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Strategic Human Resource Management and Employee Retention: An Explainable Machine Learning Analysis of Workforce Performance and Attrition

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ABSTRACT

Employee attrition is a major concern in strategic human resource management because it can influence workforce stability, organizational continuity, and overall performance. This study examined demographic, occupational, satisfaction, compensation, and career-related factors associated with employee attrition and applied explainable machine learning to support retention-oriented HR decision-making. A secondary cross-sectional analysis was conducted using 1,470 employee records from the IBM HR Analytics Employee Attrition & Performance source. Descriptive statistics, chi-square tests, independent-samples t-tests, and Pearson correlation analysis were applied, while Logistic Regression and Random Forest models were developed for attrition prediction. Model performance was assessed using accuracy, precision, recall, F1-score, and ROC-AUC, and SHAP analysis was used to interpret the better-performing model. Attrition was significantly associated with job role, job level, business travel, job satisfaction, environmental satisfaction, job involvement, work-life balance, overtime, and stock option level. Employees experiencing attrition were generally younger, had lower monthly income, fewer total working years, and shorter organizational tenure. Logistic Regression produced better recall and F1-score than Random Forest and was therefore selected for explainability analysis. SHAP identified years since last promotion, environmental satisfaction, job satisfaction, overtime, managerial continuity, role tenure, and job involvement as important predictors. The findings show that explainable machine learning can provide practical and interpretable evidence for targeted employee-retention strategies.

KEYWORDS: Employee attrition; Employee retention; Strategic human resource management; Machine learning; Explainable artificial intelligence

1. Introduction

Strategic human resource management is becoming more critical in support of workforce stability, continued performance and enhanced long-term organizational effectiveness. Human resources are an important asset of the organization, and retaining skilled human resources can impact its productivity, continuity, knowledge protection, and competitiveness. Employee turnover can, therefore, be a significant challenge for human resource managers, as frequent turnover can create disruptions in operations, require more recruitment and training activities, and reduce workforce stability. Studies in the last few years have focused on the application of data-driven models to determine factors that influence an employee's decision to leave and to help inform better retention policies. The use of explainable artificial intelligence (AI) has been proposed as a useful method since it provides the ability to understand the factors that influenced the model prediction, which makes HR analytics more practically useful for strategic decision-making (Marín Díaz et al., 2023).

Machine learning has also given HR teams greater power in detecting trends in employee data which might not be obvious using descriptive analytics. The use of predictive modelling with explainable AI can help in the clear determination of factors that lead to attrition and offer interpretable evidence for HR practitioners (Al-Ali et al., 2026). XAI-based approaches are particularly pertinent in situations where the outcomes of predictions need to be converted into management actions; for instance, finding employees or groups of employees who may need special attention to retain them (Baydili & Tasci, 2025). Predictive analytics has also been linked to better talent-retention planning, as it allows organizations to consider various factors related to employees at once (Căvescu & Popescu, 2025). The use of ensemble and hybrid machine learning methods has shown promise in modelling employee turnover based on multidimensional HR information (Alyousef et al., 2026), and predictive workforce intelligence frameworks have been increasingly adopted in organisational HR systems for employee turnover prediction (Parasa, 2024). Besides, explainable attrition-risk scoring can enhance the understanding of the model's outputs by managers and offer more actionable insights for retention decision-making (Pavithran & Vadivel, 2025).

Although machine learning has increasingly been used in studies about employee attrition, there are still some key research gaps. Most of the current research focuses on the predictive validity of the models and the comparison of the models, and the integration of prediction with other

strategic human resource management and workforce-retention decisions is relatively underemphasized. While advanced methods like explainable machine learning and graph-based approaches have enhanced the technical ability to recognize attrition patterns, an important research need has been the translation of the outputs of these methods to actual HR strategies (Makanga et al., 2024). Also, machine-learning-based employee turnover predictions have been reviewed, revealing that there is an increasing diversity of models available for HR predictions, and that more research is needed to shift the focus from prediction to the development of interpretable managerial applications (Iyiade et al., 2025).

A second constraint is that there are several interrelated features of the workforce that impact workforce stability, such as compensation, satisfaction, work environment, job involvement, career progression, organizational tenure, and performance-related indicators. Comparative machine learning studies have explored these factors; however, sometimes the strategic interpretation of their relative influence is not sufficiently developed (Haque et al., 2025). This can be overcome by explainable predictive systems, which can demonstrate the contribution of each workforce variable to the prediction of attrition, leading to increased transparency and managerial relevance (Hamja et al., 2025). Likewise, ensemble methods using SHAP have shown promise in generating explainable information from the responses of complex models for HR decision intelligence (Melon et al., 2026). Hence, the need for an integrated approach, consisting of workforce analysis, predictive modelling and explainability, still exists.

The basis of the rationale for the present study is the need to relate employee attrition prediction with strategic and interpretable HR decision-making. Explainable AI can aid in employee-retention management by understanding what factors contribute to employee retention and ensuring transparency in the prediction process, especially if the results of this process are used to inform organizational policy and intervention planning (Nguyen et al., 2026). The integration of traditional statistical analysis with machine learning can also create a holistic view of attrition, taking into account observed differences in the workforce and predictive relationships (Srivastava & Patnaik, 2025). While the predictive power of advanced ensemble models is impressive, their application in HR practice requires an understanding of how certain factors increase the risk of employee departure (Konar et al., 2025). Thus, AI-driven predictive decision-making systems hold promise in enhancing HR retention efforts, enabling the translation of workforce data into actionable insights for strategic initiatives. To this end, the current research examines workforce demographic, occupational, satisfaction, compensation, performance and

career-related variables and aims to explain the most significant factors and predict employees' attrition using explainable machine learning.

Research Objectives

- 1.To examine the demographic, occupational, performance, satisfaction, compensation, and career-related characteristics of employees according to attrition status.
- 2.To develop and compare machine learning models for predicting employee attrition using workforce and strategic HR-related variables.
- 3.To identify and interpret the most influential predictors of employee attrition using explainable machine learning techniques to support employee-retention decision-making.

2. Methodology

2.1 Study Design

The technique of this study was a secondary data-based analytical design that was quantitative and predictive. A cross-sectional analysis of employee-level human resource records was performed to find out the characteristics of the workforce that lead to employee attrition and to build predictive models to identify employees at higher risk of leaving the organization.

2.2 Data Source

The publicly available IBM HR Analytics Employee Attrition & Performance records from Kaggle (Pavan Subhasht, 2017) were used for the study. The source contained employee demographic, occupational, compensation, satisfaction, performance, and career-related information that was appropriate for workforce analysis and employee attrition prediction.

2.3 Study Population and Sample

1470 employee records were analyzed, corresponding to employees from various departments, job roles, education levels, job levels, age groups and organizational tenure categories. All available records were included due to the completeness of the study variables required for the planned statistical and machine learning analysis.

2.4 Study Variables

They used employee attrition (Yes or No) as the primary outcome variable and included age, gender, marital status, education, education field, department, job role, job level, business travel,

distance from home, monthly income, per cent salary hike, stock option level, job satisfaction, environment satisfaction, relationship satisfaction, job involvement, work-life balance, overtime, performance rating, training times last year, total working years, years at company, years in current role, years since last promotion, and years with the current manager as predictor variables.

2.5 Data Preparation

Prior to analysis, the records were checked for missing values, for duplicate observations, for the type of variables, and for consistency. If applicable, non-informative variables were dropped that had constant values. The categorical variables were encoded, and the numerical variables were standardized if necessary for predictive analysis. The predictor variables were then split from the attrition outcome, and the data were split into training and testing sets for machine learning analysis.

2.6 Statistical and Machine Learning Analysis

Frequencies and percentages were used for categorical variables, while mean and standard deviation were used for continuous variables. The chi-square test was used to determine associations between categorical workforce characteristics, and the chi-square test for independence was used to compare continuous variables between the retained and attrited employees. To examine the relationship among selected numerical workforce variables, the Pearson correlation analysis technique was used. Logistic Regression and Random Forest models were created to predict attrition based on training and testing data subsets. The accuracy, precision, recall, F1-score, ROC-AUC and confusion matrix were used to assess the model performance. SHAP (SHapley Additive Explanations) was applied to the better-performing model to determine the top contributors to employee attrition, both in terms of workforce factors and related HR factors. A p-value of < 0.05 was used to determine statistical significance.

3. Results

3.1 Workforce Profile and Baseline Characteristics

1,470 employees were analysed, and there were no missing data or duplicate records. The mean age was 36.92 ± 9.14 years, mean monthly income was $6,502.93 \pm 4,707.96$, mean total working experience was 11.28 ± 7.78 years, and mean organizational tenure was 7.01 ± 6.13 years. The majority of the employees were male, married and working in the Research and Development (R&D) role. Employees reported overtime at lower rates and a higher percentage in the

performance category. Table 1 shows the frequency and percentage distribution of the selected demographic and workforce characteristics.

Table 1. Selected Demographic and Workforce Characteristics

Characteristic	Frequency	Percentage
Female	588	40.00%
Male	882	60.00%
Married	673	45.78%
Research & Development	961	65.37%
Sales	446	30.34%
Overtime: Yes	416	28.30%
Overtime: No	1,054	71.70%
Performance rating = 3	1,244	84.63%
Performance rating = 4	226	15.37%

Selected workforce characteristics were statistically different by demographic, departmental, overtime and performance categories. These characteristics are shown in Figure 1.

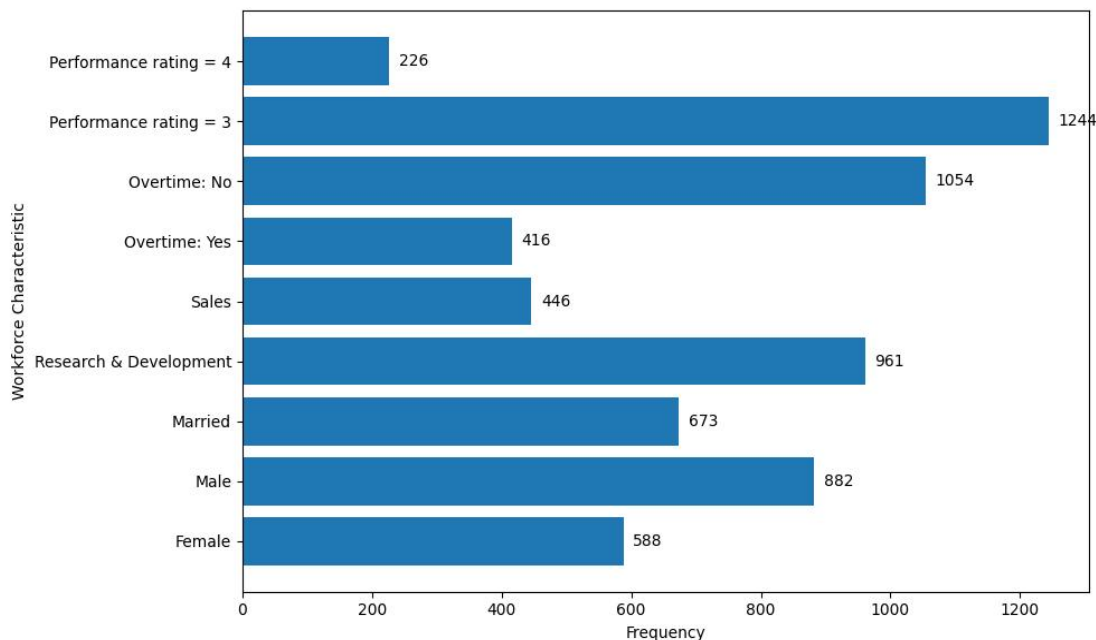


Figure 1. Frequency Distribution of Selected Workforce Characteristics

The numbers suggest that certain workforce categories were much more prevalent than others, in this case, performance rating category 3, non-overtime workers and workers in Research and Development. By comparison, the number of overtime and performance rating category 4 employees was relatively small.

3.2 Employee Retention and Attrition Distribution

Retention was significantly more prevalent than attrition, suggesting that the majority of employees remained in their jobs during the period of observation. The retained group clearly outweighed the attrition group, as depicted in Figure 2, and the distribution was very skewed towards the two employment outcomes. This suggests that the proportion of employees leaving their jobs was relatively small compared to the total number of employees.

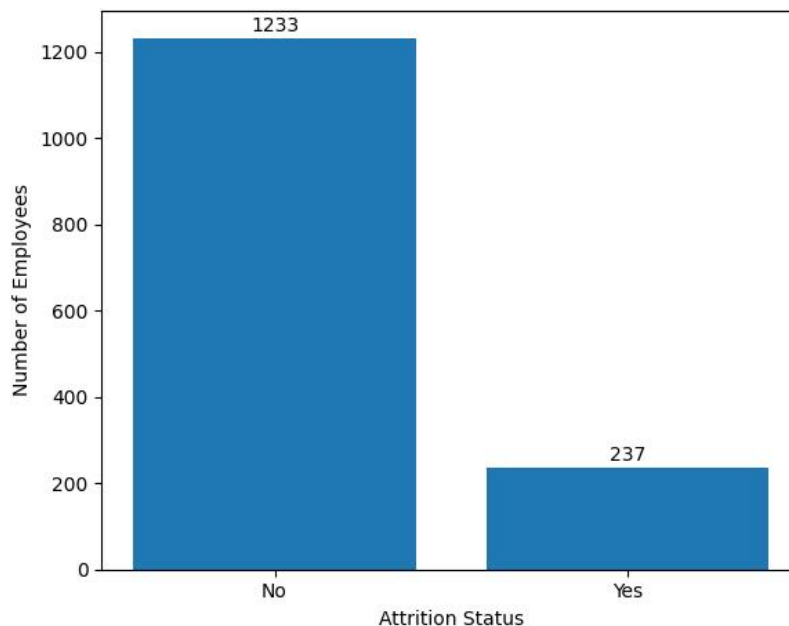


Figure 2. Employee Distribution by Attrition Status

The figure also makes it clear that there is a significant gap between retained and attrited employees. The smaller attrition group suggests that employee turnover was not pervasive throughout the workforce, but the fact that there was attrition is significant, as even a relatively small number of employees leaving the organisation can signal the quality of employee experience, career development, pay, workload, and engagement.

3.3 Categorical Workforce Factors Associated With Attrition

A number of categorical workforce aspects were found to be statistically significantly associated with employee attrition. Marital status, department, job role, business travel, job level, job satisfaction, environment satisfaction, job involvement, work-life balance, overtime and stock option level were found to be significantly associated. Gender, education, relationship satisfaction and performance rating, however, were not correlated with attrition. Of the significant factors, overtime, job role, job level and stock option level exhibited relatively high

chi-square statistics, indicating greater variation in attrition within these groups. Table 2 provides a summary of the main categorical variables of the workforce that are associated with attrition.

Table 2. Categorical Workforce Factors Associated With Attrition

Variable	Chi-square	df	p-value
Marital status	46.164	2	<0.001
Department	10.796	2	0.0045
Job role	86.190	8	<0.001
Business travel	24.182	2	<0.001
Job level	72.529	4	<0.001
Job satisfaction	17.505	3	0.0006
Environment satisfaction	22.504	3	0.0001
Job involvement	28.492	3	<0.001
Work-life balance	16.325	3	0.0010
Overtime	87.564	1	<0.001
Stock option level	60.598	3	<0.001

3.4 Differences in Continuous Workforce Characteristics by Attrition

There were significant differences between those who left and those who stayed on the job between two groups of employees on a number of continuous workforce characteristics. The attrition group was younger in age, had a lower monthly income, fewer total working years, shorter organizational tenure, fewer years in the current role and fewer years with the current manager. Additionally, the attrition group had employees who had a lower average number of training opportunities in the prior year and a greater average distance to work. There were no notable differences between groups for per cent salary increase or "time since last promotion. The main continuous workforce characteristics according to attrition status are presented in Table 3.

Table 3. Continuous Workforce Characteristics According to Attrition Status

Variable	Retained Mean $\pm$ SD	Attrition Mean $\pm$ SD	p-value
Age	37.56 $\pm$ 8.89	33.61 $\pm$ 9.69	<0.001
Distance from home	8.92 $\pm$ 8.01	10.63 $\pm$ 8.45	0.0041
Monthly income	6,832.74 $\pm$ 4,818.21	4,787.09 $\pm$ 3,640.21	<0.001
Total working years	11.86 $\pm$ 7.76	8.24 $\pm$ 7.17	<0.001
Training time last year	2.83 $\pm$ 1.29	2.62 $\pm$ 1.25	0.0204
Years at company	7.37 $\pm$ 6.10	5.13 $\pm$ 5.95	<0.001
Years in current role	4.48 $\pm$ 3.65	2.90 $\pm$ 3.17	<0.001

Years with current manager	4.37 ± 3.59	2.85 ± 3.14	<0.001
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3.5 Relationships Among Workforce and Career Variables

Correlation analysis revealed that compensation, job level, work experience and organizational tenure were highly related. The highest correlation was found between monthly income and job level, and total working years were strongly correlated with both monthly income and job level. Tenure-related measures exhibited consistently positive relations; that is, those who were with the organization longer tended to be with their current job longer, and with the same manager. Figure 3 provides an overall picture of the relationships between the variables selected for the workforce.

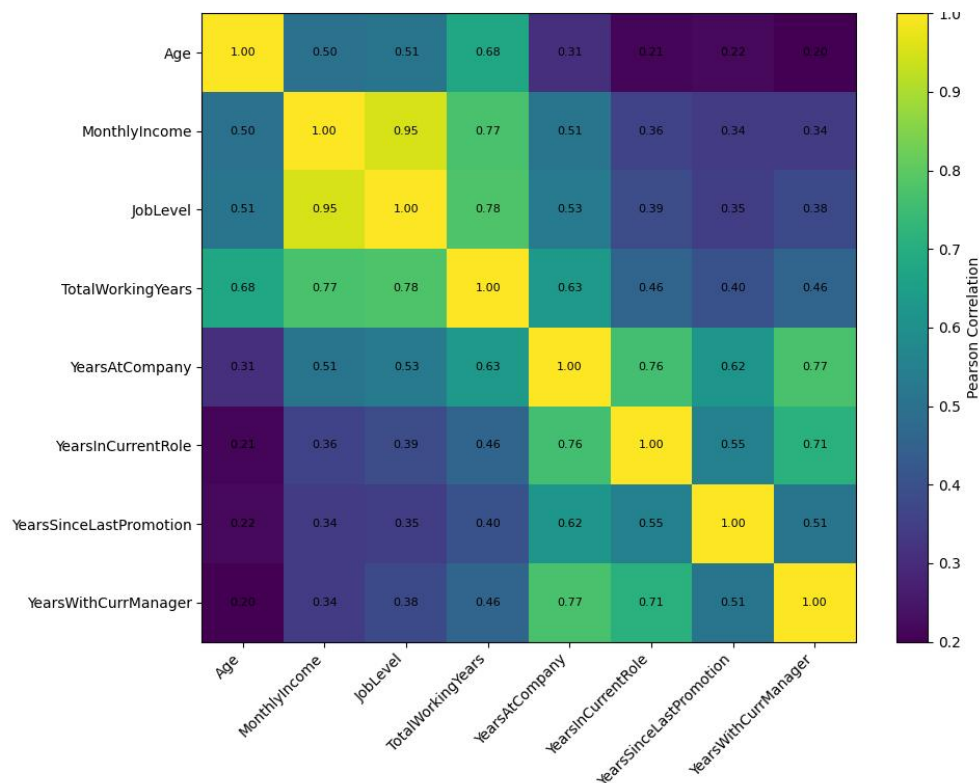


Figure 3. Correlation Among Selected Workforce Variables

As indicated by the heatmap, all of the relationships displayed were positive, but the strength of the relationship varied significantly. Relationships were strong between income and job level, total working experience and tenure variables, and weaker relationships were revealed between age and role duration, timing of promotion, and managerial tenure. These patterns suggest that there is a relationship between career advancement and organizational experience, but it is not consistent for all workforce characteristics.

3.6 Machine Learning Performance for Employee Attrition

The same sets of training and test data were used for the employee attrition prediction with both Logistic Regression and Random Forest. A difference was found in the ability of both models to identify the minority attrition class, as both models had similar overall accuracy and ROC-AUC. Logistic Regression performed better with regard to recall and F1-score, while Random Forest performed slightly better on precision and ROC-AUC. Recall and F1-score were thought to be crucial for model selection since attrition was the minority outcome. Based on this, Logistic Regression was chosen as the model of choice for further explainability analysis. Table 4 shows the comparative performance of the two machine learning models in terms of prediction.

Table 4. Performance of Employee Attrition Prediction Models

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
Logistic Regression	0.861	0.615	0.340	0.438	0.805
Random Forest	0.850	0.636	0.149	0.241	0.808

3.7 Explainable Machine Learning and Key Attrition Predictors

SHAP analysis was used to select the Logistic Regression model and to find out which workforce variables were more significant in predicting attrition. The most influential factors were years since last promotion, environment satisfaction, job satisfaction, overtime, years with current manager, years in current job, job involvement, frequent business travel, distance from home, stock option level, total years worked, age and work-life balance. These predictors are a mixture of career progression, job satisfaction, workload, organizational tenure and employee experience. Table 5 lists the variables that were most important in the explainable machine learning model.

Table 5. Most Influential Predictors of Employee Attrition Based on SHAP

Rank	Predictor	Mean Absolute SHAP Value
1	Years since last promotion	0.4415
2	Environment satisfaction	0.4054
3	Job satisfaction	0.3737
4	Overtime – No	0.3591
5	Overtime – Yes	0.3551
6	Years with current manager	0.3508
7	Years in current role	0.3459
8	Job involvement	0.3265

9	Frequent business travel	0.2831
10	Distance from home	0.2722
11	Stock option level	0.2625
12	Total working years	0.2414
13	Age	0.2289
14	Work-life balance	0.2089

4. Discussion

The current study revealed that a mixture of demographic, occupational, satisfaction, compensation and career factors were associated with employee attrition. Retention rates were higher than attrition rates, but there were still clear differences between the employees that stayed and those that left. Those who were experiencing attrition tended to be younger, had lower monthly earnings, fewer total years at work, fewer years with the organization, fewer years in current position and fewer years with current manager. Categorical analysis also revealed significant relationships with job role, job level, overtime, job satisfaction, environmental satisfaction, job involvement, work-life balance, business travel and stock options. In combination, these results suggest that employee retention is a result of a combination of workforce attributes rather than just one. The result of the predictive analysis also revealed that Logistic Regression had a more balanced performance on detecting attrition than Random Forest. Both models gave a comparable overall accuracy and discrimination, but Logistic Regression provided better recall and F1 score and thus was more effective in identifying employees in the smaller attrition group. Of course, this discovery is relevant given that high rates of overall accuracy may be masking poor actual detection performance for employees who are actually leaving. The explainability analysis was also useful as it revealed that years since last promotion, environmental satisfaction, job satisfaction, overtime, managerial continuity, current-role tenure and job involvement were among the most important predictors. These findings suggest that career development and workplace experiences have a significant role in creating employee stability.

The results of the current study align with earlier studies that have proven that machine learning can reveal significant patterns in employee churn and aid proactive HR planning. Varghese et al. (2025) also highlighted the value of predictive HR analytics in predicting turnover and pinpointing the workforce factors associated with employee attrition. The findings of the present study are also consistent with Jiang et al. (2025), who noted that explainable AI is a way to link

attrition prediction with workforce stability and managerial understanding. The relative performance of Logistic Regression and Random Forest is also, in a general way, consistent with past results that no model is best in all evaluation measures. Govindarajan et al. (2025) showed the usefulness of comparing the different machine learning methods for employee attrition analysis with IBM HR information. Strategically, the current focus on retention factors also aligns with Krishna and Borah (2023), who defined predictive analytics as a means to aid sustainable employee-retention strategies. In a similar context, Patil and Kadam (2025) connected the application of machine learning in HR with turnover analysis and employee performance analysis. Lastly, aligning predictive outcomes with explainable AI to enhance managerial insights is in line with the findings from Ansari et al. (2026), who emphasised the need to combine predictive capabilities with explainable AI to bolster human decision-making, particularly in the context of employee attrition management.

The findings have a number of implications for strategic HRM. As an organization may gain from tracking a variety of combinations of career progression, satisfaction, overtime, job involvement, managerial continuity and job tenure, exclusive attention to their demographic characteristics or performance ratings may be insufficient. Those workers with more than one poor workforce condition may be considered a focus for supportive retention efforts. The findings also indicate that promotion prospects, working conditions, job satisfaction, workload management and manager-employee turnover are areas of special concern. Explainable prediction can also help HR managers better understand the reasoning behind why an employee is flagged as being at a higher risk of leaving, and provide analytical outputs to complement managerial judgment.

There are some caveats to take into account. The cross-sectional design does not allow for conclusions to be drawn on causal relationships between workforce characteristics and attrition. Certain variables related to the organisations were not available and could potentially have influenced the results, such as leadership style, organisational culture, employee engagement and external labour-market conditions. There was also little variation in performance rating, which limits its usefulness in differentiating between employees. Furthermore, the predictive models were based on only one type of employee records, so they might not be applicable to other industries, organizations, or geographical contexts.

Further studies should confirm these results with data from other organisations, industries and

countries. Longitudinal studies may consider the impact of increased or decreased satisfaction, compensation, workload, promotion and managerial relationships on turnover over time. Other organizational factors – including leadership, workplace culture, engagement, flexible working arrangements, and career-development opportunities – should also be taken into consideration. Future research could also explore the potential of combining simple interpretable prediction methods with explainable machine learning to create actionable HR decision support systems that provide predictions of attrition risk while retaining transparency and manager friendliness.

5. Conclusion

This study showed that employee turnover is influenced by a variety of factors, including demographic, occupational, satisfaction, compensation, and career factors, and not by any one factor alone. Leavers tended to be younger, earn less per month, have fewer years in the workforce, fewer years at the organization and fewer years with their supervisors. There were also significant relationships for job role, job level, business travel, job satisfaction, environmental satisfaction, job involvement, work-life balance, overtime and level of stock options. All of these suggest that the retention of employees is related to both career advancement and work-life balance. Results of the predictive analysis indicated that Logistic Regression outperformed Random Forest in achieving a balanced recall and F1 score, making it more appropriate for the smaller group (attrition). Explainable machine learning also showed that years since last promotion, environmental satisfaction, job satisfaction, overtime, managerial continuity, role tenure, and job involvement are significant factors in determining attrition. The results indicate the importance of using both traditional statistical techniques and interpretable machine learning in the field of strategic human resource management. Overall, the study argues for a data-driven perspective on employee retention, offering potential insights to enhance promotion planning, job satisfaction, workload distribution, manager-employee dynamics, and retention measures. The findings would be more broadly applicable with future validation in different organisational contexts.

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