PREDICTING EMPLOYEE RETENTION REPORT

1. Problem Statement

1.1 Objective

This assignment aims to build a Logistic Regression model to predict binary outcomes, such as whether an employee will stay or leave. This task deepens understanding of logistic regression, its assumptions, implementation, and evaluation, especially for classification tasks.

1.2 **Business Objective**

A mid-sized technology company seeks to improve employee retention by identifying employees who are likely to stay. Traditionally, the focus was on managing turnover post-occurrence. This model aims to shift the focus toward proactive retention—understanding who is likely to remain and why. By analyzing demographic details, job satisfaction, performance, tenure, and more, this model provides HR with actionable insights to improve retention strategies and foster a stable, satisfied workforce.

1.3 Data Objective

The goal is to build a reliable model that predicts the likelihood of employee retention using the provided dataset. The challenges include:

- Identifying the most influential predictors of attrition.
- Handling missing or redundant features.
- Optimizing the model to guide HR in decision-making.
- Balancing sensitivity and specificity.

2. Dataset Overview

2.1 <u>Dataset Information</u>

- Shape: 74,610 rows X 24 columns
- Key feature: Age, Gender, Monthly income, Job role,
 Distance from home, Job satisfaction, Performance rating,
 Overtime, Job level, Education level, Attrition (target), etc.
- Class distribution:
 - > 52.15% of employees stayed.
 - ➤ 47.85% of employees left.

2.2 Initial Data Exploration

- Average age: 38.53 years (± 12.08).
- **Monthly Income:** Mean = \$7,344 (Range: \$1,226 \$50,030).
- **Promotions:** Average = 0.83.
- Missing values: Found in distance from home (2.56%) and Company tenure (3.23%).

2.3 Data Types

- Categorical: Object (e.g., Gender, Job role, Work-life balance).
- Numerical: int64, float64 (e.g., Age, Income).

3. Methodology

3.1 **Data Preprocessing**

- Missing values: Rows with missing values were removed for data integrity.
- Feature engineering:
 - ♠ Redundant features (e.g., Employee ID, Employee recognition) were removed.

- ♠ Categorical variables were encoded using dummy variables.
- **Feature scaling:** Numerical features were standardized using a standard scaler.

3.2 Feature Selection

• Statistical tests:

- Chi-square & Mann-Whitney U tests are confirmed feature significance.
- Correlation analysis ruled out multicollinearity.

• Recursive feature elimination (RFE):

Selected 15 key predictors, including:

- Gender- male, Work-life balance- fair/poor
- ➤ Job satisfaction- low/very high, Performance rating-low/below average.
- Overtime- yes, Education level- PhD, Remote workyes.
- Marital status- Single, Job level- mid/senior, Company reputation- poor/fair.

3.3 Model Building

 Logistic Regression: The model was developed utilizing statistical models that included a constant term.
 Coefficients, p-values, and Variance Inflation Factors (VIFs) were assessed for their interpretation.

3.4 Threshold Optimization

- **ROC Curve AUC**: 0.8261 (indicating strong performance)
- Youden's J Statistic: Optimal threshold = 0.5513

3.5 Model Evaluation

Iteration 1 (Threshold 0.5) -

Metric	Current Value	Ideal Target	Action Plan
Accuracy	73.64%	75-80%	Aim to improve overall performance by adjusting features and optimizing the model.
Sensitivity	74.79%	80-85%	Increase sensitivity by adjusting the threshold to capture more at-risk employees.
Specificity	72.40%	70-75%	Slight drop in specificity is okay if it increases sensitivity.
Precision	74.61%	70-75%	Maintain reliability while focusing on improving recall.
False Negatives	2,779	<2,000	Focus on reducing false negatives by refining features and threshold.
False Positives	2,806	~3,000	Slight increase in false positives is acceptable if interventions are low-cost.

Experimenting with different thresholds:

Threshold	Accuracy	Sensitivity	Specificity	Precision	False Positives (FP)	False Negatives (FN)	MCC	Youden's J
0.436	73.12%	80.57%	65.04%	71.42%	3554	2142	0.4628	0.4561
0.4681	73.61%	77.48%	69.41%	73.31%	3110	2483	0.4708	0.4689
0.5000	73.41%	75.58%	71.31%	73.95%	2923	2672	0.4691	0.4689
0.5116	73.54%	73.80%	73.27%	74.97%	2717	2889	0.4704	0.4707

1. Threshold = 0.4681:

- This is the best balance: it catches 77.48% of employees who are likely to leave (Sensitivity) while avoiding too many false alarms (69.41% Specificity).
- MCC (0.4708) shows the model is performing well overall.

2. **Threshold = 0.5000** (default):

- Slightly lower Sensitivity (**75.58**%) means it might miss some employees who would leave.
- Slightly better Specificity (71.31%) reduces false alarms but might miss some at-risk employees.

3. Threshold = 0.5116:

Best Precision (74.97%) and Specificity (73.27%)
mean fewer false alerts, but it misses more at-risk
employees (73.80% Sensitivity).

4. Threshold = 0.436:

 Highest Sensitivity (80.57%) catches most leavers, but it causes too many false alarms (65.04%
 Specificity), leading to wasted efforts.

Using a threshold of 0.4681 because it strikes the best balance

between:

- **Capturing at-risk employees**: It finds **77.48%** of those who will leave.
- * Reducing false positives: False alarms are kept at manageable levels.
- ❖ Strong overall performance: With an MCC of 0.4708, the model stays balanced and stable.

Iteration 2

Metric	Current Value	Previous Value	Difference
Accuracy	73.61%	73.61%	No Change
Sensitivity (Recall)	77.48%	74.79%	+2.69%
Specificity	69.41%	72.40%	-2.99%
Precision	73.31%	74.61%	-1.30%

Current Confusion Matrix:

	Predicted: Stay	Predicted: Leave
Actual: Stay	7,056 (True Negative)	3,110 (False Positive)
Actual: Leave	2,483 (False Negative)	8,542 (True Positive)

Previous Confusion Matrix:

	Predicted: Stay	Predicted: Leave
Actual: Stay	7,360 (True Negative)	2,806 (False Positive)
Actual: Leave	2,779 (False Negative)	8,246 (True Positive)

Difference in Values:

	Current Value	Previous Value	Difference
True Negative (TN)	7,056	7,360	-304
False Positive (FP)	3,110	2,806	+304
False Negative (FN)	2,483	2,779	-296
True Positive (TP)	8,542	8,246	+296

Key Improvements:

- o 296 fewer False Negatives.
- o 296 more True Positives.
- Trade-off: 304 more False Positives (acceptable for HR interventions).

4. Key Insights

4.1 Factors Contributing to Attrition

- High Risk:
 - **Low job satisfaction.**
 - ♣ Below-Average performance.
 - **4** Overtime work.
 - Low education.
 - Single marital status.
 - Entry-level roles.
 - Remote work.
 - Poor company reputation.

4.2 Feature Insights

- > Positive Coefficients (increase attrition probability):
 - ♠ Gender- Male, Remote Work- Yes, Senior Job Level, PhD
- ➤ **Negative Coefficients** (decrease attrition probability):
 - ♠ Poor Work-Life Balance, Low Job Satisfaction, Single Status, Poor Reputation.

4.3 Insights

- Age: The mean age of employees is approximately 38.5 years, with a standard deviation of 12.08, indicating a relatively diverse age range. The distribution appears roughly normal with a slight platykurtic shape.
- Attrition: 47.85% of employees left the company, while 52.15% remained, indicating a relatively balanced distribution of attrition.

- Company Reputation: 50% of respondents rated the company as "Good," while 20.25% rated it as "Poor." The chi-square test results indicate that the company's reputation significantly impacts customer retention.
- **Company Size**: 50.1% of employees work in mediumsized companies, and 29.9% in small companies. The chisquare test suggests that company size is related to attrition, with smaller companies having higher turnover.
- **Company Tenure**: Average tenure is 56 months, with a standard deviation of 25.4 months. The tenure distribution exhibits a slight positive skew, with most employees having medium tenure.
- **Distance from Home**: The average distance from home is 49.89 miles, showing a normal distribution.
- Education Level: The majority of employees have a
 Bachelor's Degree (30%), followed by an Associate
 Degree (24.86%). Education level is significantly linked to
 attrition.
- **Gender**: 55% of employees are male, with 45% female. Gender significantly affects attrition.
- **Innovation Opportunities**: 83.86% have no innovation opportunities, and this is crucially related to attrition.
- Job Level: Most employees are in Mid or Entry-level roles, with job level strongly linked to attrition.
- **Job Satisfaction**: 50.18% of employees have high job satisfaction, and this factor is closely corelated to attrition.
- Leadership Opportunities: A majority (95.11%) do not have leadership opportunities, and this is

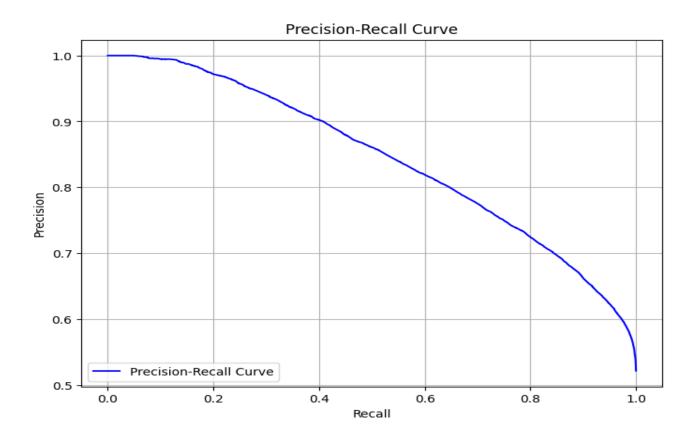
significantly related to attrition.

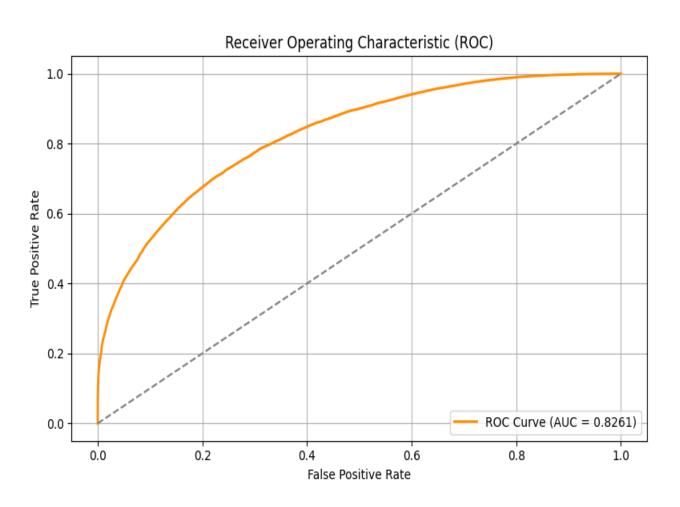
- Marital Status: Most employees are married (50.3%), with marital status significantly influencing attrition.
- Monthly Income: The average monthly income is \$7,347.36, with a high skewness, indicating some highincome outliers.
- **Number of Dependents**: The average number of dependents is 1.66, with a slight positive skew.
- **Number of Promotions**: The average number of promotions is 0.83, with a right-skewed distribution.
- **Overtime**: 67.54% do not work overtime, with overtime status significantly linked to attrition.
- **Performance Rating**: Most employees have an average performance rating (59.99%), with lower performance strongly linked to attrition.
- **Remote Work**: 82.24% do not work remotely, with remote work strongly linked to attrition.

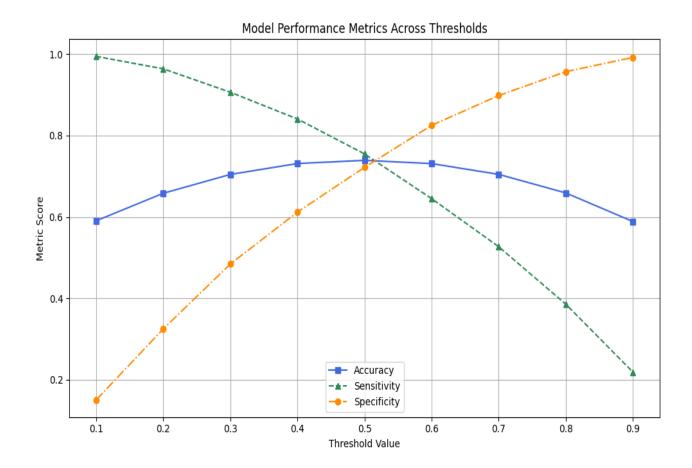
5. Techniques Used

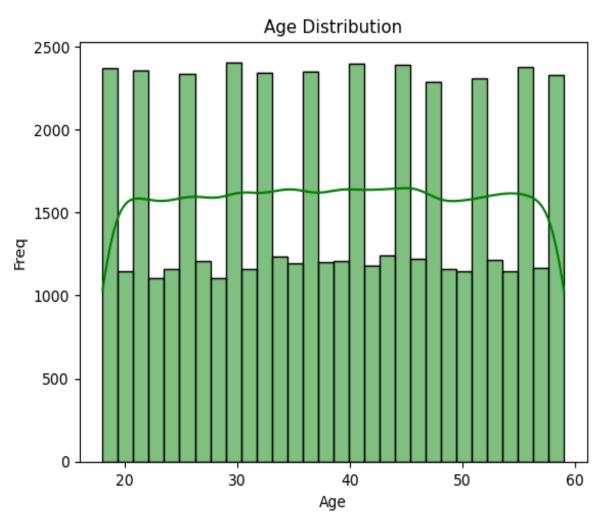
- **EDA**: Summary statistics, missing value handling, correlation matrix.
- **Feature Engineering**: Dummy variables, feature scaling, feature elimination.
- **Feature Selection**: Variance threshold, mutual information, RFE.
- Modeling: Logistic Regression.
- Threshold Optimization: ROC analysis, Youden's J.
- **Evaluation Metrics**: Accuracy, Sensitivity, Specificity, Precision, Confusion Matrix.

6. Visualizations and Plots

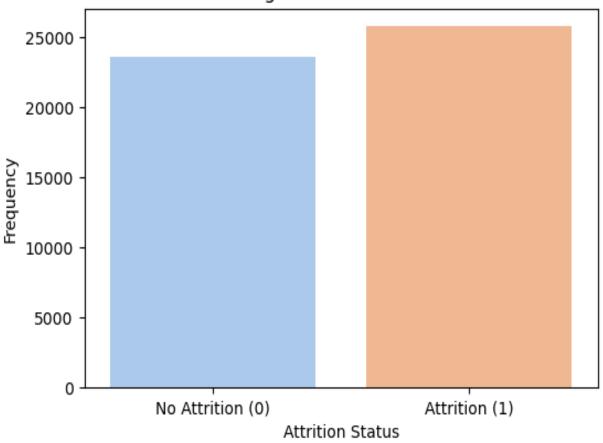


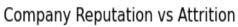


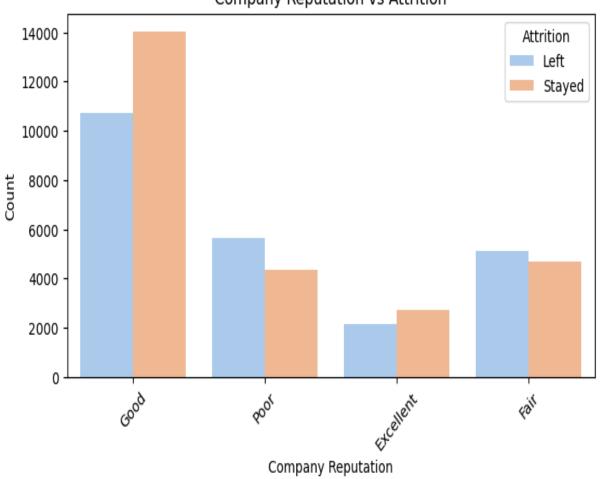


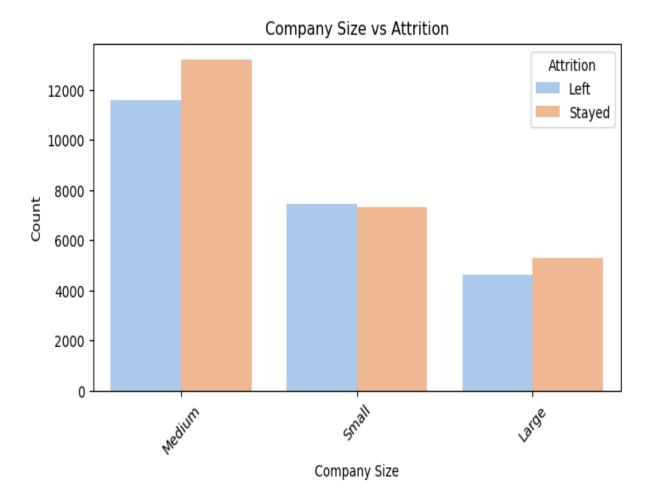


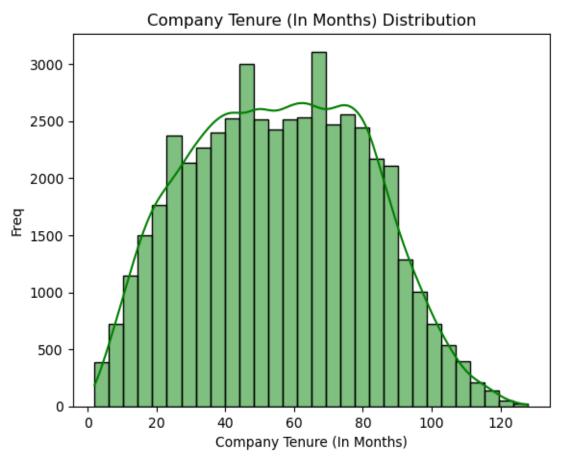


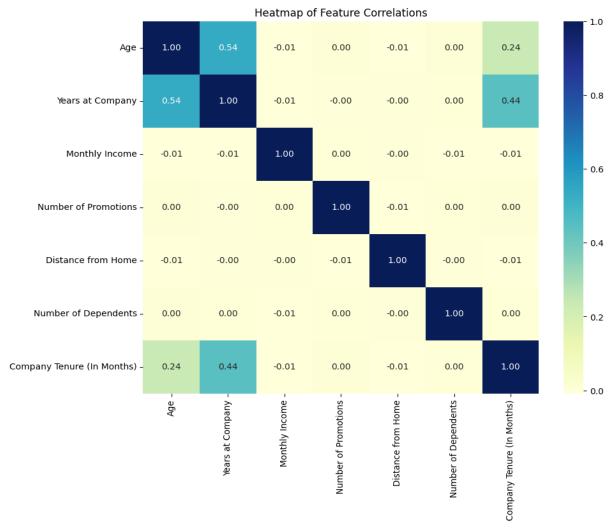


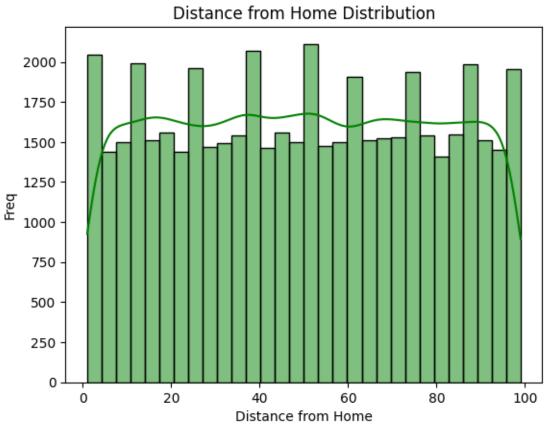




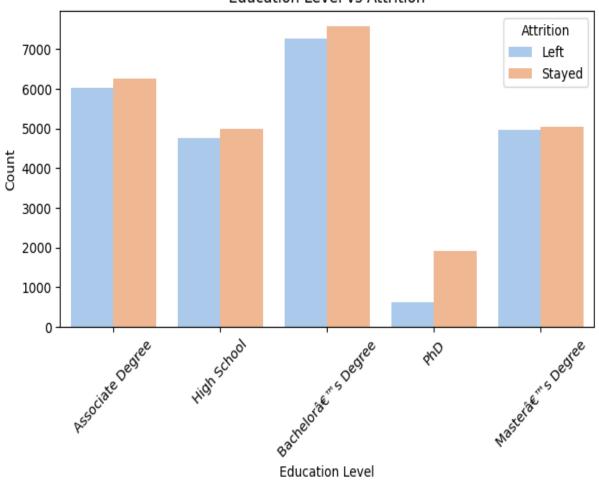




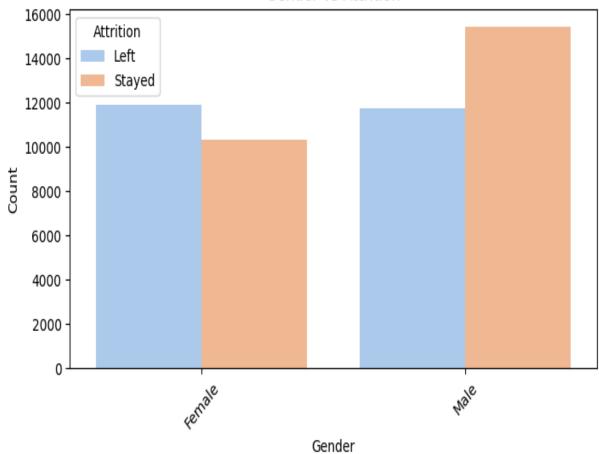


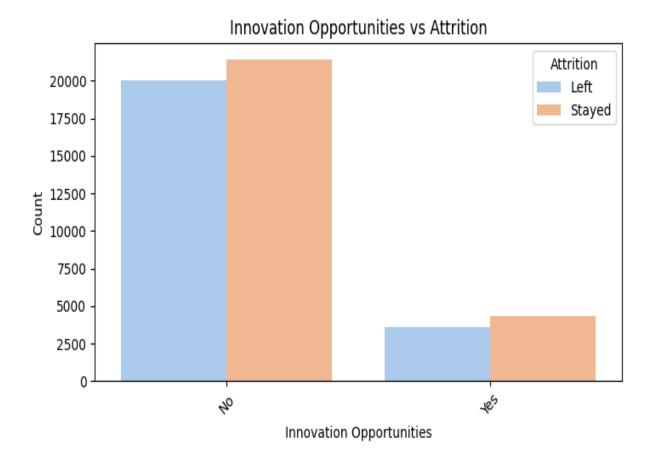


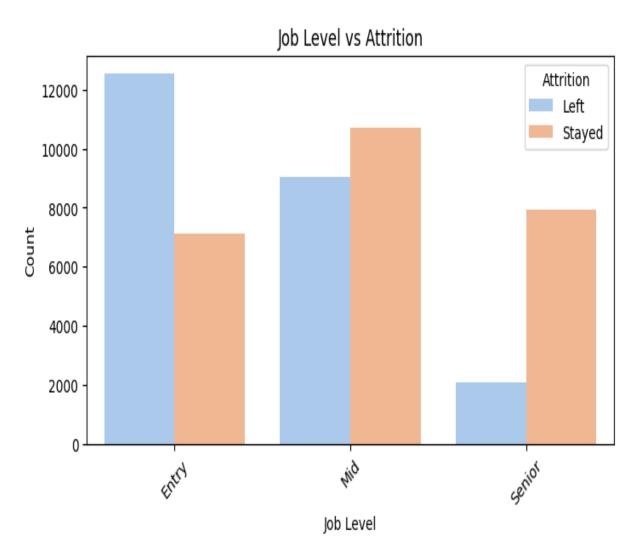


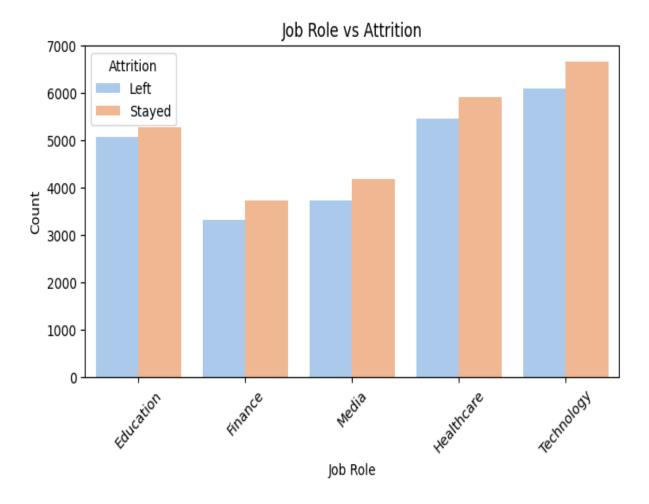


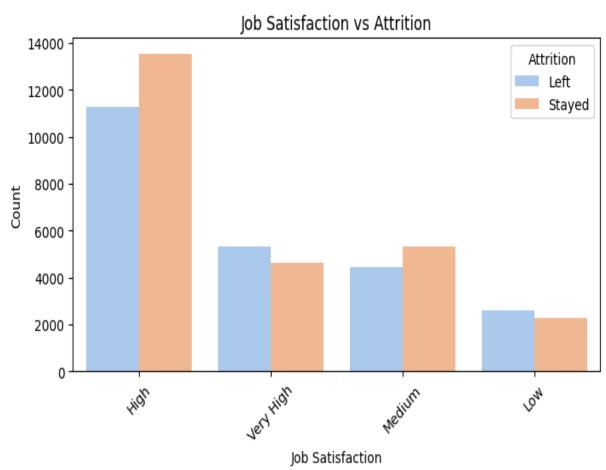
Gender vs Attrition

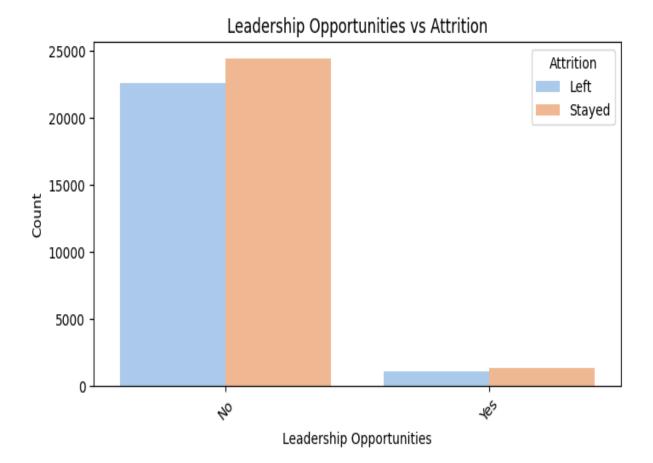


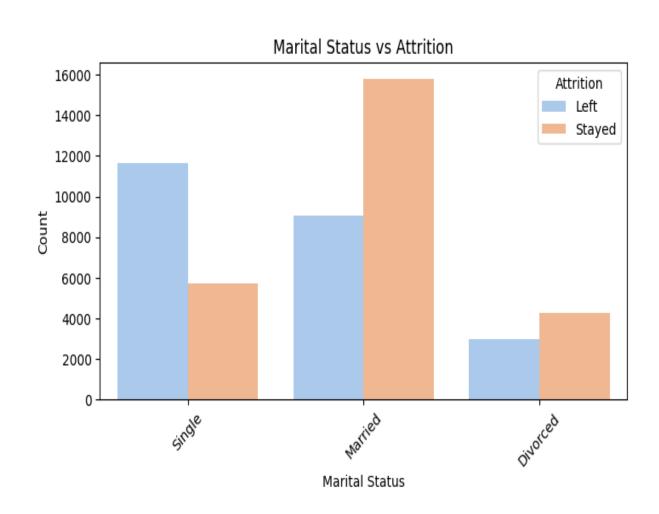


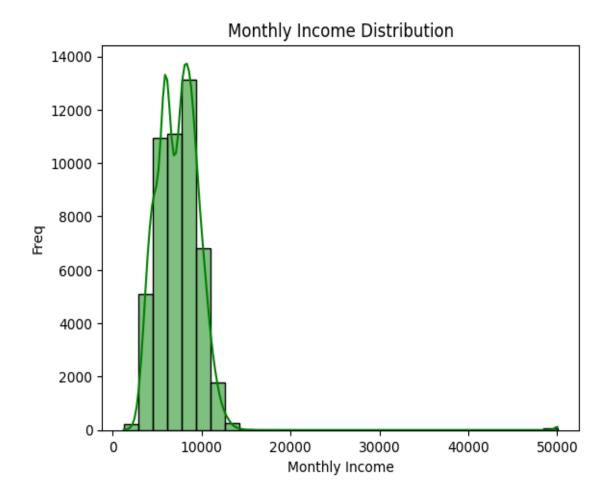


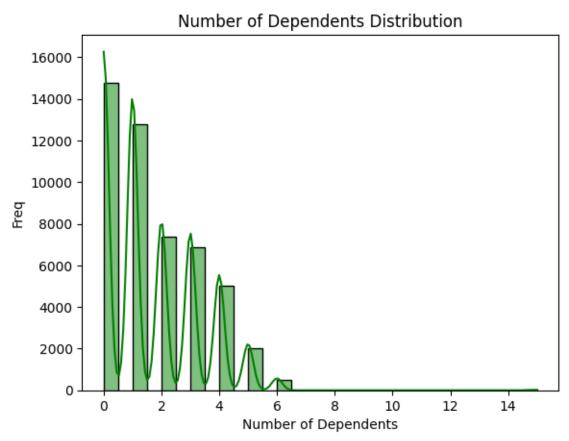


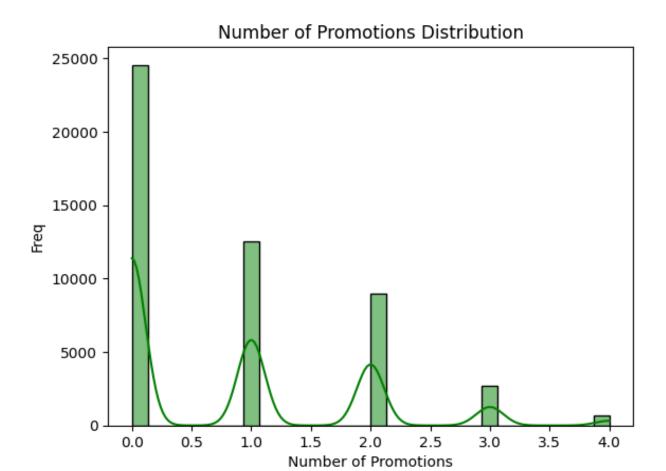


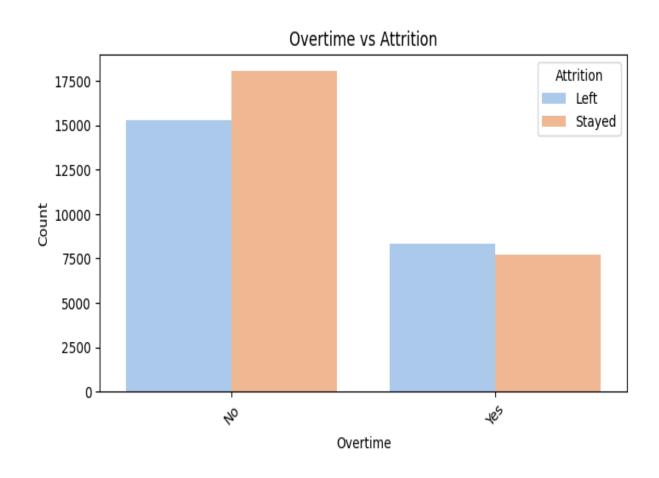


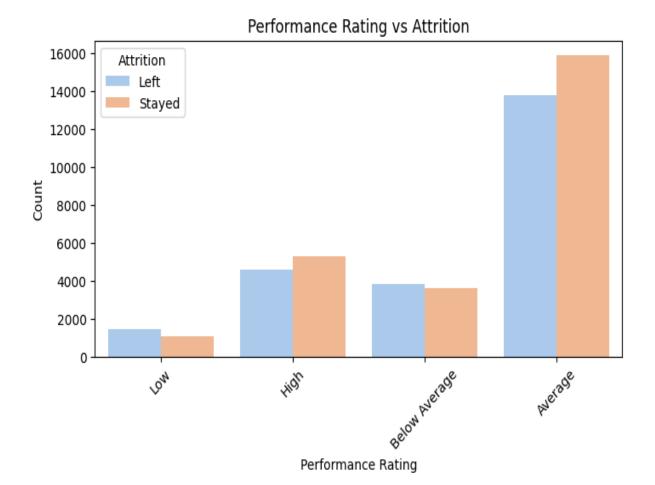


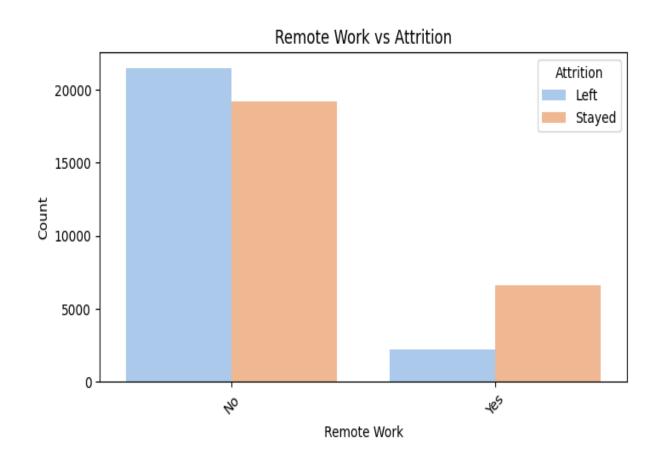




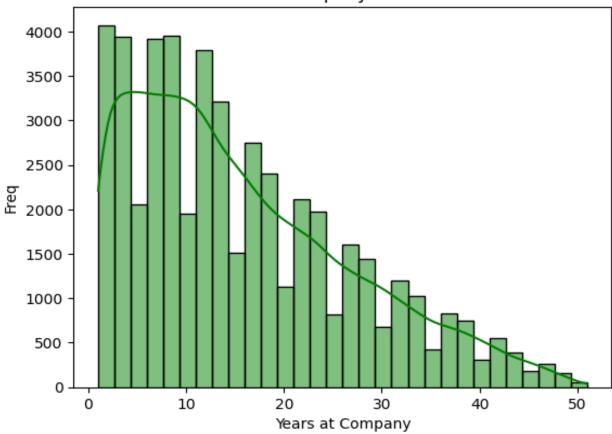












7. Recommendations

- Proactive Retention Strategies:
 - Its main focus is on improving job satisfaction and performance ratings, as they are key predictors of employee attrition.
 - ♣ Address work-life balance and overtime issues to ensure that employees are not overburdened, which can contribute to higher turnover.
 - ♣ Enhance company reputation and provide leadership opportunities, which can improve both employee retention and satisfaction.
 - Support single employees and those in entrylevel positions, as they appear to be more at risk of leaving the company.

• Targeted Interventions:

♣ Use the model's predictions to identify at-risk employees and proactively engage with them through tailored retention efforts, such as personalized support, career development programs, and wellness initiatives.

• Continuous Monitoring:

Keep track of company size, promotion opportunities, and education levels, as they also play important roles in retention and should be regularly reviewed.

8. Conclusion

The final model, which uses Logistic Regression with an optimised threshold of 0.4681, has a balanced trade-off between precision and sensitivity, and it has great promise for predicting staff retention. Understanding the main causes of turnover, such as job happiness, working overtime, and corporate reputation, helps HR teams make proactive retention improvements.

By implementing these findings, the business may cultivate a more devoted workforce, lower attrition, and raise general employee satisfaction—all of which will eventually contribute to a more stable and effective work environment.