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EXPLAINABLE MACHINE LEARNING FOR PREDICTING EMPLOYEE ATTRITION: A HUMAN RESOURCE ANALYTICS FRAMEWORK FOR STRATEGIC WORKFORCE MANAGEMENT

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ABSTRACT

Employee attrition presents a major challenge to workforce stability, productivity, and organisational continuity. This study developed an explainable human resource analytics framework for predicting employee attrition and identifying the principal factors associated with employee departure. A quantitative, cross-sectional secondary-data design was adopted using the IBM HR Analytics Employee Attrition dataset, comprising 1,470 employees and 35 variables. Microsoft Excel was used for data cleaning, descriptive analysis, statistical testing, logistic regression modelling, visualisation, and model evaluation. The overall attrition rate was 16.1%. Employees who left were generally younger, earned lower monthly incomes, lived farther from work, and had shorter organisational and managerial tenure. Over time, frequent business travel, single marital status, distance from home, number of previous companies worked, and years since the last promotion significantly increased attrition likelihood. In contrast, job satisfaction, environmental satisfaction, job involvement, work–life balance, age, job level, training, tenure in the current role, and years with the current manager reduced attrition risk. The model explained approximately 30.0% of attrition variation and achieved an area under the ROC curve of 0.810, indicating good discrimination. Lowering the classification threshold from 0.50 to 0.25 improved sensitivity from 34.0% to 63.8% and increased the F1-score from 44.4% to 55.0%. The findings support ethical, targeted, and proactive retention strategies based on interpretable workforce evidence.

Keyboard: Employee attrition; Explainable machine learning; Human resource analytics; Logistic regression; Strategic workforce management

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1. Introduction

Employee turnover is considered a significant strategic issue due to the number of skilled workers that are leaving voluntarily, leading to a drop in productivity, higher recruitment expenses, loss of institutional knowledge and lower workforce stability. When there are more competitors in the labour market, employees are more likely to leave when they do not get paid enough, are not being promoted, are not satisfied with their pay or job satisfaction, or are not happy with their work–life balance. HR Analytics provides an organised way to turn HR data into evidence that will help inform retention planning and strategic decision-making. Through machine learning analysis of employee attrition, organisations can leverage their employee information to detect meaningful employee attrition patterns and inform real-life retention strategies (Avrahami et al., 2022).

Traditional methods of retaining employees, such as exit interviews, employee surveys and manager observations, tend to be reactive because they only discover problems after an employee has quit. Predictive analytics, on the other hand, offers a more proactive solution by examining factors like demographics, work characteristics, pay, satisfaction and career trajectory, before employees begin to think about quitting. Machine-learning methods can assess multiple aspects of the employee and can identify complex relationships between employee aspects that may not be apparent in a conventional descriptive analysis. Previous studies have shown that these techniques can differentiate between those employees who stay and those who leave and are useful, in terms of predictive accuracy (Fallucchi et al., 2020).

Artificial Intelligence has revolutionised the career of technology in the recruitment process, performance management, workforce planning, employee development and retention. But artificial intelligence can only contribute to the value of the organisation if analytical systems help achieve a wider HR strategy and managerial goals. Thus, there is a need to integrate three sides of Artificial Intelligence (AI) with Human Resource (HR) and organisational goals (Malik et al., 2023). The advent of generative AI has also added to the discussion about automated workforce analysis and sparked concerns about governance, accountability, employee trust, skills and human resource professionals' roles (Budhwar et al., 2023).

However, just predicting accuracy isn't enough to make a responsible employee attrition management. Many advanced algorithms are a black box, so it can be hard to understand why an employee is deemed to be at high risk of leaving. Explainable AI (XAI) overcomes this challenge by pinpointing which factors impact predictions. In attrition analysis, explainability can be used to determine if there is a relationship between overtime, job satisfaction, business travel, income, tenure or career progression and risk. Interpretable predictive methods, therefore, boost the usefulness of analytics by linking the outputs of the analytics models with interpretable workplace conditions (Das et al., 2023).

Explanation is given extra weight as sometimes the predictions of attrition can affect decisions related to sensitive factors such as retaining offers, career opportunities, workload adjustments, and managerial support. As illustrated by the transparent models, these models provide managers with a way of focusing on the conditions of their organisations that can be improved, instead of simply stating that employees are at risk of leaving the organisation (Marín Díaz et al., 2023). Shapley additive explanations offer both global explanations of which factors in the workforce influence the model, as well as local explanations of which factors are involved in specific predictions. Random forest-based and SHAP-based models have been proven to be useful for developing interpretable attrition models with good performance (Ipmawati & Kusnawi, 2026).

More recent explainable analytics frameworks have taken this approach one step further by linking the probabilities of attrition to intelligent decision support. These types of systems can determine that similar risk levels can come from varying reasons, such as overwork, lack of promotion, lack of satisfaction or work/life balance. This is to allow for more tailored and meaningful human resource interventions (Jia, 2026). However, ensemble learning has also been gaining attention because by using multiple algorithms, the stability of the model and classification could be improved. However, complex models should be statistically sound and easily interpretable to enable their use in organisations (Nassreddine et al., 2026).

Today, talent analytics has evolved to include a range of technologies, including machine learning, deep learning, natural language processing and explainable AI. These techniques can be used for turnover forecasting, evaluation, skills analysis and allocation. As they are increasingly adopted, the importance of technical innovation and human-centred organisational practices is evident, underscored by the need for an integrated approach (Qin et al., 2025).

While all this is great, there are significant ethical dangers with people analytics. Over-monitoring, breaches to privacy, algorithmic bias and the abuse of predictive scores can lead to a decrease in the employee's trust and to the transformation of complex human behaviour into simple scores. However, critical research has cautioned that analytics can have negative side effects if there is a focus on efficiency, over workplace health and safety (Giermindl et al., 2022). To implement these responsibly, there is a need for transparent data practices, proper governance, human oversight, accountability, fairness, protection of privacy and employee participation (Bujold et al., 2024).

Ethical issues are particularly paramount when generative AI is used in making recommendations for employment. Organisations need to consider how their data quality, discrimination risks, transparency, and potential impact of automated decisions (Andrieux et al., 2024). However, AI should be used alongside, not in place of, HR professionals' expertise and experience in making decisions that are fair and considerate of employees, in the context of the organisation. (Stone et al., 2024). Ethically, predictive systems should also uphold employee dignity and autonomy, as well as employee fairness, and not be used for surveillance, exclusion and discriminatory decision making (Varma et al., 2023).

Based on this observation, this study proposes an explainable machine learning model that can predict employee attrition and assist in the strategic management of employees. It explores demographic, job-related, pay, satisfaction, work–life balance, and career-related predictors, looks at model performance, and decodes the most significant predictors of attrition. The study aims to finally contribute to the ethical, targeted and proactive employee retention measures.

2.Methodology

2.1Research Design

The study was a quantitative research design, cross-sectional, and secondary data research type to predict the employees' tendency to turn over by a human resource analytics approach. Data cleaning, statistical analysis, visualisation, prediction and interpretation were done exclusively in Microsoft Excel. The objective of the study was to examine factors that were important for employee turnover and to create a model comprehensible for strategic human resource management. The purpose of the study was to determine factors that are crucial for employee turnover and to formulate an understandable prediction model of strategic human resource management.

2.2Dataset and Variables

The data set for this study was the IBM HR Analytics Employee Attrition data set, which has 1,470 employees with 35 attributes. The rows were for each employee, and the columns were for information about their demographics, work, salary, satisfaction, performance, and career development.

Employee attrition was the dependent variable, with “Yes” indicating those who left the organisation and “No” indicating those who did not. There were 237 employees in the sample who experienced attrition and 1,233 who experienced no attrition.

Predictor variables were age, gender, marital status, education, department, job role, job level, business travel, overtime, monthly income, distance from home, total working years, years at the company, years in the current role, years since the last promotion, years with the current manager, job satisfaction, environment satisfaction, work-life balance, job involvement, training frequency, and stock-option level.

2.3 Data Cleaning and Preparation

The data were entered into a spreadsheet (Microsoft Excel) and were reviewed with filters, sorting, conditional formatting and formulas. A duplicate record was detected by removing the duplicates from the record in Excel and then by using the COUNTIF function. Blank-cell filters and the COUNTBLANK function were used to check missing values. Values for numerical variables were examined for being invalid, negative or unrealistic.

The variables Standard Hours, Over18, and Employee Count were omitted since they resulted in one value for all the employees and could not help in predicting. The Employee Number was also deleted as it was merely an ID number.

Attrition of employees was recoded as a dichotomous variable with “Yes” (1) and “No” (0). Some categorical variables, like overtime (yes or no) and gender (male or female), were also recoded as numbers with the IF function. Other multi-categorised variables such as department, job role, marital status and business travel were converted into separate dummy variables.

2.4 Descriptive and Exploratory Analysis

Data Analysis ToolPak of Microsoft Excel was used to perform descriptive statistics by using the appropriate formulas. Categorical data were presented as frequencies and percentages, and numerical data were presented as mean, standard deviations, median, minimum and maximum values.

The attrition rates for gender, department, job role, marital status, overtime, business travel, degree level and job satisfaction were examined using PivotTables. The attrition rates were determined as the percentage of employees who left in each category.

The age, monthly income, distance from home, total years on job, year with the company and year since promotion were compared between the employee group with and without attrition. The main patterns of attrition were presented using bar charts, pie charts, histograms, clustered column charts and box-and-whisker plots.

2.5 Statistical Association and Predictor Selection

Chi-square tests were used to examine the association between categorical variables and employee attrition. Contingency tables were generated, and a CHISQ. The statistical significance was determined using the TEST function.

Independent-samples t-tests were used for numerical variables to compare the groups of employees who left and when they found a job. Independent-samples t-tests were performed on numerical variables to compare the groups of employees who had left and those who had found a job. Numerical predictors were analysed by Pearson correlation using the Correlation option in the Data Analysis ToolPak. Highly correlated variables were considered, and repetitive information was avoided in the prediction model. The selection of predictors was determined by their statistical significance, their practical importance and their relevance to human resource management.

2.6 Employee Attrition Prediction Model

All the analyses were conducted using a binary logistic regression model, built from scratch in Microsoft Excel with the aid of the Solver add-on. The data set was randomly split into training and testing sets. Random values were produced with the RAND function, and about 80% of the records were used for training and 20% used for testing.

For each employee, a prediction score was calculated using an intercept and the selected predictor coefficients. The prediction score was converted into an attrition probability using the logistic formula:

Predicted probability = $1 / [1 + e^{-(\beta 0 + \beta 1x1 + \beta 2x2 + \ldots + \beta nxn)}]$

Excel Solver was used to estimate the model coefficients by maximising the total log-likelihood value. The Generalised Reduced Gradient nonlinear method was selected in Solver. Only relevant predictors were included to avoid making the model unnecessarily complex.

2.7 Model Evaluation

Those who had a predicted probability of 80% or higher were designated as likely to leave, and those who had a predicted probability of less than 80% were designated as likely to remain. The initial threshold was set at 0.50 and was followed by a consideration of other thresholds, as there were fewer cases of attrition.

An Excel confusion matrix was created to compute true positives, true negatives, false positives and false negatives. Accuracy, sensitivity, specificity, precision and F1 Score were used to evaluate the model performance.

A receiver operating characteristic (ROC) curve was also generated by computing the sensitivity and rates of false-positive (FPR) for each probability threshold. These values were plotted in Excel, and the area under the curve was approximated using the trapezoidal method. In this study, greater weight was placed on sensitivity, and the F1 score as identifying employees who might be at risk of leaving was one of the significant aims of the study.

2.8 Model Interpretation and HR Framework

Interpretation of the prediction model was performed through regression coefficients, odds ratios and predicted probabilities. Odds ratios were computed by using the EXP function. A value greater than 1 for the odds ratio suggested that the predictor was associated with an increased risk of attrition, while a value less than 1 was associated with a decreased risk of attrition.

A risk categorisation of employees was made based on their probability of attrition, which was determined by their predictions. Employees were categorised into low, moderate, and high-risk groups based on their predictions of attrition. The direction and size of the coefficients were used to identify the main factors contributing to attrition risk.

The findings were converted into real HR strategies, such as overtime management, salary, promotion opportunities, job satisfaction, employee development, work-life balance and managerial support.

2.9Ethical Considerations

The data was anonymised secondary data, which did not contain employees' names or direct identifiers. Risks of attrition were considered informational and not as a basis for action under the employment contract. When interpreting and applying the results, the need for employee privacy, fairness, confidentiality, and managerial supervision was deemed essential.

3.Results

3.1 Overall Attrition Profile

The data had 1470 employees, 237 of whom had departed from the organisation, and 1233 employees had stayed. Overall, 16.1% of employees, roughly 1 in 6, were lost due to attrition. There was no missing data in the data set. Figure 1 shows the distribution of employees by attrition status overall.

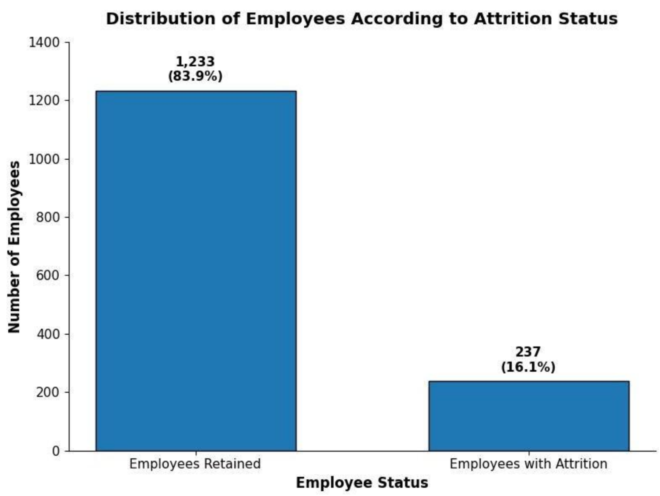

Figure 1. Distribution of employees according to attrition status

3.2 Demographic Differences

Most of those who left the organisation were younger than the employees who stayed within the organisation. The mean age of employees who had left the organisation was 33.61 ± 9.69 years, while that of employees who had remained was37.56 ± 8.89 years. The odds of employee attrition were greater for male than for female employees (OR = 1.460; p = 0.032). The marital status was also correlated with attrition. Single employees had a higher attrition rate of 25.5% compared to divorced employees and were about 3.10 times more likely than divorced employees to leave (β = 1.130, OR = 3.096, p = 0.001). The attrition rate of married and divorced workers was lower, respectively, at 12.5% and 10.1%.

3.3 Employment and Compensation Characteristics

Those leaving had a lower mean monthly income (4,787.09) than those who stayed (6,832.74). For the employees who left, the average distance travelled from home was 10.63 units, and the average distance for the retained employees was 8.92 units. Logistic regression revealed that distance was associated with increased odds of attrition, with each additional unit of distance associated with an increase in odds of 4.4% (OR = 1.044, p < 0.001).

The average years of total working experience was 8.24 years for employees who had attributes of 'attrition' and 11.86 years for those who had retained attributes. They had also worked for previous organisations. An increase of 18.7% (OR= 1.187, p < 0.001) was observed with each additional company previously worked for. Table 1 compares the demographic, compensation and employment attributes of those who have left the company and those who have not left.

Table 1. Demographic and Employment Characteristics of Employees According to Attrition Status

Variable	Employees retained, Mean ± SD	Employees with attrition, Mean ± SD
Age, years	37.56 ± 8.89	33.61 ± 9.69
Monthly income	6,832.74 ± 4,818.21	4,787.09 ± 3,640.21
Distance from home	8.92 ± 8.01	10.63 ± 8.45
Total working years	11.86 ± 7.76	8.24 ± 7.17
Years at company	7.37 ± 6.10	5.13 ± 5.95
Years in current role	4.48 ± 3.65	2.90 ± 3.17
Years with current manager	4.37 ± 3.59	2.85 ± 3.14

3.4 Overtime and Business Travel

One of the most important factors in predicting employee retention was overtime. The overtime-working employees' attrition rate was 30.5%, while the employees who did not work overtime had an attrition rate of 10.4%. Regression analysis revealed that employees who worked overtime had an OR of 5.890 of leaving the organisation, with a β of 1.773 ($p < 0.001$).

Attrition was also shown to be significantly related to business travel. Frequently travelling employees had an attrition rate of 24.9%, while rarely travelling employees had an attrition rate of 15.0%, and the non-travellers had an attrition rate of 8.0%. Travellers were 6.83 times more likely to suffer from attrition than non-travellers (β = 1.921, OR = 6.830, $p< 0.001$). Frequent travellers were also significantly less likely to leave (OR = 0.631, $p = 0.010$). Employees who travelled rarely were also significantly more likely to leave (OR = 2.919, $p = 0.004$). As shown in Figure 2, there are differences in the rate of employee turnover over time and the business travel requirement.

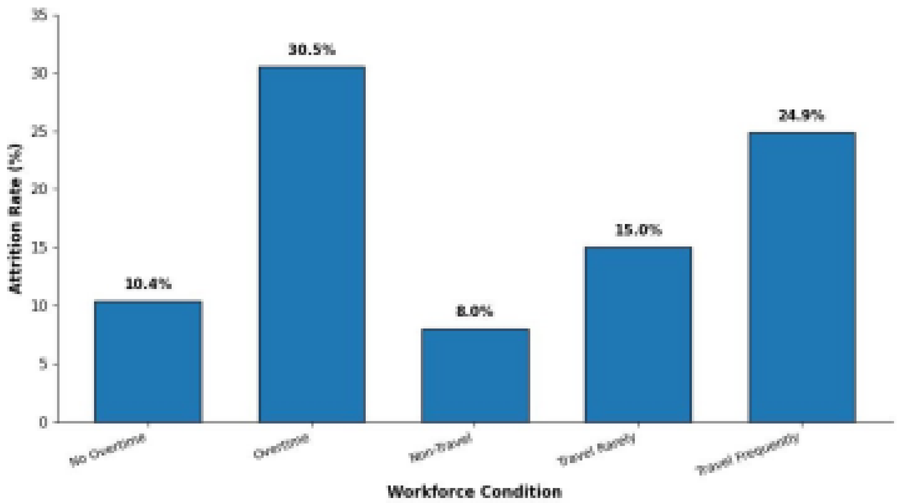

Figure 2. Employee attrition rates according to overtime and business-travel requirements

3.5 Departmental and Job-Role Patterns

The top three departments with the highest departmental attrition rate are Sales (20.6%), Human Resources (19.0%) and Research and Development (13.8%). The department, however, was not statistically significant when other predictors were entered into the regression model.

There was a wide range within job roles. The highest rates of turnover were observed for sales representatives (39.8%), laboratory technicians (23.9%), and human resource workers (23.1%). Research directors had the lowest level of attrition at 2.5%. The results showed that a higher number of employees were leaving customer-facing and operational jobs compared to senior and specialised jobs.

3.6 Satisfaction, Involvement, and Work–Life Balance

Employees with the lowest level of satisfaction had the highest turnover of 22.8%, compared to 11.3% for the employees with the highest level of satisfaction. A one-unit increase in job satisfaction had an OR of 0.661 ($p<0.001$) for reducing the odds of attrition. Attrition risk was also significantly lowered by environmental satisfaction. An increase in environment satisfaction by one unit was associated with a drop of 33.1% in the odds of employees leaving the job (OR = 0.669, $p < 0.001$), while those who had the lowest level of environment satisfaction had twice the likelihood of leaving the job (OR = 2.54, $p = 0.000$). An increase in job involvement lowered the odds for attrition by about 43.6% (OR = 0.564, $p < 0.001$). Employees who reported work–life balance score were associated with 31.2% attrition rate, while for every unit increase in work–life balance score, the odds of attrition were decreased by 27.9% (OR = 0.721, $p = 0.006$). Table 2 shows the attrition rates for key categories of employment, demographic and workplace characteristics.

Table 2. Employee Attrition Rates Across Major Workforce Categories

Factor	Category	Employees with attrition, n	Total employees, n	Attrition rate (%)
Overtime	Yes	127	416	30.5
	No	110	1,054	10.4
Business travel	Frequently	69	277	24.9
	Rarely	156	1,043	15.0
	Non-travel	12	150	8.0
Marital status	Single	120	470	25.5
	Married	84	673	12.5
	Divorced	33	327	10.1
Department	Sales	92	446	20.6
	Human Resources	12	63	19.0
	Research and Development	133	961	13.8
	Level 1	66	289	22.8
	Level 2	46	280	16.4

Job satisfaction	Level 3	73	442	16.5
	Level 4	52	459	11.3
Work–life balance	Level 1	25	80	31.3
	Level 2	58	344	16.9
	Level 3	127	893	14.2
	Level 4	27	153	17.6

3.7 Career Progression and Organisational Tenure

The average length of service was 5.13 years for employees who departed, but 7.37 years among those who remained. They stayed in their current job for an average of 2.90 years, compared to 4.48 years for those who stayed in their job. They had reported with fewer years of service in their current role, as 2.85 years compared with 4.37 years among those who are retained.

For every year since the last promotion, the odds of attrition rose by 19.0% (OR = 1.190, $p < 0.001$). By comparison, older age, higher level of job, further training, more time in current position and more years with current manager had a significant negative impact on the likelihood of attrition. After adjusting for the other predictors, stock-option level and total working experience were not statistically significant. Figure 3 displays the ORs of those predictors of employee turnover that were significantly different from 1.0 when the ORs were adjusted for all other predictors listed in Table 1.

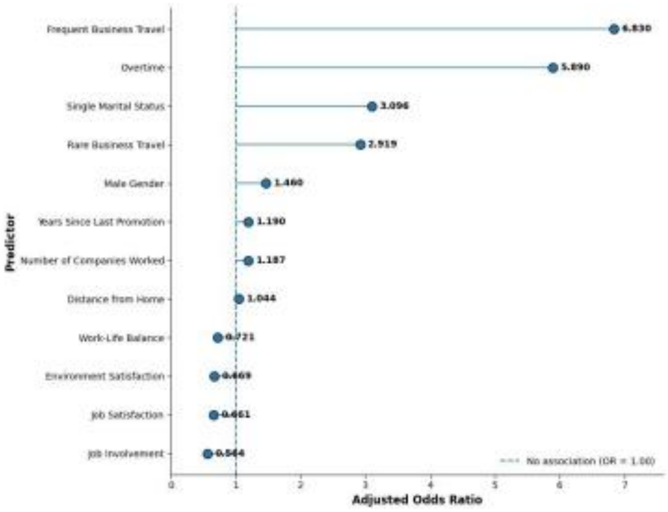

Figure 3. Adjusted odds ratios of the significant predictors included in the employee attrition model

The statistically significant predictors of employee attrition identified through logistic regression are summarised in Table 3.

Table 3. Significant Predictors of Employee Attrition in the Logistic Regression Model

Predictor	Regression coefficient, β	Odds ratio	p-value	Interpretation
Male gender	0.378	1.460	.032	Increased attrition odds
Single marital status	1.130	3.096	.001	Increased attrition odds
Overtime	1.773	5.890	< .001	Increased attrition odds
Frequent business travel	1.921	6.830	< .001	Increased attrition odds
Rare business travel	1.071	2.919	.004	Increased attrition odds
Distance from home	0.043	1.044	< .001	Increased attrition odds
Number of companies worked	0.171	1.187	< .001	Increased attrition odds
Job satisfaction	−0.414	0.661	< .001	Reduced attrition odds
Environment satisfaction	−0.402	0.669	< .001	Reduced attrition odds
Job involvement	−0.573	0.564	< .001	Reduced attrition odds
Work–life balance	−0.327	0.721	.006	Reduced attrition odds
Years since last promotion	0.174	1.190	< .001	Increased attrition odds

3.8Model Performance

McFadden's pseudo-R^2 determined that the logistic regression model accounted for approximately 30.0% of the variance in employee attrition, making it a statistically significant model. The accuracy of the model was 86.4% at the probability threshold of 0.50, the specificity was 96.4%, the precision was 64.0%, the sensitivity was 34.0%, and the F1 score was 44.4% at the same probability threshold.The sensitivity increased to 63.8% when the classification threshold was lowered to 0.25, while the accuracy stayed at 83.3%. Here, specificity was 87.0%, precision was 48.4%, and the F1-score went up to 55.0%. Model performance in predicting the status of species is compared at the 0.50 and 0.25 classification thresholds in Table 4.

Table 4. Predictive Performance of the Employee Attrition Model at Different Classification Thresholds

Performance measure	**Threshold = 0.50**	**Threshold = 0.25**
Accuracy (%)	86.4	83.3
Sensitivity (%)	34.0	63.8
Specificity (%)	96.4	87.0
Precision (%)	64.0	48.4
F1-score (%)	44.4	55.0
Area under the ROC curve	0.810	0.810

The area under the receiver operating characteristic curve was 0.810, demonstrating good discrimination between employees who left and those who remained. The receiver operating characteristic curve demonstrating the predictive performance of the logistic regression model is shown in Figure 4.

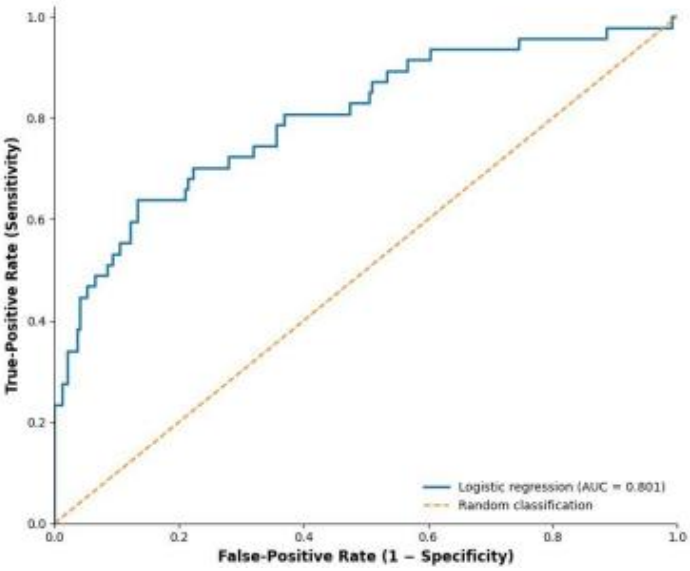

Figure 4. Receiver operating characteristic curve of the employee attrition prediction model

Overall, overtime, frequent business travel, single marital status, distance from home, previous companies worked, delayed promotion, low satisfaction, poor job involvement, and poor work–life balance were the principal predictors of employee attrition.

4.Discussion

This study focused on employee attrition through an explainable human resource analytics framework including 1,470 employee records. Employees leaving the job was a major issue with employee management, with an overall attrition rate of 16.1%. The results showed that overtime, business travel, marital status, distance from home, job satisfaction, environmental satisfaction, job involvement, work–life balance, and career progression and organisation tenure were associated with attrition. This is in line with the idea that staff turnover is a multi-faceted phenomenon of an organisation and not a consequence of one factor of the employment relationship. Therefore, based on those conditions, predictive analytics can help HR managers determine what combinations of circumstances can make it more likely for people to quit. (Agrawal et al., 2024).Generally, employees who left the organisation were younger and had lower monthly incomes than those who stayed on. Younger workers might have more job mobility and may be more inclined to look for external job opportunities where they can get better pay, development or flexibility. A similar pattern of dissatisfaction can occur when there is a discrepancy in the relationship between effort and rewards in the organisation, and when lower income is also faced. The same pattern of dissatisfaction may also happen if lower income is faced, and the employees perceive there is an imbalance in the relationship between effort and rewards in the organisation. Al-Darraji et al. (2021) has also pointed out that demographic and employment characteristics are also important inputs to the deep-learning employee attrition prediction system.

Single employees had a much higher attrition rates than married and divorced employees. After adjusting for other predictors, they were about three times more likely to quit than divorcees. Single staff members might have less family or geographical barriers and are more likely to be willing to switch organisations. Male employees had a slightly higher rate of attrition than female employees. But the demographic predictors should not be taken at face value as they are not directly actionable and may be unfairly used without ethical safeguards. There is a particular need for explainable attrition models to help identify between demographic associations and organisational factors that could be tackled through policy change (Al-Ali et al., 2026).

Overtime had one of the highest rates of predicting attrition. Overtime workers were almost six times more likely to quit, compared with those who did not work overtime. Extended work hours may lead to fatigue, stress, work–family conflict, especially if there is no recognition, compensation or recovery time for the extra effort. This is also consistent with earlier research on model comparison, which has revealed that overtime often plays a significant role in the classification of employee attrition (Guerranti & Dimitri, 2023).

High frequency of business travel was another significant contributor to a high rate of turnover. Those employees who travelled regularly were over 6 times more likely to leave than those employees who did not travel at all. Travel requirements can interfere with personal habits and routine, limit opportunities for recovery, and compromise work–life balance. Reducing this burden could be achieved by adopting virtual meetings, shifting the travel burden and offering compensation time.

According to machine-learning studies, travel frequency may provide valuable information to predict attrition, coupled with other factors in the employment situation (Mansor et al., 2021).

Overall levels of job satisfaction had a significant negative effect on attrition risk. The lowest-ranked employees had a much higher turnover rate than did the highest-ranked employees. Satisfaction is a general assessment of the job, such as employees' perceptions of recognition, role demands, management support and equity of rewards. The results of the large-scale employee reviews data also suggest that job satisfaction is one of the most crucial factors affecting employee turnover (Sainju et al., 2021).

Environmental satisfaction was also protective. Those who had a positive attitude about their work environment were less apt to quit. This could be an outcome of interpersonal relationship, physical environment, management and organizational culture. Choosing and understanding key elements of the workplace can help to boost predictive accuracy and managerial relevance (Najafi-Zangeneh et al., 2021).

Job involvement was a significant negative predictor of attrition, with higher levels of involvement resulting in lower risk of attrition. Work with meaning and psychological involvement in responsibilities can foster employee's organisational attachment. Low involvement, however, may reflect role ambiguity, lack of autonomy, and/or lack of recognition. The contribution of meaningful work to enhance employee retention has been proven by making them feel positively attached to the organisation (Kuancintami and Heryjanto, 2023).

Another key protective factor was the quality of work–life balance. Those with the poorest balance had a higher than 30 per cent turnover rate. Therefore, flexible working hours, manageable workloads and respect for personal time can help to minimise avoidable staff turnover. Work–life balance has also been found to be an important mechanism between workplace conditions, and turnover intention (Saufi et al., 2023).

There was a positive correlation between years since last promotion and attrition, suggesting career stagnation. Fewer employees remained employed if they did not get a promotion for a long time. These may, in turn improve retention, as there are transparent progression requirements and other avenues for internal mobility and professional development. Machine-learning attrition models have also made a huge contribution from career-related variables (Raza et al., 2022). Attrition risk was decreased by having a longer duration in the current role and having a longer duration with the current manager. Favourable relationships between management may lead to increased levels of trust, communication and support. Explainable turnover research also points to a variety of factors that can affect a person's decision to stay or go, including some interactions in the workplace that push them away and keep them attached (Lazzari et al., 2022).

Frequently, the number of previous companies had an impact on the risk of attrition, indicating that people with a track record of moving from one company to another may be more willing to hear about other offers. However, there should be no exclusion on the basis of an applicant's career. To support fair interventions instead of discriminatory decisions, a transparent model is needed to ensure the prediction process is both transparent and accurate (Heidemann et al., 2024).

The discrimination of the model was good with an AUC of 0.810. In terms of accuracy, the 0.50 threshold was very good, yet, due to the minority class nature of the attrition cases, sensitivity was relatively low. Scaling down the threshold increased sensitivity and F1 score, showing that the choice of threshold should be tailored to the needs of the organisation. Therefore, comprehensive frameworks for the evaluation of attrition suggest considering accuracy along with recall, precision, specificity and F1-score (Sinap & Karadenizli, 2026).

The results show that, rather than punitive action, supportive action is better directed based on predictive analytics. Staff with the potential to be at risk should be reviewed for workload, have career discussions, development opportunities and flexible working support. When strategic workforce planning is interpreted in the context of the organisation, supervised learning can improve predictions (Veglio et al., 2025).

Overall, there seemed to be several combined push factors – workload, travel, lack of satisfaction, lack of career prospects – that were causing employees to turn in their notice. Psychological explanations of attrition also attribute the reasons for departure to the interactions between pressures and the external attractions (Saurabh et al., 2026).

5.Conclusion

This study demonstrated that employee attrition can be predicted with useful accuracy through an explainable human resource analytics framework. Analysis of 1,470 employee records produced an overall attrition rate of 16.1% and confirmed that departure is shaped by a combination of demographic, occupational, satisfaction, workload, mobility, and career-progression factors. Overtime and frequent business travel were the strongest risk factors, while single marital status, greater distance from home, previous employment mobility, and delayed promotion also increased attrition likelihood. Conversely, job satisfaction, environmental satisfaction, job involvement, work–life balance, training, higher job level, longer role tenure, and stronger continuity with the current manager reduced the probability of leaving. The logistic regression model achieved good discriminatory performance, with an area under the ROC curve of 0.810. Although the conventional 0.50 threshold produced high accuracy and specificity, its sensitivity was limited. Reducing the threshold to 0.25 improved the identification of employees at risk and produced a better F1-score, indicating that threshold selection should reflect organisational retention priorities rather than accuracy alone. The findings provide practical guidance for strategic workforce management. Organisations should prioritise overtime control, manageable travel requirements, transparent promotion systems, employee-development opportunities, supportive supervision, and improved work–life balance. Predicted risk scores should be used only as decision-support indicators and not as automatic grounds for adverse employment action. Human oversight, transparency, privacy, and fairness remain essential. Overall, explainable analytics can help organisations move from reactive turnover management toward proactive, evidence-based, and ethically responsible employee-retention planning.

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