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Predictive HR Analytics for Employee Retention in the IT Sector: A Machine Learning Approach – A Systematic Review

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Abstract:
HR analytics has become one of the most important tools that help organisations to manage the challenges associated with the workforce in the age of digitalisation. Employee retention is more critical in the Information Technology (IT) sector, where talent shortages continue to beacome a problem coupled with high levels of attrition and an increasing cost of recruiting and training talent. Old fashioned descriptive approaches to HR though good in terms of historical reporting do not have the power to predict and obstruct turnover. This systematic review examines the usage of the machine learning (ML) in predictive HR analysis and focuses on its relevance in anticipating employee loss and developing proactive retention strategies. The review compiles results of the recent literature (20152025) on the various ML approaches to turnover behavior, namely, supervised learning, ensemble methods, and deep learning and points out their efficacy in modelling turnover behavior. Among the key findings of ML, one should pay attention to its ability to increase the accuracy of predictions, guide data-driven workforce planning, and provide concrete knowledge on employee engagement, performance, and satisfaction measurements. But there are still gaps in domain-specific data set, model interpretability, and ethics associated with HR decision-making. In future research, the consolidation of real-time analytics, IoT-based workforce observation, and hybrid ML-psychological functions should work to maintain accuracy and transparency. The paper highlights how predictive HR analytics have the potential of revolutionizing retention practices and maintaining competitive edge in IT industry.
Keywords: HR Analytics, Employee Retention, Machine Learning, Predictive Analytics, IT Sector, Workforce Management.

1. INTRODUCTION

Background

Retention of employees has emerged as one of the most serious issues in Information Technology (IT) industry. In contrast to a variety of other industries, IT organizations have to contend with a constant attrition prompted by the progressive technological progress, the presence of a global market, and increased market requirements regarding the specific expertise (Nosratabadi et al., 2022). Talented employees often jump to other firms that pay more, have improved work-life balance, or offer more chances to grow professionally (Raza et al., 2022). Such turnover has a considerable impact on organizational stability resulting in a delay in the implementation of projects, decreased productivity, and higher operational cost (Ajit, 2016). Attrition is a strategic issue and need not be ignored by both the HR manager, as well as the business leaders due to the losses in recruitment and onboarding costs and loss of organizational knowledge (Saadallah, 2025). Therefore, strategic ways to retain talent are no longer optional as it constitutes the necessity to stay in competition in the realm of IT.* 2024 (Nagpal et al.)

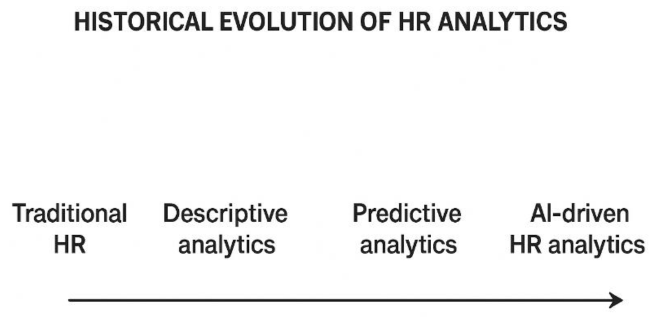

Figure 1: Evolution of HR Analytics

Role of Predictive HR Analytics

In the traditional HR analytics, descriptive statistics have been used to make sense of the historical patterns in the workforce behaviour (Kumari Jaya Kumar, 2024). Despite their worth in the provision of insight, they do not go far to predict future performances or employees that are at risk of leaving (Sanjay & Khalsa, 2025). In recent years, there has been a trend towards the use of predictive HR analytics that use such advanced data processing methods as data analysis and modeling to predict employee behaviour (Das & Samal, 2025). The use of predictive models also helps HR professionals to transform their responses into proactive ones, such that beneficial interventions can be implemented on time before retention problems can deteriorate (Kaushal et al., 2023). Predictive analytics allows organizations to devise the workforce planning, succession planning, and employee well-being strategies specifically by combining different types of data, including performance reviews, employee engagement surveys, promotion histories, as well as demographic profiles (Miglani & Arora, 2025). It is a paradigm shift in the HR using transition descriptive analytics to predictive analytics that is also representative of the larger shift toward data-driven decision making in organizations. Probably, hundreds of thousands of people considered the reality around them to be a collection of micro-influences (Hossain et al., 2025).

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Importance of Machine Learning

Machine learning (ML) is playing a key role when it comes to the development of predictive HR analytics. In contrast to traditional statistical techniques, ML algorithms have the ability to identify multidimensional, non-linear correlations between multiple variables of the workforce and, therefore, are specifically well-suited to the modeling of workforce turnover (Kaushal et al., 2023). Logistic regression, random forests, gradient boosting and deep neural networks are techniques that have proven to be good predictions in attrition modelling (Hossain et al., 2024). Instead of making ML more accurate, it also takes dynamic changes in workforce patterns into consideration, which means that it offers scalable and dynamic solutions (Shafie et al., 2024). To give a specific example, ML-based models have the ability to scrutinize minor behavioral cues e.g., a drop in engagement scores or anomalous performance measures that can lead to attrition but that may not be identified using conventional approaches (Bamini et al., 2025). Further, explainable artificial intelligence solutions are also on the rise, to enable predictive precision and fairness between the need to ensure that HR choices can be explained (Álvarez-Gutiérrez et al., 2022). The ML-driven predictive analytics can give an organization a competitive advantage in the IT sector where the attrition rates are considerably higher than in other sectors since through the tool, organizations are able to intervene early. To achieve a new level of centrality, (Siandri et al., 2025)

Purpose & Scope of the Review

This is a systematic review aimed at appraising critically the application of machine learning in predictive HR analytics, specifically that of employee retention in the IT industry (Konda, 2024). The review unites the perspectives of studies that have been conducted over the last several years since 2015 and as such, unveils the existing trends, the positive and negative aspects of utilizing ML-based methods (Nawaz et al., 2025). It focuses on the role of supervised learning algorithm, an ensemble model, and deep learning model in attrition prediction, and it also points out the limitation of data accessibility and interpretability of models, in addition to ethical issues (Seixas et al., 2023). This review is limited by three essential parameters: (1) the industry, which is the IT sphere, (2) the methodological approach, which was ML-based models as predictors, (3) the outcome parameter, namely retention among employees. The abstracts state that (Fallucchi et al., 2020).

This research can have a contribution to the body of literature and the HR practice in various ways. First, it provides a combination of discoveries made over ten years of research, giving a condensed body of knowledge and thought to the scholars and practitioners (Adeusi et al., 2024). Second, it sources out what the current literature lacks, thus establishing an agenda of future research that incorporates recent technologies e.g. IoT and federated learning (Suswaram et al., 2024). Lastly, the review notes the strategic value of predictive HR analytics in preventing attrition risks and maintaining the performance levels of organisations (Elanwer, 2021). The potential to focus machine learning-driven predictive HR analytics on predicting human capital management, combined with technological advancement, has the potential to transform the way in which workforce is managed in the IT industry. The research was conducted in Croatia (Paigude et al., 2023).

METHODOLOGY OF THE REVIEW

A systematic review methodology was adopted to ensure comprehensive coverage of existing research on predictive HR analytics in employee retention within the IT sector(Chowdhury et al., 2023). Following established guidelines for evidence synthesis, the review process was structured into three stages: search strategy, inclusion and exclusion criteria, and data extraction with synthesis.

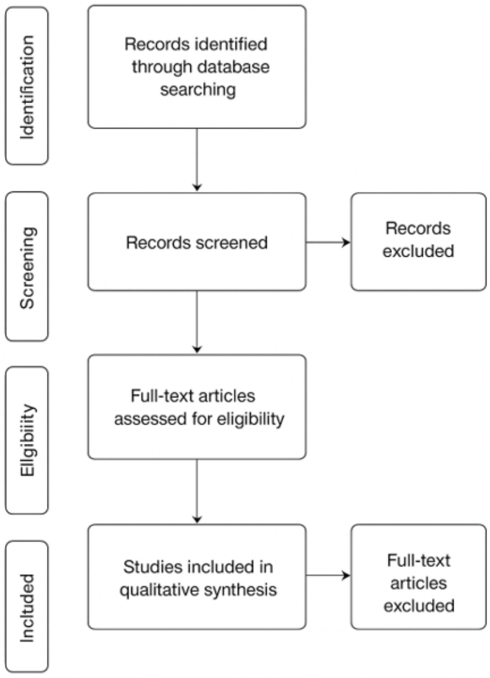

Figure 2: PRISMA Flow diagram

Search Strategy

To identify relevant studies, a comprehensive search was conducted across multiple academic and professional databases, including **IEEE Xplore, Scopus, Web of Science, and Google Scholar**. These databases were selected due to their extensive coverage of interdisciplinary research in computer science, management, and organizational studies.

The search focused on a combination of keywords and Boolean operators to maximize coverage. Core terms included:

- *"HR Analytics" OR "Human Resource Analytics"*
- *"Employee Retention" OR "Attrition" OR "Turnover"*
- *"Machine Learning" OR "Predictive Analytics"*
- *"IT Sector" OR "Information Technology Industry"*

Boolean strings such as:

("HR Analytics" AND "Employee Retention" AND "Machine Learning" AND "IT Sector") were used to refine the search. In addition, backward snowballing (examining references of key papers) and forward citation tracking were employed to capture influential studies missed in the initial search.

Inclusion and Exclusion Criteria

To ensure the relevance and quality of selected literature, the following **inclusion criteria** were applied:

- **Timeframe**: Studies published between **2015 and 2025**, reflecting the rapid evolution of machine learning applications in HR analytics.
- **Domain relevance**: Research focusing specifically on **employee retention, turnover, or attrition prediction**.
- **Methodological relevance**: Studies employing **machine learning or predictive analytics techniques** rather than purely descriptive or theoretical approaches.
- **Sector focus**: Priority given to studies within the **IT sector**, but cross-industry studies were included if they offered transferable insights into IT workforce dynamics.
- **Publication type**: Peer-reviewed journal articles, conference proceedings, and high-quality book chapters.

Exclusion criteria included:

- Studies outside the timeframe (pre-2015).
- Research not employing predictive analytics (e.g., descriptive statistics only).
- Articles without clear empirical or methodological contribution (e.g., opinion pieces, editorial notes).
- Publications in non-English language, due to translation limitations.

Data Extraction and Synthesis Process

The review process followed a structured pipeline to ensure consistency and transparency. Initially, duplicate records were removed across databases. Titles and abstracts were then screened to eliminate irrelevant studies. Full texts of shortlisted papers were examined against the inclusion criteria.

For each included study, a structured data extraction template was applied, capturing:

- **Authors and Year of Publication**
- **Dataset characteristics** (size, source, domain)
- **Machine Learning techniques applied** (e.g., logistic regression, random forest, deep learning)
- **Performance metrics** (e.g., accuracy, F1-score, ROC-AUC)
- **Key findings and contributions**

A narrative-synthesis and comparative analysis approach was used to synthesize the data extracted. Thematically, the studies were grouped under ML methodology, predictive focus and contextual application in the IT industry. A critical analysis of models pointed out the advantages and limitations of current approaches, the pitfalls (e.g., data quality, interpretability of models), current research areas.

This process of methods provided a solid unbiased rational level of review that has delivered confidence-building findings regarding the status of predictive HR analytics in terms of employee retention in the IT market.

HR ANALYTICS IN THE IT SECTOR

Overview of HR Analytics

Human Resource (HR) analytics is an area that has changed tremendously in recent 20 years, where it was a descriptive reporting tool and has evolved to predictive and prescriptive systems of decision-making. In the past, HR management was mainly based on administrative efforts, its conventional operations rely on pay roll processing, the number of employees, and simple attrition reports. These descriptive solutions gave retrospective information but contained little indication of future challenge of the workforce. The introduction of big data analytics and other advanced computing features has changed the role that HR plays and turned it into a key strategic business partner instead of an operational role (Al-Shammari et al., 2024).

Cutting edge HR analytics deploys data-driven strategies, which combine a variety of sources of workforce data on employees. The most popular data include Human Resource Information Systems (HRIS) data, performance appraisals, and employee engagement and satisfaction surveys, demographic characteristics of the employee and behavioral patterns. Studies show that when heterogeneous data is incorporated in the body, predictive modeling to detect departures and engineer recruitment interventions targeting such employees can be done (Sahoo et al., n.d.; Mishra & Jadeja, 2025).

New research stresses that HR analytics does not just take into account operational decisions only but, more often, strictly business dimensions, such as workforce planning and succession, and organizational competitiveness (Elugbaju et al., 2024; Gurusinghe et al., 2021). Take, for instance, Mishra and Jadeja (2025) note that AI-enhanced HRIS will help increase employee engagement and retention by giving real-time data on workforce trends. On the same note, Ramachandran et al. (2024) report that the uptake of HR analytics around the globe is picking up pace, with companies engaging predictive tools to align HR outcomes with the long-term business objectives in mind.

Table 1: below summarizes some key contributions to the evolution of HR analytics.

Authors	Focus	Methods/Data Sources	Key Findings
Al-Shammari et al. (2024)	Big data & predictive analytics in HRM	Systematic literature review	HR analytics evolves into a strategic decision-making tool.
Shilpa et al. (2024)	Customer/employee retention via ML	ML techniques applied in HR industry	ML improves predictive accuracy in employee churn.
Mishra & Jadeja (2025)	AI-enhanced HRIS impact on retention	Literature synthesis	AI-driven HRIS improves engagement & retention.
Sahoo et al. (n.d.)	Demographic & behavioral data	Survey/secondary data	Behavioral metrics improve attrition prediction.
Gurusinghe et al. (2021)	Predictive HR analytics & talent management	Conceptual framework	Analytics aids succession planning & talent strategies.
Elugbaju et al. (2024)	HR analytics as strategic tool	Case applications	Supports workforce planning & leadership pipelines.
Kilponen (2025)	Use cases in wellbeing services	Applied research	HR analytics applied in public sector for wellbeing.
Ramachandran et al. (2024)	Global adoption of HR analytics	Systematic review	Rapid global acceptance and implementation.

Employee Retention Challenges in IT

Retention in IT sector is differentiated in different industries. Constant high rates of attrition are an issue that plague IT organizations the factors that contribute to high rates of attrition include the lack of worldwide skilled talent, intense attacks by rival firms, changes in technological changes that can result in a mismatch of employees and their skills organizations need. The loss of personnel in the IT sector is indeed costly but more broadly it can effectively alter projects, client ties, and knowledge capital of an organization (Talebi et al., 2025).

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Figure 3: Key Challenges in Employee Retention within the IT Sector

Several researchers resort to the use of machine learning (ML) that helps to overcome these issues. The ML algorithms stark learning, decision trees, and ensemble methods can learn the subtle behavioral traits that lead to turnover, which comprise early warning systems on the HR managers (Sharma et al., 2024). Garg et al. (2022) state that the IT industry has a special interest in ML-driven analytics because it has high-volume and high-velocity data on workforce.

Comparative approach points at the fact that retention issues in IT field are reflected all over the world with research conducted in the U.S. and other countries portraying the same factors driving their predicament: dissatisfaction with work, career stagnation, and pay disparity (Gazi et al., 2024). Further, IT predictive analytics has started associating model of attrition to the organizational performance where the employee continuity has been shown to have a direct influence on project delivery, customer satisfaction and also overall profitability (Nalla, 2025; Kambhampati & Rao, 2024; Kiran et al., 2024).

Table 2: Challenges in Employee Retention and ML Approaches

Authors	Context	ML Methods	Key Findings
Talebi et al. (2025)	Systematic review on ML turnover prediction	Various ML approaches	Attrition prediction models effective across industries.
Sharma et al. (2024)	HR retention via deep learning	Deep learning models	Improved accuracy for retention prediction in IT.
Garg et al. (2022)	ML in HRM	Review of ML applications	ML enhances HR predictive capabilities.
Gazi et al. (2024)	U.S. employee attrition	ML models	Attrition factors transferable to IT workforce.
Nalla (2025)	Employee retention & performance	ML models	ML links retention to performance metrics.
Kambhampati & Rao (2024)	Attrition models in IT	Ensemble ML models	Identifies gaps & future opportunities in attrition research.
Kiran et al. (2024)	Attrition & organizational performance	SCM-TBFO framework	Retention strongly tied to firm performance.

Business Impact of Retention Strategies

Employee retention has a business benefit which protrudes outside HR yardstick into the financial and the strategic bottom line. A high level of turnover inflation Higher Recruitment and training costs, decreasing productivity and projects failure to meet its deadlines. On the other hand, efficient retention measures help stabilize organizations, improve employer branding, and the morale of the workforce (Pachghare et al., 2024).

Predictive analytics is another application of AI that is especially effective in the context of turnover measurement with the financial consequences. As an example, Basnet (2024) demonstrates the use of predictive modeling to assist organizations in the distribution of resources more optimally by outlining high-risk categories of employees. On the same note, Ara (2025) illustrates the application of business intelligence tools in the transformation of HR as a support unit to render the HR as a strategic engine of organizational performance.

According to a number of studies, the retention strategies are directly related to project success, employee engagement, and customer satisfaction. Ahmed et al. (2025) point out that predictive HR analytics have the capacity to predict project success on the basis of employee stability, and Wibowo et al. (2025) underline the synergistic aspect of HR analytics in ensuring workforce decisions made in accordance with business strategy. Notably, when it comes to retention-oriented analytics, it will also enhance employer branding with IT firms able to establish themselves as destinations in the stiff talent marketplace (Hamraaia, 2024; Arora et al., 2021; Saxena et al., 2024).

Table 3: Business Impact of Retention Strategies

Authors	Focus	Key Findings
Pachghare et al. (2024)	ML churn prediction	Attrition directly linked to financial costs.
Basnet (2024)	AI-driven predictive analytics	Improved allocation of retention resources.
Ara (2025)	Business intelligence & HR	HR becomes strategic driver of performance.
Arora et al. (2021)	AI in HR transformation	HR analytics transforms organizational decision-making.
Ahmed et al. (2025)	HR analytics & project success	Workforce stability predicts project outcomes.
Wibowo et al. (2025)	Data-driven HR decision-making	Analytics integrates HR with business strategy.
Hamraaia (2024)	Engagement + analytics	Engagement fosters organizational success.
Saxena et al. (2024)	AI's strategic HR role	Predictive HR shapes long-term competitiveness.

The IT sector is shown to have three important insights of HR analytics. To begin with, its historical development evidences that it is based on a fundamental transition of descriptive to predictive, ML-based decision-making. Second, IT retention issues continue to be high in terms of skill shortages and competitive forces and as such, predictive modeling is necessary. Lastly, the retention strategies have significant business implications as far as the financial performance, project success, and employer branding is concerned. A combination of these findings makes the concept of predictive HR analytics as a critical strategy to revolutionize IT workforce management and competitive advantage viability.

MACHINE LEARNING IN PREDICTIVE HR ANALYTICS

ML Techniques Used in HR Analytics

ML has largely extended the capability of predictive HR analytics, particularly in both employee attrition and retention modeling. Organizations used to use regression-based methods of turnover risks. A logistic regression is still effectively interpretable and continues to be applied on such data, but contemporary HR datasets which are frequently skewed and of high dimension, with high variability in their behavior, ask for more advanced methods.

The most frequently used models are known as supervised learning. Research evidences found tools such as decision trees, random forests, and gradient boosting (XGBoost) to be used in the non-linear correlation of the HR variables. An example is Alqahtani et al. (2024) who discovered random forest and XGBoost to be more accurate in predicting behavior than regression based models, especially when they are applied on large HRIS data. The same is the case with ensemble methods, which Al-Shammari and Ghanem (2024) have systematically evaluated as model consolidation enhancing their resistance to data noise.

Neural networks have increasingly been applied to determine deeper patterns of behaviors that are not found using traditional models. In contrast to tree-based models, unlike tree-based models, neural networks can read both structured HR information and non-structured information including responses to an engagement survey or staff feedback. According to Al-Alawi and Ghanem (2024), the value of neural networks is particularly relevant when the organizations are capable of gathering multimodal datasets. Salunkhe (2018) demonstrated earlier that deep learning is promising in HR retention prediction and current work embeds the models in enterprise HR solutions (Ho-Peltonen, 2024).

Table 4: Machine Learning Techniques for Attrition Prediction

Authors	ML Techniques	Key Insights
Alqahtani et al. (2024)	Logistic Regression, Random Forest, XGBoost	Ensemble models outperform regression in accuracy.
Al-Shammari & Ghanem (2024)	Hybrid ML models	Combining classifiers improves robustness.
Al-Alawi & Ghanem (2024)	Neural networks, SVM	Neural networks effective for complex HR patterns.
Salunkhe (2018)	Neural networks	Early empirical demonstration in HR attrition.

Feature Engineering in Employee Retention

The quality of feature engineering is more important to predictive HR analytics than the selection of the ML algorithm. Models that embrace employee retention need to be well crafted using HRIS, survey, and performance variables. Typical examples are work length of service, job position, pay level, levels of advancement, and performance indicators (Shron et al., 2025).

The new strategies are aimed at engagement and behavior indicators. Krishna et al. (2024) point out that it is more efficient to combine structured HR records with sentiment analysis of employee communications to predict dissatisfaction. On the same note, Priyanka et al. (2024) point to the fact that AI can be used to capture the emerging retention risks as a result of integrating recruitment, performance and engagement data throughout the employee lifecycle.

Figure 4: Common Features used in Employee Retention Prediction

The application of feature engineering has gone higher to the organization level measures as well. According to the information provided by Akter and Al Maruf (2025), the use of SQL-driven data pipelines and visualization tools such as Power BI can support modeling of turnover risks in the real- time context helping with the process of workforce forecasting. The transition implies that HR analytics is changing to a perspective of retrospective analysis to constant supervision systems.

Simultaneously, Kang et al. (2021) demonstrate that perceived HR practices (including recognition, training, and work-life balance) are highly predictive of turnover intention than pay in certain situations. This discovery moves the discussion to the area of inclusion of psychological and cultural measures in predictive calculations.

Therefore, feature composition in the HR analytic domain is developing towards multiple level personnel profiles incorporating not merely some performance, behavioral but also contextual features to increase the predictiveness and explainability of prediction accuracy.

Performance Metrics in Retention Prediction

There are performance measures that need to be used in the evaluation of retention prediction models. Accuracy is the most frequently used measure; however, when applied to the datasets with imbalance between the attrition and retention cases it overestimates the effectiveness.

To deal with this, experiments are coming to use F1-score, precision, recall, and ROC-AUC. It is argued that ROC-AUC gives a more global measurement of a model against a threshold of discriminative ability (Muthugala et al., 2024; Pereira, 2024). Indeed, a comparison of various algorithms provided by Al-Alawi & Ghanem (2024) revealed that, in spite of the moderate performance of such an algorithm as logistic regression, random forests, and gradient boosting were shown to provide ever higher F1-scores and AUC values and thus had a better tradeoff between false positives and false negatives.

Comparative benchmarking is also involved in the recent work. Haque et al. (2025) carried out the cross-model study where they proved the stability and predictive power of the former (ensemble classifiers) being greater than that of the latter (single models) ones. Similarly, Abu-Faty et al. (2025) demonstrated that generative AI methods have the potential to be used alongside machine learning and can be used to model complex retention dynamics that increase precision and interpretability.

Table 5: Performance Metrics in Retention Prediction Models

Authors	Methods Evaluated	Metrics Used	Key Findings
Pereira (2024)	Multiple ML models	Accuracy, ROC-AUC	AUC superior to accuracy for attrition imbalance.
Muthugala et al. (2024)	Supervised learning	Accuracy, Recall, F1	Recall crucial for HR decisions.
Haque et al. (2025)	Comparative ML study	F1, ROC-AUC	Ensemble classifiers most stable.
Abu-Faty et al. (2025)	Generative AI + ML	Precision, AUC	Hybrid improves precision & interpretability.

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Predictive HR analytics is being transformed by machine learning where attrition is a crucial risk in the IT industry. Ensembles of supervised models are the most pervasive practice, whereas complex data is increasingly using neural networks. The success of these models is however dependant on robust feature engineering and such features are no longer limited to demographics but have now percolated into behavior, psychological and even organizational-level features.

Measurement on performance is still changing and it is now preferable to state F1-score and ROC-AUC instead of straightforward accuracy. The agreement among the articles is that an ensemble and hybrid model are better than single algorithms and can provide both predictive content and explanability. Finally, the intersection between machine learning/feature engineering and deep metrics is making HR analytics a strategic driver of retention management in the IT sector.

LITERATURE REVIEW & COMPARATIVE ANALYSIS

Review of Existing Studies

The currently increasing body of research literature on predictive HR analytics shows that a lot of research publications are concerned with issues of employee attrition and retention, particularly in IT. The various machine learning (ML) models employed by the researchers to predict turnover are regression, decision trees, ensemble models and neural networks.

Current research indicates the increasing use of predictive analytics and artificial intelligence in dealing with employee turnover and improving the decision-making of HR. Initial mathematical models like the proposed by Zhao et al. (2018) and Pessach et al. (2020) helped to prove the efficiency of machine learning to conduct a stable prediction of attrition. Further developments merged deep learning and optimization, whereas Park et al. (2024), Hariri et al. (2024), and Yadav et al. (2025) focused on an AI-enhanced HR analytics to ensure organizational sustainability. In the same line of argument, Abrar et al. (2025) and De Vos et al. (2024) presented evidence that HR systems can have an AI and boost the agility, benchmark the state-of-the-art prediction techniques of their workforce.

Applications are also observable in the sectors. As an example, HR analytics in voluntary turnover and HRIS-based retention were examined by Erkkil (2020) and Jadeja (2025), whereas the focus of Madhyvadany and Shakthipriya (2025) was systematic literature reviews in predictive HRM. Furthermore, such studies as Benabou and Touhami (2025), and Okon et al. (2024) used data-driven frameworks and classification trees to describe turnover intentions and enhance their usage in decision-making.

Regarding methodological approaches, Qamar and Samad (2022) used bibliometrics and structural modeling, and the studies by Arora et al. (2023), Thakral et al. (2023), Seo et al. (2025) and Goswami (2024) focused on the field of HR analytics regarding strategic HRD and improved performance. These works together underline the transformative nature of AI in the area of HR and suggest the need to be more transparent and practical in business organizational environments.

As an example, Alqahtani et al. (2024) reviewed the application of machine learning models and demonstrated that tree-based ensembles (Random Forest and XGBoost) are superior to the traditional regression in the capability of entity predictions. In the same way, another study by Al-Alawi & Ghanem (2024) noted the excellent performance of the neural network in modelling complex, non-linearly, driver of attrition.

Alternatively, Pereira (2024) applied a case study to Willis Towers Watson Lisbon Hub, in which logistic regression and ensemble learning models were compared. Their analysis revealed that the transparency of logistic regression is inferior to the ensemble methods in terms of more precise prediction performance, particularly, when the data are imbalanced.

The need to consider feature engineering, as well as the inclusion of variables, like employee tenure, promotions, and satisfaction scores, has been highlighted in such studies as Priyanka et al. (2024) and Krishna et al. (2024). They claim that data preprocessing and quality of HRIS incorporation are key determinants of the predicting capacity of any model.

Along with that, Abu-Faty et al. (2025) also proposed generative AI along with classical ML classifiers, which appear to be more precise and interpretable. This goes in line with the wider research tendency of incorporating AI-powered HRIS systems (Mishra & Jadeja, 2025) that incorporate both structured and unstructured HR-information.

Table 6: Comparative Review of Studies in Predictive HR Analytics

Study	Models Evaluated	Accuracy (%)	F1-Score	AUC (ROC)	Notes
Alqahtani et al. (2024)	LR, RF, XGBoost	LR: 72, RF: 85, XGBoost: 87	0.68–0.82	0.75–0.90	Ensemble models outperform regression.
Pereira (2024)	Logistic Regression, Ensemble	LR: 74, Ensemble: 86	0.70 vs 0.84	0.78 vs 0.91	Case study (Lisbon Hub).
Abu-Faty et al. (2025)	ML + Generative AI	89–92	0.85–0.90	0.92	Hybrid improves both precision & interpretability.
Poornappriya & Gopinath (2021)	Decision Trees, LR	DT: 76, LR: 70	0.71	0.77	Small-scale HR dataset.
Al-Alawi & Ghanem (2024)	Neural Networks, SVM	NN: 91, SVM: 85	0.88	0.93	Neural networks effective for nonlinear attrition drivers.

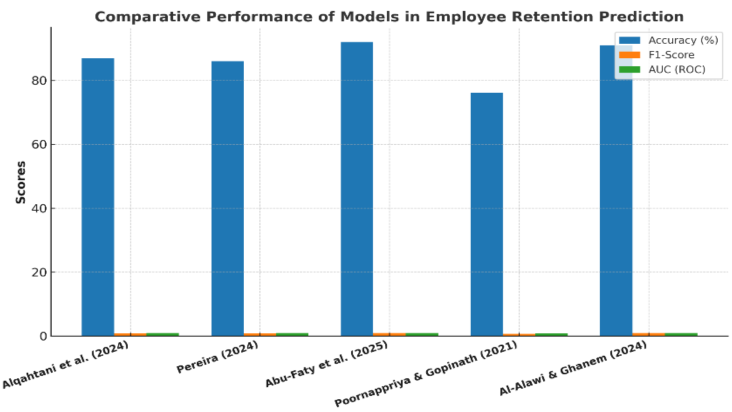

Figure 5: Graphical Representation of Comparative Review of Studies in Predictive HR Analytics

Strengths and Weaknesses of Existing Approaches

The reviewed studies highlight both **strengths and limitations** in current predictive HR analytics approaches.

Strengths:

- **High predictive accuracy**: Ensemble methods (RF, XGBoost) consistently outperform classical regression.
- **Scalability**: ML models handle large HR datasets effectively, making them suitable for enterprise-scale HRIS systems.
- **Integration of behavioral and demographic data** improves predictions compared to demographic-only models.

Weaknesses:

- **Interpretability vs. Accuracy Trade-off**: Neural networks and ensembles are accurate but less interpretable compared to logistic regression, which remains popular due to its transparency in HR decisions.
- **Data quality issues**: Many HR datasets are imbalanced (few attrition cases), incomplete, or biased. This reduces the reliability of predictions.
- **Lack of contextual insights**: Some models emphasize accuracy without explaining underlying employee motivations, limiting their practical application in HR strategy.
- **Generalizability challenges**: Studies often rely on single-organization or sector-specific datasets, reducing external validity.

Trends in Recent Research

Recent developments in predictive HR analytics indicate three prominent trends:

Increasing use of Deep Learning:

- Deep neural networks and hybrid AI models are being deployed to capture complex, non-linear employee behaviors.
- Studies like **Al-Alawi & Ghanem (2024)** and **Abu-Faty et al. (2025)** demonstrate the potential of combining neural networks with generative AI for both accuracy and nuanced insights.

Shift Toward Explainable AI (XAI):

- Organizations demand transparency in predictive models to ensure HR decisions are fair and unbiased.
- Techniques such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) are being integrated into retention prediction frameworks.
- This balances the **interpretability–accuracy gap**, allowing HR managers to understand why a model predicts a particular employee's attrition risk.

Integration of Multi-Source Data:

- Modern HR analytics systems are evolving beyond HRIS to integrate **performance reviews, engagement surveys, communication logs, and even wearable data**.
- AI-driven HRIS platforms (Mishra & Jadeja, 2025) show that multimodal data enhances prediction reliability and provides actionable retention strategies.

Ethics and Fairness in HR Analytics:

- A growing body of research highlights the risk of algorithmic bias in HR models. Ensuring fairness, data privacy, and compliance with labor regulations is becoming a central theme in recent work.

RESEARCH GAPS AND CHALLENGES

Nevertheless, a number of key research gaps and challenges have been identified despite the fast development of HR analytics and machine learning as an application in the employee turnover prediction.

Absence of General Synthetic Datasets that are publicly accessible and domain specific

Among the predominant constraints in the field, there is a lack of open and domain-specific HR data sets, especially those of the IT type. Other work is usually based on internal HRIS (Human Resource Information System) data, which are the user-owned and confidential and cannot be freely disseminated. Academic research is therefore commonly relying on small or artificial datasets and therefore findings may not be representational overall. Compared to the studies, it is also challenging to benchmark models due to highly fragmented knowledge.

Condensed adoption of real-time analytics.

Although predictive models sound high on their accuracy, a growing number of research based on historical data are being done at the expense of the potential offered by real-time analytics. Attrition indicators in the rapidly evolving IT setting, like a productivity plunge or a shift in employee engagement toward work platforms, must be identified in a dynamic way. The existing HR analytics systems have minimal integration with streaming data of workplace tools (e.g., Slack, Jira, Microsoft Teams) so any intervention tends to be reactive and after-the-fact.

Little-Explored Explainability of ML Models

One more issue is predictive HR models explainability. Complicated models like deep neural networks or ensemble models tend to be a black box and they give little information on why an employee is likely to quit. Accuracy is relevant, but HR managers require interpretations that can be acted upon in order to formulate viable retention plans. Few studies have examined the use of such approaches as SHAP or LIME to address this gap, which indicates that more research on explainable AI (XAI) in the HR contexts is required.

Need for Ethical Frameworks in HR AI Usage

The most dangerous issue perhaps is the ethical aspect of predictive HR analytics. Problems like algorithm bias, data breach, and discrimination is also a threat. To take an example, as long as the demographic information (age, gender, ethnicity) affects the predictions, the organizations might end up enhancing the inequality at the workplace unintentionally. Moreover, they lack transparency of how they use their information leading to a mistrust among the employees. There are few established ethical provisions, which is why it is difficult to guarantee the fairness, accountability, and the adherence to the labor laws.

FUTURE RESEARCH DIRECTIONS

The identified gaps will call upon new and multi-disciplinary research. The field of HR analytics in the IT field can be taken in several appealing directions in the future.

IoT and Wearable Data Integrated Monitoring of the Workforce

New HR analytics models might be able to interact with the IoT and wearable sensors to decipher employee health, stress and productivity levels in real time. As an example, wearable devices are capable of tracking tiredness, sleep cycles, and physical activity and may provide early warning signs of burnout. Predictive models may be enhanced by adding behavioral and physiological data through IoT-enabled monitoring of the workplace (e.g., data collected by digital badges indicating how efficiently teams collaborate, or how workloads have been assigned). This may empower proactive retention strategies. Nevertheless, in this solution, data governance should be very robust to protect employee privacy.

Privacy-Preserving HR Analytics with Federated Learning

Federated learning (FL) is one potential way of resolving the privacy and data scarcity dilemma. Rather than concentrating personal information about employees on the organization-owned central repositories, with FL, organizations may train machine learning models on the local resource and, therefore, share only model parameters, but not raw data. This will allow the joint optimization of attrition prediction models without data privacy being lost. Federated HR analytics may be able to generate powerful models across the industry level without any violation of confidentiality in the IT industry where the attrition is prime especially in different companies.

Hybrid Models Combining ML with Psychological Assessments

Employee turnover is not just a quantitative issue but it is also a psychological, social and organizational issue. In the future, the machine learning methods need to be integrated into the psychological ones, e.g., into the personality assessment, motivation survey, and stress evaluation. Included in the hybrid models would be the possibility of capturing cognitive and emotional matters that drive turnover. This would result in more holistic and person centered forecasts whereby the divide between quantitative analytics, and qualitative personnel insights would be shortened**.**

Advancement in Explainable and Ethical AI

Future studies should focus on explaining trust in predictive HR systems by highlighting ethical AI systems and explainable AI. The purpose of creating domain-specific XAI tools that could work in the context of HR is to ensure that managers will know which variables have the greatest impact on the risk of attrition. Also, bias can be addressed by introducing fairness metrics (e.g. ldemographic parity, equalized odds) into evaluation steps. It will be important to establish a standardized ethical model, like that of medical research procedures that can moderate the conflicting covetousness of predictive power and the rights of employees.

Cross-sectoral and Cross-cultural Research

Lastly, a good proportion of the existing research is compartmentalized within a particular organization or geography. Future studies ought to be cross-sectoral and cross-cultural in nature, where retention drivers are compared between IT hubs (e.g. Silicon Valley, Bangalore or Eastern Europe). This type of comparative knowledge will help in making the predictive models more generalizable and will help in developing universal HR policies that can be used everywhere.

CONCLUSION

In the context of the IT industry, analyzed in this review, the power of predictive HR analytics justified the potential of the approach that can be summed up by using machine learning (ML) approaches. The review of the literature synthesis shows that ML models, both simple, such as logistic regression or decision trees, and advanced, such as neural networks or ensemble methods, have enhanced the accuracy of employee attrition by a large margin. The models capitalize on a variety of data, including HRIS data and other performance metrics and engagement surveys to give organizations actionable guidance with regards to workforce management.

One of the main lessons learned is that as opposed the descriptive, reactive nature of the traditional HR practices, predictive analytics methods make it possible to be proactive, predict at-risk individuals in IT companies, and prevent resignations. Such transition is especially important to the case of the IT industry, where the elevated churn rate and the inability to find talent costs a fortune and productivity. When utilizing ML-driven models, organizations are capable of not only enhancing retention, but also overall workforce planning, employer branding, and overall long term organizational competitiveness.

Meanwhile, the review highlights that some of the challenges still remain, including a shortage of open and domain-specific data, the poor existence of real-time analytics usage, undeveloped explainability of ML models, and data privacy and bias issues. The best solution to these limitations is to include the newly developed technologies that may include IoT and federated learning, and incorporating explainable and ethical AI frameworks in HR analytics systems.

To sum up, predictive HR analytics with the help of machine learning is not the technological breakthrough but a strategic boost to the IT industry. Organisations will be able to create more resilient, adaptable and engaged workforces when they incorporate data-driven intelligence with humanistic practices to retain their staff. The next step in the evolution of HR is using ML to not only predict, but design transparent, equitable, and sustainable experiences with employees.

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