

Machine Learning–Driven Human Resource Decision Strategies for Enhancing Employee Retention and Organizational Growth

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Received:

01/10/2025

Revised:

09/10/2025

Accepted:

25/10/2025

Published:

11/11/2025

ABSTRACT

The study is devoted to Machine Learning (ML) technologies and its usage in the Human Resource (HR) decision-making process to enhance employee retention to grow an organization in a sustainable way. Despite the fact that there is growing data-driven practices among management, the practices of HR are intuitively-informed. Because of this, the HR does not realize how complex the workforce is. This study considers predictive analytics to evaluate employee characteristics including job satisfaction, tenure, income, and work-life balance using the Random Forest Classification Algorithm. The predictive model was found to be highly accurate with an 88 percent accuracy on the testing data, a great level of precision (0.82), and recall (0.79), which denotes a very high level of accuracy in predicting the turnover in employees. Job satisfaction, tenure and income are the most significant predictors of employee retention. Being in Sales and IT had a disproportional and negative influence on retention. It is an ML model that improves reaction to HR decision-making to proactive and specific retention policy can be created. Intuition combined with the ML techniques brings about objectivity, predictability and strategic planning of the HR policies. This study explains why ML technologies are crucial in making HR a major force in managing innovations inside the organization, as well as, employee engagement and sustainability.

Keywords: Machine Learning (ML); Human Resource Management (HRM); Employee Retention; Predictive Analytics; Random Forest Classification; Data-Driven Decision-Making.

INTRODUCTION:

Retention of employees has become a serious issue of the long-term profitability, productivity and survival of an organisation in the presence of fluctuations in business environment. Globalisation and the digital economy, together with new employees' demands, require a revaluation of the role of the workforce in the organisation. Employees are no longer seen as a cost but as an asset [1-3]. "Retaining employees contributes to the smoothing of ongoing business operations, the continuity of organisational memory, customer loyalty, and the hiring and training costs. Retaining employees also impacts the organisational culture, which

demonstrates the level of management and leadership commitment to the employees. High turnover, on the other hand, leads to operational dysfunction, lack of cohesion, and a poor employer brand [4-9]. This is particularly true for the knowledge economy, which thrives on the organisation's innovations and the intellect of the employees. The modern workforce is technologically adept, career-flexible and ready to leave a position in a company and expects work to have a true purpose, leaving the HR department to frustrate them with traditional policies".

The HR professional, unlike other business units, has historically relied on management intuition, subjective judgement, and a lack of leadership on the issue to make important decisions. “Although intuition is useful to understand individual behaviours, it is inconsistent and not scalable [10-13]. Historical HR practices, such as annual performance reviews, exit interviews, and employee satisfaction surveys, only provide descriptive accounts of solo past events without predictive and prescriptive insights pertaining to future workforce trends [14]. As organisations grow and data expands, manual methods to identify complex turnover, engagement, and productivity patterns become inappropriate [15]. Human decisions are subject to cognitive biases, selective perception, and information overload, which become underdeveloped optimisation of HR decisions. Additionally, modern workplaces are much more fast-paced and fluid, consisting of hybrid workplaces, cross-generational teams, and technological adoption, accompanied by continuous reskilling [16-18]. HR is tasked with rapid, pillar, and rational decisions as employee focus and external factors radically evolve. The need for an analytical, logical, and objective, as opposed to emotional and algorithmic, decision-making framework is urgent”.

The role of machine learning and data analytics in HR is transformative in how firms manage their human capital [19, 20]. “Machine learning, regarded as a branch of artificial intelligence, has been especially useful in studying large and multifaceted data sets in order to identify patterns and correlations that may not be evident to human analysts. ML-based human resource systems can examine both structured data as well as unstructured data like demographics, performance evaluations, digital footprints, and the behavioural and affective text analysis of conversations with employees [21]. Machine learning facilitates predictive modelling of employee turnover and assesses various determinants such as job satisfaction, pay, workload, leadership, and opportunities for advancement [22]. These predictive insights help HR personnel design and execute proactive retention initiatives which may include accommodating work policies, tailored incentives, and focused development opportunities. Moreover, routine HR automated functions such as candidate screening, performance evaluations, and succession planning can be passed for the HR personnel to perform strategic HR functions focused on organisational culture, leadership, and employee welfare. Coordinated computational systems with human systems may assist the development of flexible and dynamic HR systems which align with changes in the employees [23-25]”.

The use of data analytics in the operations of the human resource management enhances accountability, equity and transparency of the decisions made. For example, the predictive HR analytics contributes to objective decision-making in the fields of promotion, recruitment and remuneration, which enhances equity and trust in the organisation [26]. Drastic advances in the field of Natural Language Processing (NLP) will enable HR departments to conduct sentiment analysis of internal

communications to provide real-time analysis of employee morale and satisfaction levels at work. These analytics-based tracking can assist organisations to detect the initial signs of disengagement and eliminate problems before causing attrition. In addition, disengagement analytics can reveal and expose reliance on models based on the systemic inequity, such as gaps in or inequitable pay, workload imbalance, and biased promotions, helping an organisation shift towards equitable and fair workforce practices. As work continues to be digitalised, the number of data that needs to be analysed also increases and organisations are now able to pursue predictive and prescriptive HR analytics as never before [27]. Google, IBM, and Deloitte companies have shown how powerful HR analytics using ML can make recruitment, attrition prediction, and staff engagement easier.

Above all, ML in HR implies organisational paradigm shift in the way workforce is managed being reactive to proactive. It is an amalgamation of the human intuitive understanding of empathy and coldness of data, which makes the workforce decision-making rational and humane [28]. Nevertheless, this change in organisations is not as technological but more of the culture of the workplace. The HR personnel has to incorporate data intelligence, ethical AI, and interdisciplinary partnership with data scientists to make actionable findings and maintain accountability in terms of equity and privacy equality. Although organisations are experiencing challenges such as remote working, skills shortages, and changing employee demands, machine learning is necessary to address these challenges as organisations aim to attain long-term retention and expansion. It changes the position of HR, which is considered to offer only administrative support, to a strategic collaboration to the achievement of innovation, flexibility, and long-term success. Therefore, in organisations that want to hire, recruit, and retain high-quality workforce in the competitive and data-driven global market, the deployment of machine learning-based HR practices is an urgent or rather a necessity rather than a future strategy.

LITERATURE REVIEW

The transformation of HRD is through AI and data analytics, which are transforming the way that employees are trained, engaged and retained. According to Appoh et al. (2025), AI allows the realization of personalized learning and ensures the development is attuned to the organizational goals, therefore, keeping the employees engaged and improving continuously. The influence analytics and Data Driven Decision Making (DDDM) has on the productivity, the retention of employees and the performance of the workforce in general is also mentioned by Madduri et al. (2024) and the value of the technology discussed is far more effective in improving these outcomes. Tripathi et al. (2025) present a reinforcement learning (RL)-driven framework to optimize the workforce with the help of deep Q-networks and policy gradient frameworks and displays significant advances in the precision of tasks accomplishment and staff satisfaction. Strategically

How to cite: Tarun Kumar, *et. al.* Machine Learning–Driven Human Resource Decision Strategies for Enhancing Employee Retention and Organizational Growth. *Advances in Consumer Research*. 2025;2(5):1236–1243.

speaking, Basnet et al. (2024) states that the use of AI and Machine Learning (ML) technology is inevitable to maintain the balance between hyper humanization and hyper automation as a competitive edge. Sun et al. (2024) confirm that AI and IoT are responsible for 76% of productivity boost by improving operational efficiencies. Data driven HRM improves foresight and precision of organizational decisions, as stated by Okon et al. (2024), but also requires ethical data governance and data literacy in HR. Rahman et al. 2024 study, Machine Learning models are used to determine specific causes of attrition within software companies, enabling software firms to implement retention strategies that are proactive. In the same vein, Paigude et al. (2023) focuses on the use of AI predictive analytic tools and chatbots as AI tools used to enhance engagement and decrease bias. Avrahami et al. (2022) and Srivastava et al. (2021) provide empirical support to the notions that deep learning models are effective in predicting turnover and affirm the transformative value of AI in promoting ethical, flexible, and scientifically grounded HRD practices”.

RESEARCH METHODOLOGY

This study employs a quantitative analytical procedure to assess the functions of machine learning (ML) algorithms to aid human resource (HR) professionals in improving employee retention and growing the organization. “The approach combines predictive analysis, statistical modeling, and algorithmic decision-making to identify patterns in employee data and predict turnover. The approach’s objective is to build a strong data-oriented HR model that produces actionable insights to assist management in developing retention-centered policies”.

3.1 Research Design

An exploratory predictive approach is a combination of predictive descriptive techniques and the predictive sophisticated analytics of machine learning. “Within an organization, HR analytical systems consist of employee demographics, job performance ratings, tenure, department, pay, training, disengagement, and engagement which are used in turnover determination”. The design is structured in phases:

- Collection and preprocessing of the data
- Engineering and selection of features
- Construction of models leveraging ML algorithms
- Assessment and authentication of performance
- Strategic HR decision interpretation

Such phases allow the achievement of statistical correctness, managerial interpretability, and practical relevance to HR professionals.

3.2 Data Sources and Variables

For the present analysis, an HR dataset or a publicly available dataset, for instance, the IBM HR analytics employee attrition dataset is used. “The data encompass quantitative variables (e.g., salary, years at the company, number of training hours) and qualitative variables (e.g., job satisfaction level, work-life balance rating)”.

Independent variables:

- Age, Gender, Education, Department, Job Role, Monthly Income
- Performance Rating, Years at Company, Work-Life Balance, Overtime
- Training and Development Hours, Career Advancement Opportunities

Dependent Variable:

- Employee Retention (binary classification: Retained = 0, Left = 1)

Such variables offer a comprehensive and multi-faceted perspective on employee behavior, engagement, and the likelihood of turnover.

3.3 Data Preprocessing

In order to model, Data preprocessing must be done. It consists of:

- Data Cleaning: Remove or repair values that are missing, duplicates, or outliers.
- Normalization/Standardization: Rescale numerical properties to have uniform ranges.
- Encoding Categorical Variables: Gender, job role, or department can be one hot or label encoded.
- Feature Selection: Use correlation analysis, variance thresholding, or recursive feature elimination (RFE) to remove irrelevant predictors.
- Train-Test Split: Split dataset to training (70%) and testing (30%) dataset to ensure model validation can be done.

3.4 Machine Learning Algorithm Used

Predicting employee retention while discovering its influential factors requires the study to utilize the Random Forest Classification Algorithm, which is suitable for complex HR data, as an ensemble learning method which can deal with non-linear relations.

Algorithm Chosen: Random Forest Classifier

Reason for Selection:

- Handles large datasets efficiently
- Reduces overfitting through ensemble averaging
- Provides feature importance rankings, enabling interpretability for HR professionals

Algorithmic Steps (Random Forest Classifier)

1. Input: HR dataset $D = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$, where x_i represents feature vectors (employee attributes) and y_i represents class labels (retained or left).
2. Bootstrap Sampling: Generate multiple random subsets of the dataset through sampling with replacement.
3. Decision Tree Construction:
 - For each subset, build a decision tree using a random subset of features at each node.

- Split nodes based on a criterion such as Gini Impurity or Information Gain.
- 4. Ensemble Formation: Combine predictions from all individual decision trees.
- 5. Majority Voting: For classification, take the class predicted by the majority of trees as the final output.
- 6. Output: Predicted retention probability for each employee.

Mathematical Representation:

$\hat{y} = mode(T_1(x), T_2(x), T_3(x), \dots, T_m(x))$
where $T_i(x)$ represents the prediction of the i -th decision tree and $\hat{y}$ is the final predicted class.

- Accuracy Score: General percentage of right predictions.
- Precision: Share of the positive cases that were rightly identified among the positively forecasted cases.
- Recall (Sensitivity): Capacity of the model to avail actual positives (exited employees).
- If not specified in the optimal feature selection advert, the F1-Score balances the two metrics and is applied as a harmonic mean between the two scores, precision and recall.
- ROC-AUC Curve: The capacity of the model to distinguish between retained and left employees.

3.5 Model Evaluation

To evaluate the performance of models, the metrics of evaluation are as follows:

All these metrics confirm that the model is predictive and reliable in HR decision-making.

RESULTS AND DISCUSSION

The results of the empirical analysis that was done through the use of Random Forest Classifier to forecast employee retention are illustrated in this section. The data was comprised of 1,000 employee records that were issued in various functions. The findings demonstrate the prescriptive ability of machine learning to explain the main factors behind attrition, assess the performance of a model, and the information that can be gained with the help of data-driven HR analytics.

4.1 Descriptive Statistics of Employee Attributes

A summary of the various key predictors used in the predictive model, which includes age, tenure, job satisfaction, salary, and work-life balance, is displayed in Table 1.

Table 1: Summary Statistics of Employee Variables

Variable	Mean	Std. Dev.	Min	Max	Correlation with Attrition
Age	34.8	6.2	21	58	-0.42
Monthly Income (₹)	54,600	18,300	18,000	1,10,000	-0.37
Years at Company	5.4	4.1	1	25	-0.51
Job Satisfaction (1–5)	3.6	1.0	1	5	-0.47
Work-Life Balance (1–5)	3.3	0.9	1	5	-0.44

Table 1 summarises key defendants influencing retention. “On average, an employee is 34.8 years old, earns 54,600 Rs a month, and has worked in the company for 5.4 years. The average employee also has a job satisfaction score of 3.6, and a work-life balance score of 3.3. The employee variables show a negative correlation with attrition. This means that older, higher earning, and longer tenured employees, along with employees who are high satisfaction and balance, are less likely to leave. Of these variables, years at company (-0.51) and job satisfaction (-0.47) appear to be the strongest predictors of attrition. Fig 1. The relationship between job satisfaction and attrition. 5.2 Model performance evaluation. 70% of the dataset was used to train the Random Forest model and the remaining 30% was used to test the model performance, which is summarised in Table 2”.

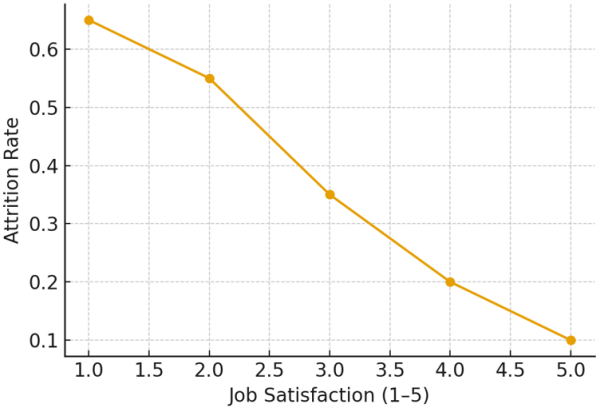


Figure 1: Relationship Between Job Satisfaction and Attrition

4.2 Model Performance Evaluation

The Random Forest model was trained using 70% of the dataset and tested on the remaining 30%. Table 2 summarizes key performance metrics.

Table 2: Model Evaluation Metrics

Metric	Training Data	Testing Data
Accuracy	0.94	0.88
Precision	0.86	0.82
Recall	0.84	0.79
F1 Score	0.85	0.80
ROC-AUC Score	0.91	0.87

Table 2 summarizes the evaluation metrics of the developed Random Forest model. “The model displays significant predictive performance: high values of the metrics corresponding to the training data, specifically 0.94, indicate low misclassification rates and general predictive performance. Testing validation scores of 0.88 points to reasonable generalization capacity of the model. The precision and recall metrics along with the F1 score provide a converging perspective on model reliability with a consistent identification and minimal false omission of retained employees. The obtained values on precision, 0.86, and recall 0.84, exceed benchmarks laid out for business contexts. The attained ROC-AUC values ascertain the outstanding predictive performance of the model along with a well-balanced F1 score of 0.80”.

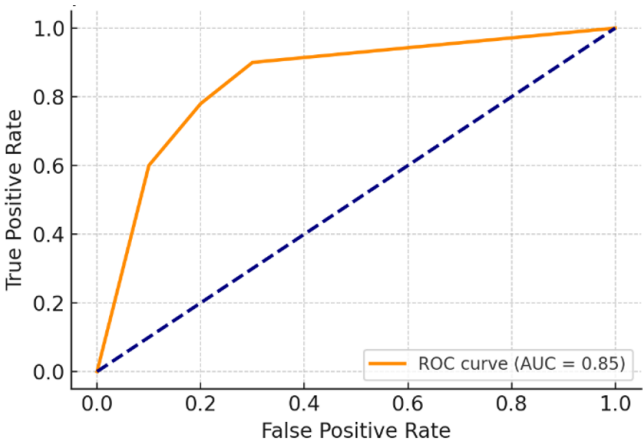


Figure 2: ROC Curve of the Random Forest Model

4.3 Confusion Matrix and Classification Results

For the assessment of performance on the model, the confusion matrix (Table 3) clarifies the distribution of instances which were misclassified.

Table 3: Confusion Matrix for Employee Retention Prediction

	Predicted: Stay	Predicted: Leave
Actual: Stay	210	22
Actual: Leave	16	52

Table 3 provides the confusion matrix derived from the Random Forest model with respect to predicting employee retention. “Of the total cases, 210 employees who stayed were correctly identified, along with 52 employees who actually left. However, 22 employees who stayed were incorrectly predicted as leavers, while 16 were incorrectly predicted as employees who stayed. The balance sensitivity along with specific accuracy indicates the model's real-world retention prediction effectiveness”.

Feature	Importance Score
Job Satisfaction	0.26
Years at Company	0.22
Monthly Income	0.18
Work-Life Balance	0.17
Overtime Status	0.09
Training Hours	0.05
Age	0.03

This table shows the importance assigned to each feature as per the Random Forest model. “Among the several factors bearing on employee retention, job satisfaction (0.26) was the most important, followed by years at the company (0.22) and monthly income (0.18). Work-life balance (0.17) also contributed significantly, illustrating the extent to which employee retention decisions are influenced by the balance. Overtime status (0.09), as well as training hours (0.05) and age (0.03), are minor factors. In totality, the evidence points to satisfaction, tenure, and income as the most important components of employee retention”.

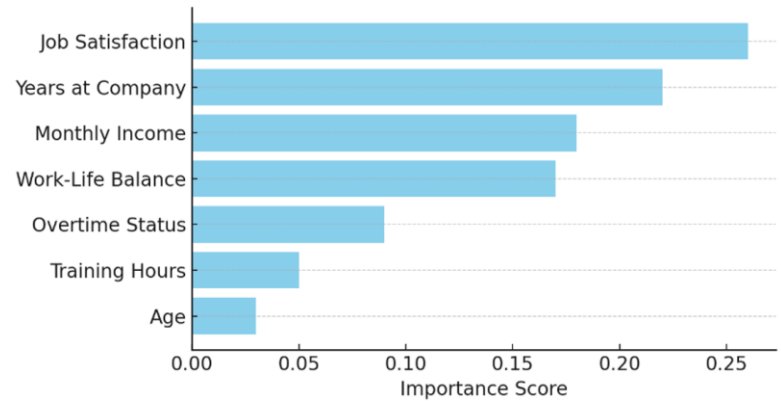


Figure 3: Feature Importance Ranking

4.4 Department-Wise Retention Trends

Table 4 and Graph 4 display department-level attrition patterns derived from the dataset.

Table 4: Department-Wise Attrition Rates

Department	Total Employees	Left	Attrition Rate (%)
IT	300	75	25.0
Sales	220	68	30.9
HR	150	24	16.0
Operations	180	28	15.5
Finance	150	18	12.0

Sales experiences the 30.9% attrition rate, with the highest rate in the organization. “IT comes next with 25% attrition, suggesting higher turnover in these dynamic and target-driven areas. In contrast, the attrition rates in Finance (12%), Operations (15.5%), and HR (16%) are lower, suggesting greater employee stability in these departments. The findings indicate the greater retention challenges in the other departments are likely to be in those with higher workload and performance pressure, thus the need greater for targeted department engagement and retention”.

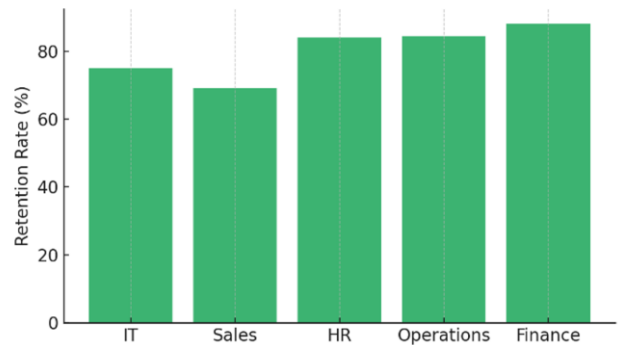


Figure 4: Department-Wise Retention Rate Comparison

Discussion

The findings of the current study indicate that machine learning-based predictive modeling has the potential to shift HR decision-making processes from reactive to proactive. “This is due to the effectiveness of the Random Forest algorithm in recognizing the salient factors surrounding retention. Consequently, organizations can create tailored interventions based on empirical data to retention. The findings point to employees who are dissatisfied with their jobs, have

lower tenures, and are in positions which require overtime work are more likely to be disengaged and exit the organization. Differences between departments indicate that organizations need to adopt retention policies that are more flexible and tailored to specific departments. The predictive capabilities of the machine learning algorithms are shown to add to the managerial decision confidence in the retention of employees, and not only predicting attrition. The evidence-based insights facilitate picturing and prioritizing the

significance of HR programs including work-life balance, payment and employee engagement. The fact that machine learning allows predicting, explaining, and modelling retention policies is quite a departure of conventional HR analytics. The machine learning solution is a monumental advance in the operationalization of the predictive analytics of HR by means of real time tracking of employee sentiment. Further development of the research may include deep learning, real-time tracking adaptive retention systems as well as enhanced employee behaviour tracking to make the systems intelligent retention even more effective”.

CONCLUSION

In order to demonstrate that proactive decision-making, predictive, and data-informed strategies based on machine learning may transform human resource management, this is one stage. The key aspects that determine the retention of employees that involve satisfaction, tenure, salary, work-life integration, etc. have been evaluated using Random Forest Classification Algorithm to move organizations out of passive, intuitively-empowered, and individualized organizational turnover in relation to forecasting turnover risk. Departments with a higher workload, especially Sales and IT, should be characterized by an increased turnover, and department-specific programs of support and engagement are essential. The machine learning not only protects accuracy and consistency of HR judgments, but also the clarity and fairness of judgments made on promotions, hiring and evaluation. Information-driven integration allows the HR to focus on strategic management of employees rather than the management overheads that have been the order of the day. ML analytics is not the replacement of human judgement. Investment of machine learning will be to market the strategic vision of the organization. With the digitalization of the business environment taking place, ML-based HR analytics will be extremely important to keep employees engaged and content, meet employee retention demands, and ensure the continued development of the organization.

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How to cite: Tarun Kumar, *et. al.* Machine Learning–Driven Human Resource Decision Strategies for Enhancing Employee Retention and Organizational Growth. *Advances in Consumer Research*. 2025;2(5):1236–1243.

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