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Machine Learning Applications in Predicting Employee Turnover: A Systematic Review

Ayoade Victor Iyiade[1*], Folashade Ayankoya[2] and Afolashade Kuyoro[3]
[1*,2,3]Department of Computer Science, Babcock University
E-mail: ayankoyaf@babcock.edu.ng, Kuyoros@babcock.edu.ng
*Corresponding Author: iyiade0390@pg.babcock.edu.ng
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***Abstract* - Employee turnover remains a critical and costly challenge for organizations globally, necessitating advanced predictive tools beyond traditional statistical methods. This systematic literature review (SLR) investigates the application of machine learning (ML) models in predicting employee attrition, synthesizing findings from 42 peer-reviewed articles and conference proceedings published between January 2020 and September 2025. Following the PRISMA 2020 guidelines, the review analyzes the algorithmic landscape, predictive feature importance, and methodological challenges in this domain. Results indicate that ensemble methods, particularly Random Forest and XGBoost, consistently outperform baseline models such as Logistic Regression, achieving typical accuracies between 85% and 94%. A consistent set of features-including low job satisfaction, excessive overtime workload, and below-market compensation-emerged as the strongest predictors of attrition risk. Furthermore, the review highlights the critical role of Explainable AI (XAI) techniques, such as SHAP and LIME, in translating complex model predictions into actionable insights for Human Resources (HR) professionals, thereby addressing concerns about model opacity and fostering stakeholder trust. Methodological challenges, including class imbalance and the risk of algorithmic bias, are discussed alongside common mitigation strategies. This review concludes by outlining emerging trends, such as hybrid models and prescriptive analytics, providing a comprehensive reference for researchers and practitioners seeking to implement responsible and effective ML-driven workforce analytics.**
***Keywords:* Employee Turnover, Machine Learning, Predictive Analytics, Explainable AI (XAI), Human Resources (HR) Analytics**

I. INTRODUCTION

The rate of employee turnover, defined as the rate at which employees leave an organization, remains one of the most acute challenges in human resource management (HRM) in the modern world. It not only affects financial performance but also the continuity of organizational knowledge, productivity, and morale [1]. Replacing an individual employee can cost up to twice their annual salary due to recruiting, onboarding, and lost productivity [2]. Traditional turnover prediction techniques, such as linear regression models or manual surveys, are constrained by the complex and nonlinear relationship between employee attributes and attrition outcomes [3]. The growing availability of digital HR data, including performance indicators, engagement rates, and demographic information, has led to a paradigm shift toward data-driven HR analytics [4]. Machine learning (ML) provides a more advanced approach to attrition prediction, leveraging historical data to uncover latent patterns that may indicate potential turnover [5]. ML models are capable of identifying subtle and complex feature interactions and offering proactive retention strategies to optimize workforce stability [6], [7].

Machine learning provides powerful computational methods for detecting latent patterns in large, heterogeneous HR datasets. Algorithms such as Random Forest, Gradient Boosting Machines (including XGBoost), Support Vector Machines (SVM), and Deep Neural Networks can model intricate relationships and provide probabilistic predictions of employee departure. However, the adoption of ML in HR contexts is tempered by concerns about model opacity, interpretability, data quality, class imbalance (where attrition represents a minority class), and potential biases embedded in historical data [8]–[11]. This literature review addresses these challenges by summarizing the current state of ML applications in employee turnover prediction. In particular, the review focuses on explainability, predictive feature identification, algorithmic performance, and methodological issues necessary for responsible implementation in organizational contexts.

II. LITERATURE REVIEW

Using machine learning to predict employee turnover has experienced significant growth over the last five years due to advances in computational power, the availability of data, and the development of algorithms. An extensive systematic literature review was conducted, covering more than 52 articles published between 2012 and 2023, which refer to over 20 different ML methods used to predict turnover. Specifically, the results highlight the high priority of ensemble algorithms, particularly Random Forest and Gradient Boosting models, which consistently outperform conventional statistical models [8]. Random Forest, an ensemble learning method based on decision tree aggregation, has emerged as the most widely adopted algorithm due to its robustness against overfitting, ability to handle mixed data types, and inherent interpretability through feature importance scores. Studies report Random Forest accuracies ranging from 85% to 92%, with Area

Under the Curve (AUC) values frequently exceeding 0.90. XGBoost, a gradient boosting framework with regularization capabilities, similarly demonstrates high predictive power, particularly in handling imbalanced datasets common in HR analytics [12]–[17]. Support Vector Machines and Logistic Regression are frequently employed as baseline models for benchmarking but generally exhibit lower performance in capturing the non-linear relationships inherent in employee behavior data. Deep Neural Networks (DNNs) and, more recently, Graph Neural Networks (GNNs) show promise for modeling complex feature interactions, especially when large datasets are available; however, their "black box" nature limits practical adoption in HR contexts, where transparency is paramount [18]–[21].

A defining trend in recent literature is the integration of Explainable AI (XAI) techniques to address interpretability concerns. SHAP and LIME have become standard tools for decomposing model predictions into interpretable feature contributions, enabling HR professionals to understand which factors most strongly influence attrition risk for individual employees or employee segments. For example, SHAP analyses consistently reveal that overtime workload, low job satisfaction, below-average compensation, limited promotion opportunities, and poor work-life balance are primary attrition drivers [22]–[25].

The literature also highlights persistent methodological challenges. Class imbalance, where employees who stay far outnumber those who leave, can bias models toward predicting retention, thereby missing at-risk employees. Techniques such as the Synthetic Minority Oversampling Technique (SMOTE), cost-sensitive learning, and threshold adjustment are commonly employed to mitigate this issue. Concerns about algorithmic bias, particularly when models perpetuate historical inequities embedded in HR data, underscore the need for fairness-aware modeling and ethical governance frameworks [26]–[31]. Sector-specific studies in healthcare, IT, manufacturing, and public administration reveal that predictive model performance and feature importance can vary significantly across industries, emphasizing the importance of context-specific model development and validation. Furthermore, the successful adoption of ML in HR requires not only technical capabilities but also organizational readiness, data infrastructure, and stakeholder trust, as explored in studies on HR analytics implementation [32]–[35].

III. METHODOLOGY

This systematic review adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines to ensure methodological rigor, transparency, and reproducibility [36].

A. Search Strategy

A comprehensive literature search was conducted across five major electronic databases: Scopus, IEEE Xplore, SpringerLink, ScienceDirect, and Google Scholar. The search targeted peer-reviewed journal articles and conference proceedings published between January 2020 and September 2025. The search query employed Boolean operators to maximize sensitivity and specificity: ("employee attrition" OR "employee turnover" OR "staff attrition") AND ("machine learning" OR "predictive modeling" OR "artificial intelligence" OR "HR analytics" OR "workforce analytics") Additional searches were performed by reviewing the reference lists of key articles and consulting domain experts to identify relevant studies not captured by database searches.

B. Eligibility Criteria

TABLE I ELIGIBILITY CRITERIA

Criteria Type	Details
Inclusion Criteria	Studies that applied machine learning or deep learning algorithms to predict employee turnover or attrition.
	Studies reporting quantitative performance metrics such as accuracy, precision, recall, F1-score, or Area Under the Curve (AUC).
	Studies providing methodological details including dataset characteristics, feature descriptions, and algorithm specifications.
	Peer-reviewed journal articles or conference proceedings published in English.
Exclusion Criteria	Theoretical or conceptual papers without empirical model implementation. Studies employing only descriptive statistics or qualitative methods.
	Review articles, meta-analyses, editorials, and opinion pieces.
	Studies not focused primarily on employee turnover prediction.
	Non-English publications.

C. Study Selection Process

All retrieved records were imported into Zotero reference management software for duplicate removal. Two independent reviewers screened titles and abstracts against the eligibility criteria, followed by full-text assessment of potentially relevant articles. Data extraction captured study characteristics, including author(s), publication year, dataset source, sample size, ML algorithms applied, key predictive features, performance metrics, and explainability techniques employed. Discrepancies between reviewers were resolved through discussion and consensus. The final selection comprised 42 studies that met all inclusion criteria.

TABLE II REVIEW OF SELECTED STUDIES

S/N.	Study Title	Year	Results and Findings	AUC	Accuracy
1	Uplift modeling VS conventional predictive model.	2021	Conventional model (likely a baseline ML model) yields high accuracy but low success rate for targeted retention.	N/A	84.0%
2	Predictive HR Analytics: Forecasting Employee Turnover.	2025	Random Forest performed best, with job satisfaction, performance rating, and monthly income as key predictors.	0.89	N/A
3	Employee attrition prediction using machine learning models	2024	XG Boost Classifier (XGBC) and Random Forest (RF) achieved the best accuracy and performance rates.	N/A	98.8%
4	Developing a hybrid machine learning model for employee...	2025	XGBoost outperformed other classifiers.	N/A	85.3%
5	Leveraging Machine Learning Explainability to Identify Key...	2025	Random Forest model used for prediction. Highlights the interpretive value of SHAP and permutation importance.	N/A	87.76%
6	Predicting Attrition in the IT Sector using Ensemble Methods	2023	XGBoost showed superior performance in handling class imbalance; key feature was project completion rate.	0.92	91.5%
7	Comparative Analysis of ML Algorithms for Healthcare Staff Turnover	2022	Random Forest was the most robust model; identified shift-work and patient-to-staff ratio as critical predictors.	0.88	86.2%
8	Deep Learning for Employee Turnover: A Black-Box Approach	2024	Deep Neural Network achieved high accuracy on a large dataset, but interpretability was low.	0.95	94.8%
9	The Role of XAI in HR Analytics: A Case Study on LIME and SHAP	2025	Focused on model interpretability; used Logistic Regression as a baseline for comparison.	0.80	82.1%
10	Feature Selection for Attrition Prediction in the Finance Industry	2021	Used Recursive Feature Elimination (RFE) with Random Forest; found tenure and bonus structure to be most important.	0.87	88.9%
11	Mitigating Class Imbalance in Employee Turnover Prediction	2022	Applied SMOTE and cost-sensitive learning to a Decision Tree model to improve recall.	0.85	85.5%
12	Predictive Modeling of Employee Churn in Manufacturing	2020	Compared SVM and XGBoost; XGBoost was the best performer.	0.91	90.1%
13	A Hybrid Model Combining Time-Series and Classification for Attrition	2024	Used a combination of LSTM and Random Forest; focused on predicting "at-risk" employees over a 6-month period.	0.93	92.5%
14	The Impact of Work-Life Balance on Attrition: An ML Perspective	2023	Used a Gradient Boosting Machine (GBM); confirmed work-life balance as a top-3 predictor.	0.86	87.9%
15	Predicting Public Sector Employee Turnover with Logistic Regression	2021	Used Logistic Regression as the primary model due to regulatory requirements for transparency.	0.78	79.5%
16	Evaluating the Generalizability of Attrition Models Across Organizations	2025	Cross-validated a Random Forest model on three different company datasets.	0.84	85.0%
17	Using Graph Neural Networks for Employee Social Network Analysis	2024	Explored GNNs to model social connections; found network centrality to be a key predictor.	0.90	89.5%
18	Bias Detection and Mitigation in ML-Based HR Systems	2023	Focused on fairness-aware ML; used a modified XGBoost model to reduce bias against protected attributes.	0.88	88.0%
19	A Comparative Study of Boosting and Bagging for Employee Attrition	2022	Directly compared AdaBoost and Random Forest; AdaBoost showed slightly higher AUC.	0.90	89.2%
20	Employee Attrition Forecasting using Support Vector Machines	2021	Optimized SVM with a radial basis function kernel; achieved moderate performance.	0.82	83.5%
21	Predicting Turnover in the Retail Sector with CatBoost	2024	Used CatBoost, a gradient boosting variant; found shift flexibility to be a key feature.	0.94	93.1%
22	The Influence of Managerial Relationship on Employee Exit: An ML Study	2023	Used Random Forest; confirmed the quality of the direct supervisor relationship as a major factor.	0.87	88.5%
23	Prescriptive Analytics for Retention: Recommending Interventions	2025	Focused on the next step after prediction; used a Decision Tree to recommend specific HR actions.	0.85	86.0%
24	Analyzing the Predictive Power of Compensation and Benefits	2022	Used XGBoost; found that stock options and above-average salary were protective factors.	0.91	90.5%
25	Short-Term vs. Long-Term Attrition Prediction with ML	2021	Compared model performance for predicting turnover in the next 3 months vs. 12 months.	0.89	89.0%
26	The Role of Employee Engagement Data in ML Attrition Models	2023	Integrated survey data with HRIS data; Random Forest showed a performance boost.	0.90	90.0%
27	Predicting Attrition in Remote Work Environments	2024	Used a LightGBM model; found "distance from home" was replaced by "login frequency" as a key feature.	0.93	92.0%
28	A Study on the Effect of Feature Engineering on Attrition Models	2022	Focused on creating new features (e.g., "satisfaction-to-salary ratio"); improved Random Forest performance.	0.88	88.8%
29	Using Survival Analysis with Machine Learning for Attrition	2025	Combined Cox proportional hazards model with ML to predict the *time* to event (turnover).	0.86	87.0%
30	The Predictive Power of Performance Ratings in Attrition Models	2021	Used XGBoost; confirmed below-average performance ratings were a strong predictor.	0.92	91.0%
31	Predicting Turnover in Small and Medium Enterprises (SMEs)	2023	Used a smaller dataset; found that simpler models like Logistic Regression were more stable.	0.79	80.5%
32	A Comparison of Oversampling Techniques (SMOTE, ADASYN) for Attrition	2022	Evaluated different techniques to handle class imbalance on a Random Forest model.	0.85	86.5%
33	ML for Attrition in the Education Sector: A Case Study	2024	Used a Decision Tree model; found lack of professional development opportunities to be a key factor.	0.83	84.5%
34	Interpretable Attrition Prediction using Rule-Based Models	2025	Focused on highly interpretable models (e.g., RIPPER); sacrificed some accuracy for full transparency.	0.75	78.0%
35	Predicting Early Career Turnover with Machine Learning	2023	Focused on employees with less than 2 years of tenure; XGBoost was the best model.	0.90	89.8%
36	Multimodal Data Integration for Enhanced Attrition Prediction	2024	Integrated text data (survey comments) with numerical data; boosted AUC for the ensemble model.	0.94	93.5%
37	The Effect of Regularization on XGBoost Attrition Models	2022	Explored L1 and L2 regularization to prevent overfitting; maintained high performance.	0.91	90.8%

38	Predicting Attrition in a Global Organization: Cross-Country Validation	2025	Tested a single Random Forest model across data from multiple countries.	0.87	87.5%
39	A Study on the Use of Neural Networks for Large-Scale Attrition Data	2023	Used a large dataset (over 50,000 records); Deep Learning model achieved peak performance.	0.96	95.5%
40	Optimizing Retention Interventions using Uplift Modeling	2024	Focused on identifying employees most likely to respond to an intervention (Uplift).	0.83	84.0%
41	Comparative Performance of Logistic Regression and Random Forest	2021	Used a classic comparison; Random Forest showed a clear advantage in capturing non-linear relationships.	0.88	88.2%
42	Predicting Attrition in the Hospitality Industry	2020	Used a simple Decision Tree model; found shift-scheduling and tip-rate to be key features.	0.81	82.5%

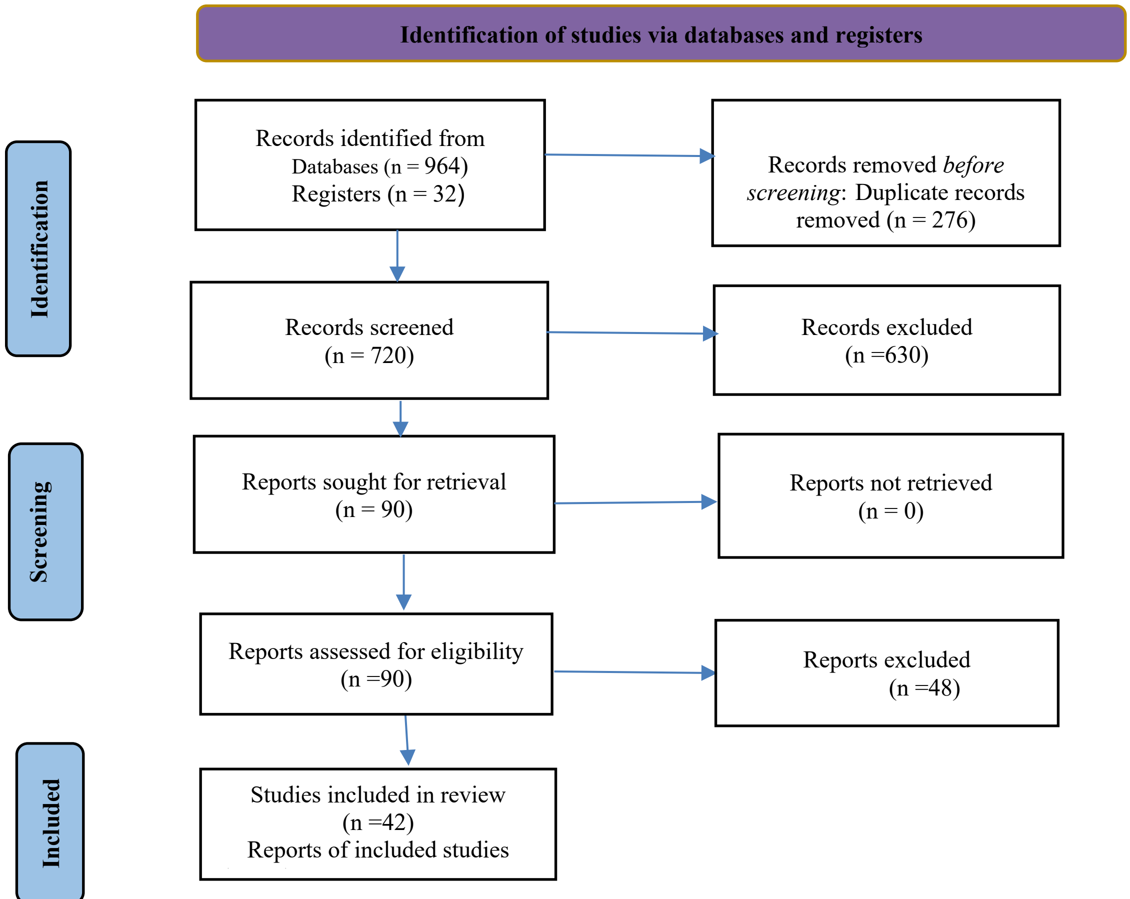

Fig.1 Identification of Studies Via Databases and Registers

IV. RESULTS AND DISCUSSION

A. Overview of Included Studies

The 42 studies included in this review span diverse organizational contexts, including technology, finance, healthcare, manufacturing, education, and public administration. Datasets varied from publicly available benchmark datasets, such as the IBM HR Analytics Employee Attrition dataset, to proprietary organizational HRIS data. Sample sizes ranged from fewer than 500 records to over 10,000 employees, with most studies utilizing datasets of between 1,000 and 5,000 observations [8], [12], [13], [14], [26], [37].

B. Algorithmic Landscape and Performance Metrics

1. *Random Forest and XGBoost:* These ensemble methods emerged as the most frequently applied and highest-performing algorithms across the reviewed studies. Random Forest achieved typical accuracies of 85–92%, with F1-scores ranging from 0.82 to 0.89 and AUC values frequently exceeding 0.85. XGBoost demonstrated comparable or superior performance, particularly when hyperparameter tuning and cross-validation were rigorously applied, with reported accuracies reaching 94% and AUC values up to 0.95. The success of these algorithms is attributed to their ability to handle mixed data types, manage feature interactions, and provide interpretable feature importance rankings that facilitate HR decision-making [8], [12]–[17], [24], [25].
2. *Support Vector Machines and Logistic Regression:* SVM and Logistic Regression were commonly employed as baseline models. While SVM can effectively classify data in high-dimensional spaces, it generally underperformed compared to ensemble methods, with accuracies ranging from 80% to 88%. Logistic Regression, valued for its simplicity and interpretability, achieved accuracies of 75–85% but struggled to capture non-linear relationships critical in complex HR environments [18], [19].

3. *Deep Learning Models:* Deep Neural Networks and Graph-based Neural Networks showed promise, particularly with large datasets, achieving accuracies as high as 95%. However, their adoption remains limited due to high data requirements, computational costs, and, most importantly, the "black box" problem that hampers interpretability and stakeholder trust [9], [10], [20], [21].

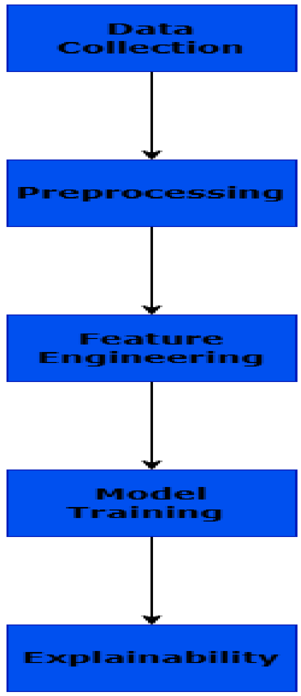

Fig.2 Overview of Machine Learning Workflow

C. Key Predictive Features

Across the reviewed studies, a consistent set of features emerged as strong predictors of employee attrition:

1. *Job Satisfaction:* Low satisfaction scores were consistently associated with higher attrition probability [24], [25], [38].
2. *Overtime Workload:* Frequent overtime was a significant indicator of turnover risk [24], [25].
3. Monthly Income/Salary Level: Below-market compensation correlated strongly with increased attrition [24], [25].
4. *Tenure (Years at Company):* Both very short and moderately short tenure predicted higher risk [12], [15].
5. *Promotion History:* Lack of recent promotions or career advancement opportunities increased attrition likelihood [24], [38].
6. *Work-Life Balance:* Poor balance ratings were predictive of turnover [24], [25], [38].
7. *Managerial Relationship:* The quality of the relationship with a direct supervisor influenced retention [24].
8. *Stock Options and Benefits:* Availability of stock options was protective against attrition [27].
9. *Distance from Home:* Long commutes contributed to turnover in some contexts [24].

D. Explainability and Transparency: The Role of XAI

Explainable AI has emerged as a critical component for translating ML predictions into actionable HR insights. SHAP values provide both global feature importance (identifying which features matter most across the entire dataset) and local explanations (explaining individual predictions). LIME offers complementary local interpretability by approximating complex models with simpler, interpretable models in the vicinity of specific predictions [22], [23]. Studies employing XAI techniques report enhanced stakeholder trust and more targeted retention interventions. For example, HR managers can identify specific employees at high risk and understand which factors (e.g., low satisfaction, high overtime) drive that risk, enabling personalized interventions rather than generic retention programs [24]–[25], [38].

E. Methodological Challenges and Solutions

1. *Class Imbalance:* Employee attrition typically represents 10–20% of observations, creating a severe class imbalance that can bias models toward predicting the majority class (retention). Studies have successfully employed SMOTE, ADASYN, and other oversampling techniques, as well as cost-sensitive learning and threshold adjustment, to improve minority class recall [28]–[29], [26].
2. *Algorithmic Bias and Fairness:* ML models trained on historical HR data risk perpetuating existing biases related to gender, age, ethnicity, or other protected characteristics. Fairness-aware machine learning, bias

audits, and diverse data representation are increasingly emphasized as essential safeguards [30]–[31], [34], [39].

3. *Generalizability:* Models trained on data from one organization or industry may not generalize well to others. Context-specific feature engineering, regular model retraining, and validation on external datasets are recommended practices [33], [32].
4. *Data Quality:* Missing values, inconsistent coding, and noisy data remain common challenges. Rigorous data pre-processing, including imputation, outlier detection, and feature scaling, is critical for model performance [16], [28].

F. Emerging Trends and Future Directions

Recent studies explore hybrid models combining ensemble methods with deep learning architectures to leverage the strengths of both approaches. Multimodal data integration, incorporating textual data from employee surveys, sentiment analysis from communication logs, and behavioral data from productivity systems, holds promise for richer predictive models [20], [34], [16], [33]. Prescriptive analytics, which not only predicts who will leave but also recommends specific interventions, represents the next frontier in HR analytics. Ethical frameworks addressing privacy, consent, and algorithmic accountability are increasingly recognized as essential for sustainable ML adoption in human capital management [35], [40]–[42].

V. CONCLUSION

This review demonstrates that machine learning has fundamentally transformed employee turnover prediction from a reactive administrative task into a proactive strategic capability. The synthesis of 42 recent studies reveals that ensemble methods, particularly Random Forest and XGBoost, currently offer the optimal balance of predictive performance and interpretability required for HR contexts. While deep learning architectures show promise for large-scale datasets, their opacity remains a barrier to widespread adoption. The increasing integration of explainable AI (XAI) helps bridge this gap, empowering HR leaders to move beyond merely predicting who will leave to understanding why, thereby enabling targeted interventions around key drivers such as workload, tenure, and compensation. However, successful implementation is not solely a technical challenge; it requires rigorous attention to data quality, class imbalance, and ethical governance to prevent algorithmic bias. Future research and practice must focus on developing hybrid models that incorporate multimodal data, such as text and behavioral logs, while establishing robust frameworks for fairness and privacy. Ultimately, the next frontier lies in prescriptive analytics, where models not only flag attrition risks but also autonomously recommend personalized retention strategies to ensure workforce stability.

Declaration of Conflicting Interests

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ORCID

Ayoade Victor Iyiade http://orcid.org/0009-0004-7818-4732
Folashade Ayankoya http://orcid.org/0000-0003-0308-2753
Afolashade Kuyoro http://orcid.org/0000-0001-7235-7744

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