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AI Based HR Analytics and Employee Retention in the IT Sector

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Abstract

In the information technology (IT) sector, employee retention has a strategic dimension because IT staffs are generally specialised, projects are ongoing, teams need to work together, and the skill set can quickly shift. Human resource (HR) analytics powered by artificial intelligence can help recognise patterns linked with employee turnover, estimate the probability of turnover, and assist in more timely retention decisions. This critical review covers predictive approaches, retention practices in technology workforces, translating analytics into managerial action, and ethical considerations for responsible use. Searches using target keywords like public sources and citation checking to find traceable research literature on turnover prediction by machine learning, IT sector employment in India, retention in technology-based teams, explainable AI, and AI-based HRM in general. Supervised machine-learning techniques, notably tree-based ensembles, are commonly employed for attrition prediction, and job satisfaction, work experience, compensation, overtime, and career-related variables are also commonly included in predictive models as per literature. There is plenty of evidence from IT-focused studies that shows not only how to model attrition (or job tenure). The usefulness of such forecasts, though, relies on how clean data is, how they work in other settings, how the risk can be explained, and how appropriate HR responses are designed. A prediction-to-retention framework is suggested, involving data readiness, risk estimation, human review, supportive intervention, and outcome evaluation under a continuous governance process. The authors identify the following key factors for organisations that want to use analytics to aid with employee retention: career development, supervisor support, workload quality, internal mobility, privacy, and fairness.

Keywords: AI-Based HR Analytics, Employee Retention, Employee Attrition, Information Technology Sector, Machine Learning, Explainable AI, Workforce Analytics, Ethical Governance

1. Introduction

1.1 Background of the Study

Employee retention has long been a concern for organisations as it can impact the continuity of operations, knowledge transfer, recruitment costs, service quality, and team performance. A meta-analysis by Park and Shaw (2013) comprising over 300 correlations concluded that turnover rates overall had a negative relationship to organisational performance and that this was moderated by organisational and contextual conditions. The impact for IT organisations can be particularly profound if employees possess product expertise, client relationships, or

unique skills that are associated with intricate project timelines. Hom et al. (2017) also summarize the shift in turnover research from explanations for leaving toward a greater focus on the psychology of staying, and attitudes and workplace conditions that influence staying.

AI-powered HR analytics goes beyond traditional HR reports to find patterns in employee data, predict risks, and inform planning. Predictive systems can include employment history, role characteristics, compensation, performance, engagement measure, training, overtime and career progression. Such models, used wisely, can guide HR teams to prioritise chats and determine organisational contexts that do need some attention. Their usefulness depends on the quality of data they produce and how the managers read and react to the result.

1.2 Problem Statement

The primary management question at heart is how to move from a risk estimate to an appropriate, fair and helpful retention response by the employee. One part of the equation is predictive accuracy. Organisations must also consider things that influence risk and determine which of those factors may be modifiable and whether the resulting interventions are effective in enhancing workforce outcomes. This is especially relevant in IT environments, where the staff members will vary in experience, skills, mobility, project assignment, work plan and career hopes.

This raises questions about employee privacy, explainability, fairness, and trust with HR analytics using AI. Employee records may contain past managerial decisions and inequities, and seemingly neutral risk scores can lead to decisions on training, promotion, workload and promotion opportunities. An effective retention plan is a mixture of analysis, employee input, executive discretion, and clear information governance practices.

1.3 Objectives of the Study

The review has four objectives:

1. To examine major AI and machine-learning approaches used to estimate employee attrition and employment tenure.
2. To synthesise the retention factors and organisational practices most relevant to IT workforces.
3. To analyse how predictive insights can be translated into human-reviewed HR interventions and evaluated outcomes.
4. To propose a practical framework for responsible, explainable, and employee-centred HR analytics.

1.4 Research Questions

1. Which predictive approaches and employee-related variables are used in AI-enabled turnover and tenure analysis?
2. How can HR analytics inform retention strategies in IT organisations?
3. What organisational, methodological, and ethical conditions shape the value of analytics-informed retention decisions?
4. How can organisations connect prediction, action, and retention-outcome evaluation in a transparent framework?

2. Review Of Literature

2.1 AI-Based HR Analytics and Employee Turnover

AI-powered HR analytics combines workforce data, statistical modeling, machine learning, and managerial decision support. Vrontis et al. (2022) examined the literature of AI, robotics and advanced technologies in HRM and found opportunities in workforce decision-making, learning, job design and employee management together with technological and ethical issues. Úbeda-García et al. (2025) also mapped the strategic tensions of HRM and AI, highlighting the relevance of synergizing technological capability and organisational knowledge while ensuring responsible management.

Historical employee data is frequently available with a labelled outcome such as an employee leaving within a specified time window, which is why supervised learning is often employed in employee turnover research. In

their 2024 study, Al Akasheh et al. analyzed 52 studies from 2012 to April 2023 and found 50 supervised studies. A review of 58 studies (Talebi et al., 2025) compared techniques such as random forests, support vector machines, logistic regression, decision trees, and neural networks. These synthesizations conclude that random forest is a widely used algorithm and job satisfaction is a regular prediction feature. These sorts of results highlight the importance of method and feature comparisons and also remind people that reported performance is related to the data, target definition, validation method, and class distribution.

2.2 Retention in the IT Sector

The IT industry is a balance of highly skilled labor, project schedules, new technology, and competing opportunities outside the company. Haque (2024) discussed 72 technology employee retention studies from the Indian context and categorized the literature on grounds for departure and reason for stay. Career opportunities, development, organisational support, work conditions and the employment relationship are key elements of the retention landscape. These themes are key to analytics because they relate directly to plotable trends in employment and conditions that managers can impact.

In 2019, Khera and Divya created a support vector machine model based on 22 features and archived HR records of three companies in India. The authors reported 85% accuracy and stronger performance in the identification of the employees, who left, as compared to those who stayed. The study demonstrates how attrition can be modeled in an IT environment. It also illustrates why it is important to present model performance using the right measure — overall accuracy does not necessarily reflect other categories of errors, which may be different between leavers and non-leavers.

Naik and Chakraborti (2025) have recently studied the prediction of employment tenure for IT professionals in India with the help of professional network information and machine learning techniques. They found total experience, seniority, education, technology certifications, and professional connections to be significant factors and suggested a categorisation-training-promotion (CTP) framework for managing them. The structure has a relationship between the risk categorisation and development opportunities. It offers a concrete example of how a predictive analysis can help guide a retention strategy, and the decision of which interventions to pursue is left to organisations to evaluate based on their own workforce's needs and circumstances.

2.3 Predictive Methods and Explainability

Logistic regression provides an interpretable baseline method, trees capture rule-like relationships, random forests can include many trees, support vector machines find separating boundaries, and gradient-boosting methods capture complex nonlinear patterns. For more complex relationships, when there is enough data and validation, neural networks can be used. Choice of method should consider purpose of model, size and structure of dataset, class imbalance, explainability requirements, and cost of prediction errors.

Jia et al. (2026) proposed a multi-layer framework based on SHAP, including global feature importance, feature effects, pairwise interactions, local explanations, threshold calibrations, fairness evaluations for subgroups, as well as cross-dataset validation. For the IBM HR Analytics benchmark, XGBoost scored a test ROC-AUC of 0.773, with a 95% confidence interval of 0.716–0.828. The study also found significant age-band recall loss and revealed that there were some differences in the rank of the features in different datasets. It is an example that can be used in practice: Explanation and fairness assessment are not optional presentation features; they are part of the model evaluation. An organisational cause/effective intervention needs more in depth interpretation and evaluation; a feature that contributes to a prediction is a model attribution.

2.4 From Prediction to Retention Action

When managers can tie the output of a model to some action, retention analytics can become operationally useful. The appropriate response can include a career discussion, training options, job transfers, workload analysis, salary evaluation, mentoring or supervisor assistance. The selection should be sensitive to the situation of the employee, and the relevant contexts in the organisation. A risk score is not the only thing needed to informthe selection of an intervention; it must be combined with employee preferences, role context and evidence of what the organisation can do.

Drawing on time-lagged data, Moin and Zhang (2025) explored workers' AI awareness and turnover intentions in project-based organizations. Their results related AI awareness to turnover intention and found that supervisor support acted as a moderator. Although this is not a model for predicting staff attrition, it clearly illustrates that there is more to retention than technical systems – it's about organisational communication and support – and that staff feel the difference. When read in conjunction with predictive studies it highlights the link between analytics and employees experience of work and organisational change.

2.5 Ethical and Organisational Governance

Human resource analytics is about being responsible, understanding who is affected, what decisions are being made, and what data is being used. Barocas and Selbst (2016) describe how these data systems can even reflect historical patterns of disadvantage in the data and proxies being utilized for analyses. Issues around promotion, pay, performance, and opportunity may reveal an organisation's past. The model built on those records can replicate those patterns unless the design, outputs, and uses are thoroughly checked.

Also, privacy is relevant, since workforce analytics might be informed by sensitive data related to performance, behaviour, communications or engagement. Organisations need to find a clear reason for all data elements, minimise access, set retention policies and communicate to employees how they are used for decision-making. Explainability should allow for sensible review, and human oversight should allow for a chance to challenge or contextualize a risk estimate. Governance is most effective when the roles and responsibilities are documented, the fairness is reviewed regularly, access controls are put in place, employees are included in the process, and there is a way to correct mistakes.

2.6 Review Synthesis and Analytical Propositions

There are three propositions in the literature for organisational evaluation. First, predictive models can provide valuable input if the validation measures are as close to the real decision situation and misclassification costs. Second, retention interventions are more defensible if they provide model explanations and are linked to another plausible organizational mechanism, such as training access or workload support. Third, continual governance and outcome monitoring can help differentiate a technically successful prediction system from a responsible retention practice. The propositions presented here inform the framework developed in Section 4.

3. Research Methodology

3.1 Research Design and Source Selection

This study is a critical narrative review with conceptual synthesis. It collects methodological reviews on machine-learning based turnover prediction, IT-specific empirical studies, research on technology-employee retention, studies about AI awareness and turnover intention, and recent explainable-AI research. The goal is to examine the evidence types and the contribution they can make to management awareness, and then to organize the implications in a prediction-to-retention matrix in which they are cohesive.

3.2 Data Sources and Search Procedure

This targeted search was performed from publicly available scholarly search results, publishers' websites, scholarly repositories, bibliographic databases and cited-reference lists. Search terms were clustered on four concepts: (1) artificial intelligence, machine learning, predictive analytics, HR analytics, and people analytics, (2) employee attrition, turnover, retention, employment tenure, (3) information technology, software professionals, technology organisations, and (4) retention strategies, explainable AI, fairness, privacy, and organisational governance. The emphasis was on traceable peer-reviewed literature that directly related to the research questions. Foundational turnover research and wider HRM reviews were preserved to clarify theory and organisational context.

3.3 Analytical Categories and Synthesis

A set of five categories were developed and used to compare the selected literature: predictive method and data context; definition of the turnover or tenure outcome; relevance to IT workforces; connection with retention

action; and governance or implementation implications. Data interpretation was based on study design. Predictive modelling, survey associations, literature reviews, and conceptual frameworks were recognized as distinct types of evidence, while recommendations were distinguished from presented empirical findings. This allows for an organized comparison while maintaining the context and limits of individual studies.

3.4 Scope and Interpretation

The review emphasizes English-language sources that were "public," available through scholarly information and public record of their publications. Literature differs in geography, population, data source, model design and outcome definition. Hence the transferability of the benchmark results, results obtained through professional networks and HR valuations in organisations varies. The synthesis is interpretive and will be used to guide research and practice; conceptual framework will serve as a foundation for future organisation-specific testing.

4. Synthesis And Discussion

4.1 Profile of the Comparative Evidence

The papers reviewed range from systematic reviews, empirical models in Indian IT context, a study on tenure prediction using professional network system, a study on AI awareness in project organisations, and recent work related to explainable turnover analytics. Table 1 summarises the main contributions and their practical interpretation.

Table 1. Selected literature and its contribution to AI-enabled employee retention

Source	Evidence type and setting	Main contribution	Practical interpretation
Khera & Divya (2019)	Predictive model; three Indian IT companies	SVM model used 22 HR features; reported 85% accuracy.	Use decision-relevant metrics and examine errors for leavers and stayers.
Al Akasheh et al. (2024)	Systematic review; 52 studies	Maps supervised ML methods used for turnover prediction.	Model comparisons should include validation and data characteristics.
Haque (2024)	Integrative review; Indian technology employees	Organises retention literature around reasons for leaving and staying.	Connect predictions with career, support, work conditions, and development.
Talebi et al. (2025)	Systematic review; 58 studies	Compares common ML methods and recurring turnover features.	Treat feature importance as dataset-specific evidence for review.
Moin & Zhang (2025)	Time-lagged study; project organisations in China	Links AI awareness with turnover intention; supervisor support moderates the relationship.	Communication and managerial support matter during technology change.
Naik & Chakraborti (2025)	Tenure prediction; Indian IT professionals	Identifies experience, seniority, education, certifications, and connections as predictive factors.	Development-oriented responses can be evaluated for local fit.

Source	Evidence type and setting	Main contribution	Practical interpretation
Jia (2026)	Explainable ML; IBM benchmark and external dataset	Integrates SHAP explanations, threshold calibration, fairness review, and external validation.	Monitor calibration, subgroup performance, and transferability.
Sangeetha & Vijayaraj (2026)	Bibliometric and thematic review; 2014–2025 literature	Maps research growth and themes in ML-based attrition prediction.	Position organisational implementation as part of the broader research conversation.

4.2 Interpreting Predictive Performance

Predictive performance is only meaningful when judged against the decision supported by the model. In settings where the cost of incorrect results does not differ significantly between classes, and the outcome classes are approximately balanced, accuracy may be informative. However, when resignation/attrition is rare, or when false alarms carry different consequences than false negatives, there is value in looking at precision, recall, F1 score, ROC-AUC, PR-AUC, and calibration. Frankly, a risk threshold should be chosen based on risk levels, available HR capacity, the level of proportionality of follow-up, and the impact on employees if a false positive arises.

The reviewed studies also show the values of external validation. Khera and Divya (2019) derived their data from three Indian IT companies, Naik and Chakraborti (2025) analyzed data from a professional network, and Jia (2026) assessed a benchmark and an independent data set. These data contexts represent varying aspects of the employment relationship. A model to be used in practice should therefore be tested on up-to-date data from the organisation and workforce where it will be applied. While feature importance can help guide investigation, the explanation of a model needs to be viewed in the context of HR knowledge and employee input.

4.3 Turning Insight into Retention Action

Ideally, the managerial pathway should start with a question: What workplace condition could account for the observed risk pattern, and what action could reasonably respond to it? For example, if a cluster consists of more younger members, and there is less opportunity for career progression, mentoring, certification support, and development pathways might be useful. An overtime and work-life balance pattern can focus on project staffing, workload forecasting, and manager practices. An internal equity review could be triggered by a compensation-related signal. These are interventions that are candidates for discussion or assessment, not automatic consequences of a score.

The answer is supposed to be about the employee. HR can use a prediction as a basis for having a discussion with the employee about support, asking about what they think works for them, and presenting appropriate options. The employee needs to make some decision in this. Then organisations can examine if the intervention was provided, found to be valuable, and if there were changes in retention, mobility, engagement or workload over time. This forms an evidence cycle from analytics to organisational learning and not a one-off classification activity.

4.4 Governance, Fairness, and Trust

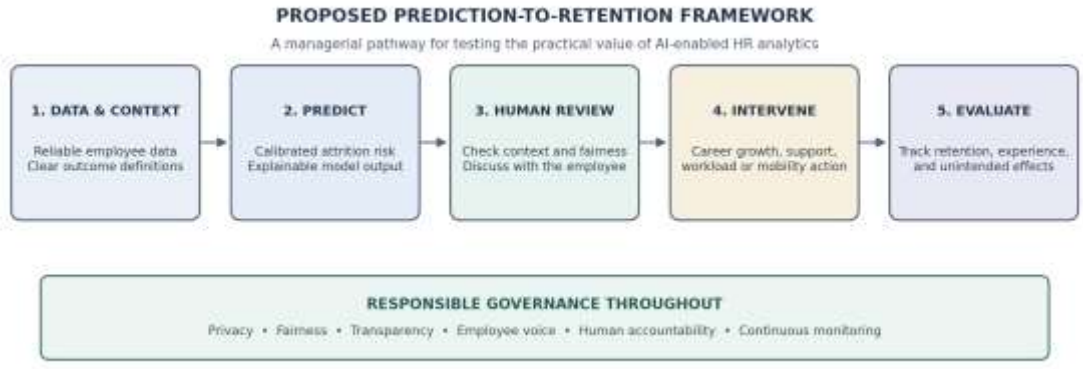
Governance should be incorporated through the lifecycle of a retention model. When preparing data, organisations should identify the intended purpose and legitimate use of each variable, account for missing data and look at how data is historically represented, and identify sensitive data records. They should review feature leakage, calibration, and subgroup performance in model development. Risk scores should be used at deployment to inform review rather than serve as stand-alone decisions on issues such as promotion, pay, access to projects, and termination. Monitoring should be conducted not only on the performance of the model, but also on how interventions are being spread across groups.

Transparency must also involve explaining where and how the data is being applied, and what would be the last human decision point. Staff must be able to ask questions about the inaccurate information and put into perspective patterns that the model cannot see. A supportive governance model sees a high risk prediction as a call to action to look at working conditions, development, manager support, and organisational practice. It also assesses if the employment of analytics leads to increased trust and a sense of fairness, as a technically competent system may lose value if employees perceive it as a surveillance or labelling.

4.5 Proposed Prediction-to-Retention Framework

Figure 1 shows an integrative pathway to include five stages: preparation of reliable data and definition of desired outcome; creation of a calibrated prediction with an explanation; human review of the context and fairness; selection of a suitable, relevant intervention; and monitoring of employee and organisational outcomes. Employee voice, fairness, transparency, privacy and accountability are present throughout. Evaluation feedback guides the next iteration of model design and retention practice.

Figure 1. Proposed framework connecting AI-based prediction with employee retention practice



Note. The framework is a conceptual synthesis intended to guide organisational implementation and evaluation.

The framework places model prediction within a larger HR process. It is determined by the decisions and outcomes it facilitates, such as employee experience and organisational learning. The framework can be tailored to varying IT organisations by defining context-specific data, thresholds for decisions, interventions, safeguards, and evaluation periods.

5. Conclusions, Limitations, And Future Research

5.1 Conclusions

By analyzing patterns that are linked to employee turnover, AI-driven HR analytics can assist in retaining teams. AI can help HR teams time their chats more effectively and prioritise employee development and workplace improvements. Studies conducted in Indian IT contexts show that attrition and employment-tenure prediction is possible, and more general reviews trace the expanding variety of machine-learning approaches to turnover analysis. More recent research into explainable-AI also points to the need for calibration, subdivision and dataset validation.

The review's chief value is its practical framework, linking data quality, prediction with human review, appropriate retention response, and outcome evaluation. The framework emphasises employee voice, fairness, privacy and accountability alongside technical performance. It's an IT mindset that enables analytics to serve both people and work design and evaluation/decision to inform future actions.

5.2 Limitations of the Review

The review relies on a purposeful, traceable sample of English-language publications identified through traceable public-source search and citation review. The evidence included differs in aspects such as organisational setting, sample studied, source of data, and type of outcome modelled. Three data sources – benchmark, professional-network data and organisational HR data – offer distinct perspectives on work behaviour. As a result, this synthesis should be used to inform practice and the design of future studies, not as an averaged estimate of the impact of AI analytics on retention.

5.3 Future Research

Future research can trace the entire journey from predictions to action. Longitudinal studies could document when risk scores are assessed, which interventions are implemented, employee response to interventions, and employee retention over a set period of time. Comparison designs might test mentoring, training supports, internal mobility and workload interventions against well-defined outcomes. Researchers should account for source of the dataset, absences, definitions of the target, calibration of models, performance of target subgroups, and when does a model transfer to a new setting. Qualitative studies on both employees and HR professionals can help understand if explanations impact employees' trust, perceived fairness, and willingness to participate in retention conversations. These practices can be combined to create more robust links between analytic capability, responsible management and sustainable retention in the IT sector.

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