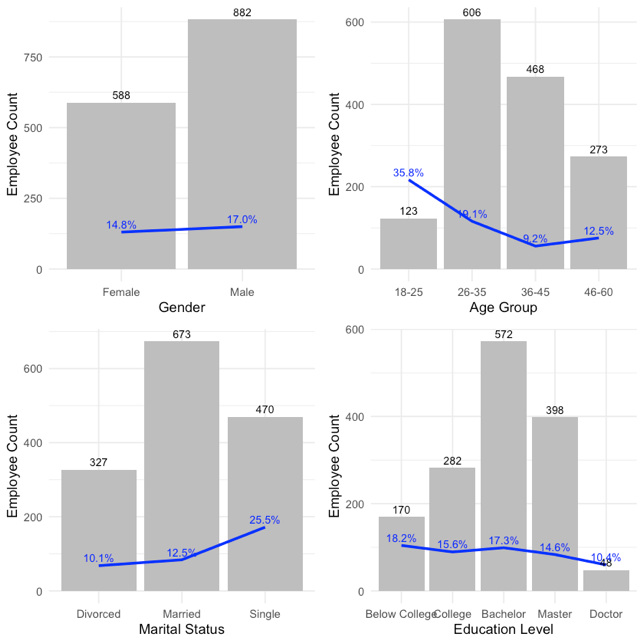


Figure 2: Age Group

**MODEL TRAINING & OPTIMIZATION**

Building on the initial EDA, we conducted a generalized linear regression (GLM) to identify factors associated with employee attrition. The model included all relevant variables from the EDA. We then employed a systematic variable selection process, retaining only those variables with statistically significant effects (p-value < 0.05) on the likelihood of attrition. The following section presents the regression results of our initial model.

## **Initial Linear Regression Model**

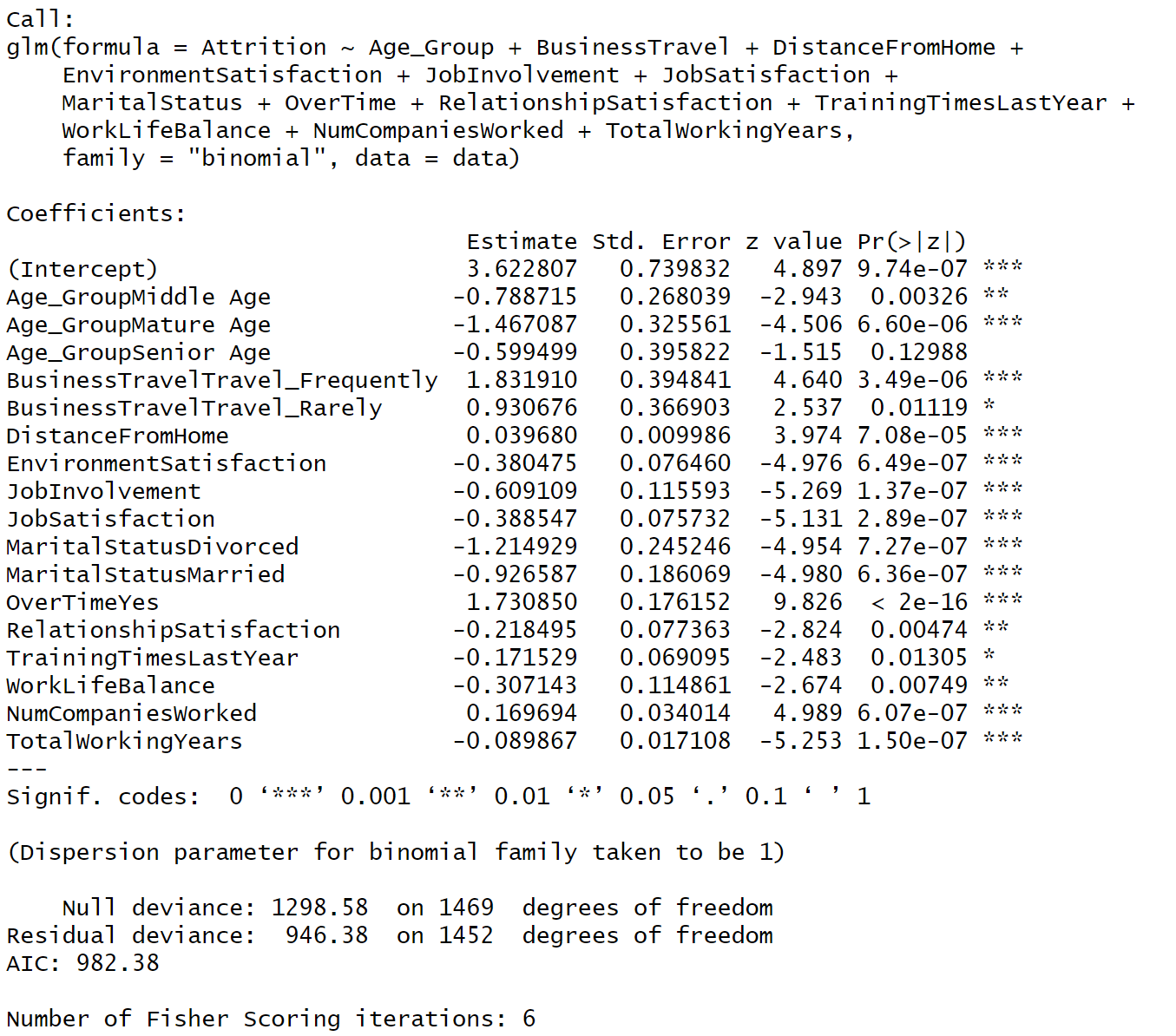


Figure 5: Linear Regression Model Results

Figure 5 shows the results of the linear regression model, with the following key findings:

**Age:** Compared to employees younger than 26 years old (Young Age), those in the Middle Age (26-35 years old, -0.79) and Mature Age (36-45 years old, -1.47) groups are less likely to leave the company. There is no statistically significant difference in attrition rates between the Young Age group and the Senior Age group (46 years old and above).

**Business Travel**: Employees who travel frequently (Travel\_Frequently, 1.83) are significantly more likely to attrite compared to those who don't travel for business. Employees who travel rarely (Travel\_Rarely, 0.93) also show a higher propensity to leave, but to a lesser extent.

**Work Environment**: Higher satisfaction with the work environment (-0.38) is associated with a lower likelihood of attrition.

**Job Satisfaction**: Similarly, employees with higher job satisfaction (-0.39) are less likely to leave.

**Job Involvement**: Additionally, higher job involvement (-0.61) is associated with a lower risk of employee attrition.

**Marital Status**: Both divorced (-1.21) and married employees (-0.93) are less likely to attrite compared to single employees (reference group).

**Work-Life Balance**: Having a poor work-life balance (-0.31) increases the risk of employee attrition.

**Distance from Home**: Increased distance from home (0.04) is associated with a higher chance of leaving.

**Overtime**: Working overtime (Yes, 1.73) significantly increases the likelihood of attrition.

**Total Working Years**: Employees with more experience (Total Working Years, -0.09) tend to be less likely to attrite.

**Training**: Attending fewer training sessions last year (TrainingTimesLastYear, -0.17) is associated with a higher chance of leaving.

**Number of Companies Worked**: Employees who have worked for fewer companies (NumCompaniesWorked, 0.17) tend to be less likely to attrite.

## **Multicollinearity Assessment**

The analysis of variance inflation factors (VIFs) indicates a low risk of multicollinearity for most variables (Figure 6). All VIF scores fall between 1 and 1.1, except for Age\_Group (1.91), NumCompaniesWorked (1.19), and TotalWorkingYears (1.78). These slightly higher VIFs suggest a weak to moderate correlation between these three variables, which is understandable. The number of companies worked (NumCompaniesWorked) and total working years likely have a positive relationship with age.

A number of numbers and letters

Description automatically generated with medium confidence

Figure 6: VIFs for Initial Model

We explored mitigating this potential multicollinearity by creating a new independent variable, "loyalty" (calculated as NumCompaniesWorked divided by TotalWorkingYears). While the VIF scores (Figure 7) improved with the "Loyalty" variable, the model's Akaike Information Criterion (AIC) worsened slightly (increasing from 982.38 to 995.84). Given this trade-off, and the overall low multicollinearity risk, we will focus on exploring other avenues for model improvement moving forward.

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Figure 7: VIFs for Model with "Loyalty Variable"

## **Random Forest Model**

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**RESULTS VALIDATION**

*This section will be added for the final report.*

**CONCLUSION**

*This section will be added for the final report.*

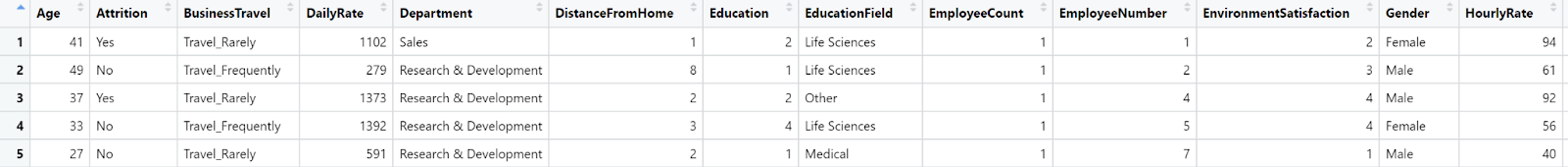
**APPENDIX A: DETAILS ON DATASET**

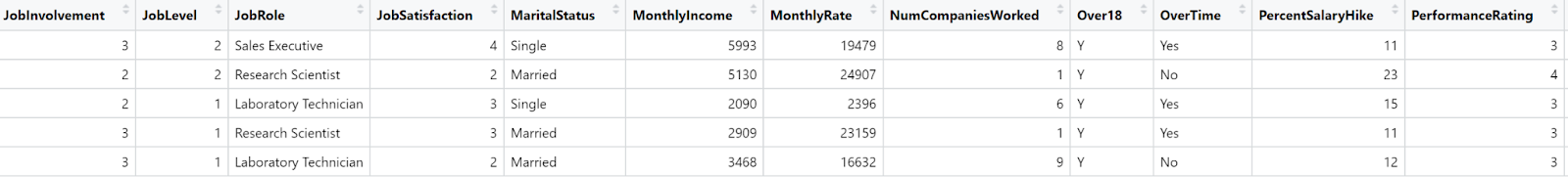
**Data Sources (links, attachments, etc.):**

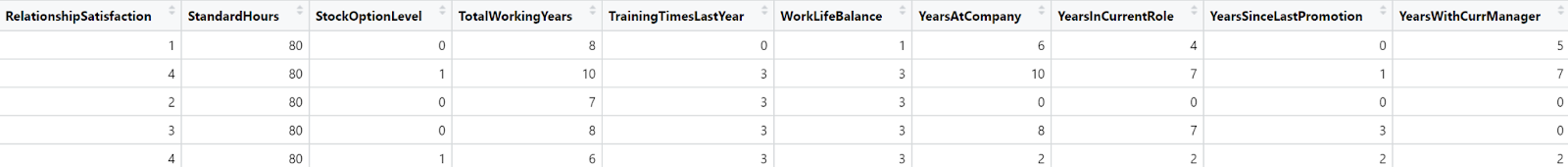
<https://www.kaggle.com/datasets/pavansubhasht/ibm-hr-analytics-attrition-dataset/data>

**Data Description (describe each of your data sources, include screenshots of a few rows of data):**

This is a fictional dataset created by IBM data scientists, and contains information about employee attrition. The data includes 35 columns, and the following figures show the column names and sample data for each column:





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**APPENDIX B: BIBLIOGRAPHY**

Erling, D. (2011). Appendix III. The Cost of a Mishire: The Story of the Bad Controller. *In Match: A Systematic, Sane Process for Hiring the Right Person Every Time*. essay, Wiley. Retrieved February 15, 2024, from <https://learning.oreilly.com/library/view/match-a-systematic/9780470878989/apc.html#you_know_jack>.

Navarra, K. (2023, December 21). *The real costs of recruitment*. SHRM. <https://www.shrm.org/topics-tools/news/talent-acquisition/real-costs-recruitment>

Santovec, M. L. (2010). Build relationships to save the cost of employee attrition. *Women in Higher Education, 19(6)*, 20–21. <https://doi.org/10.1002/whe.10066>

Zavgorodnii, I., Lalymenko, O., Perova, I., Zhernova, P., & Kiriak, A. (2020). Identification of predictors of burnout among employees of socially significant professions. *Communications in Computer and Information Science,* 445–456. <https://doi.org/10.1007/978-3-030-61656-4_30>