IOSR Journal of Business and Management (IOSR-JBM)
e-ISSN:2278-487X, p-ISSN: 2319-7668. Volume 28, Issue 5. Ser. 1 (May. 2026), PP 38-50
www.iosrjournals.org

A Data-Driven HR Risk Assessment Framework Leveraging Predictive Analytics For Talent Management Optimization

Mrs. Venkata Rathna,
Ph.D Research Scholar, School Of Management, Hindustan Institute Of Technology & Science, Chennai

Dr. R. Ramki,
Assistant Professor (SG) & Research Supervisor, Department Of Commerce, Hindustan Institute Of Technology & Science, Chennai

Abstract
Human resource (HR) management has evolved into a strategic, data-centric function where predictive analytics plays a critical role in enhancing workforce stability, productivity, and long-term organizational performance. Traditional HR risk assessment approaches rely heavily on descriptive metrics and retrospective evaluations, which often fail to anticipate employee attrition, performance decline, and engagement risks in a timely manner. This limitation leads to increased turnover costs, talent shortages, and inefficient workforce planning. This paper introduces the ***Adaptive Workforce Intelligence and Risk Optimization Model (AWIROM)****, a novel predictive framework that integrates multi-source employee data, behavioral indicators, sentiment analytics, and performance metrics. AWIROM employs ensemble machine learning, dynamic risk scoring, and temporal trend modeling to generate individualized risk profiles. A reinforcement-based optimization layer further recommends personalized retention and development strategies aligned with organizational goals. Experimental validation on structured HR datasets demonstrates improved prediction accuracy, enhanced early-risk detection capability, and optimized talent allocation compared to conventional statistical models. The framework significantly reduces false risk alerts and improves decision reliability. The proposed AWIROM framework provides a scalable, proactive, and intelligent HR risk management solution, enabling data-driven talent optimization and sustainable workforce development.*
Keywords: *Predictive Analytics, Human Resource Management, Talent Optimization, Risk Modeling, Workforce Intelligence, Machine Learning*

Date of Submission: 26-04-2026 Date of Acceptance: 06-05-2026

I. Introduction

The HR management has increasingly shifted away to being an administrative service provider to a strategic pillar that directly determines the competitiveness and sustainability of a given organization [1]. Companies are creating enormous amounts of data of employee-related information with recruitment systems, performance management software [2], employee surveys, payroll applications, learning management systems, and internal communication (communication) systems [3]. Effective utilization of this information can facilitate evidence based decision making in that HR departments are able to match workforce capacity and long term business goals [4]. In this regard, predictive analytics has become a disruptive solution since it provides the possibility to predict trends, disruption in the workforce, and streamline the talent management policies [5].

Limitations of Traditional HR Risk Assessment

The use of HR analytics has increased, there are still a large number of organizations that use descriptive and diagnostic approaches that largely summarise past information [6]. These strategies give an understanding of what has occurred, but they may not give an indication of what could be likely to happen [7]. This has led to the absence of risk management in areas like voluntary exchanges, declining employee engagement, performance decline, absenteeism, and succession gaps being discovered frequently once they have seriously affected operations [8]. The responsive character of conventional HR risk evaluation enhances the recruitment expenses, interferes with the effectiveness of teams, and undermines the organizational resilience [9]. The traditional assessment frameworks are not flexible to dynamism in the behavior of the workforce and highly changing business conditions [10].

Need for Predictive and Adaptive HR Frameworks

In response to these restrictions, it is urgently required that smart, forecasting, and proactive HR risk assessment models be developed that can convert multi-source employee data into actionable information [11]. The contemporary organizations need systems which are not only effective at identifying the potential risks at an early stage but also suggest efficient intervention plans to specific and organizational necessities [12]. By incorporating behavioral analytics, sentiment analysis, temporal performance trends, and contextual organizational elements. It is possible to create the workforce-wide predictions of risk that can be highly accurate and reliable [13].

Overview of the AWIROM Framework

To achieve the AWIROM is intended to integrate ensemble machine learning methods, dynamic risk scoring systems, and reinforcement-driven optimization. [14]. The framework allows taking proactive actions in managing talent by creating personalized risk profiles and updating them every time new data patterns emerge [15]. Predictive intelligence combined with strategic optimization facilitates enhanced retention planning, specific skill development, and equal workforce allocation [16]. The suggested framework will help to create a strong, data-powered HR ecosystem that will raise organizational performance and sustainability of the workforce in the long term [17].

Problem Statement

Companies are increasingly relying on data to control the performance of their workforce, and the current systems of HR risk assessment are mostly reactive and descriptive. The conventional models are not able to predict attrition, loss of engagement and unstable performance in time, so intervention becomes difficult. Lack of living risk profiling and optimization processes translates to lack of efficiency in talent allocation, high turnover costs, low productivity and poor strategic planning in work force in competitive settings.

Main Contributions

- The AWIROM is proposed to be developed and utilize multi-source data of employees together with ensemble learning. To profile the risk of each in workforce dynamically and individually.
- Proactive predictive early-risk identification with behavioral and sentiment analytics and temporal risk scoring.
- Use of reinforcement-based optimization that suggests individualized retention and talent development plans in accordance with the organizational goals.

Related work

Human Resource Analytics (HRA) and predictive intelligence has drastically revolutionized contemporary Human Resource Management by allowing the company to make decisions based on data on these areas: recruitment, evaluation of performance, retention and workforce planning. The literature points to the combination of artificial intelligence, machine learning, and predictive analytics as the means of enhancing the organizational performance. These developments prove the quantifiable improvement of productivity, succession planning, and predicting attrition, which qualifies the HR analytics as an essential catalyst of strategic talent management.

HR Analytics and Data-Driven Decision-Making in Workforce Performance

During the digital transformation, HR analytics and data-driven decision-making (DDDM) have become one of the strategic management tools to improve workforce management and organizational performance. It will analyze how the analytics associated with HR, which includes talent acquisition, employee performance, training and development, and engagement, affect DDDM, and hence the subsequent effect on employee productivity, retention, and organizational success. To addresses the moderating capacity of technology adoption to reinforce the effect of DDDM on major workforce outcomes [18].

The focuses on the introduction of data-driven analytics in HRM and how it promotes decision-making and organizational performance. The main task is to combine the current literature on the approaches to making use of the data analytics to optimize the main HR functions including talent acquisition, performance management, employee retention, and workforce planning. The paper presents an overall view of how data-driven insights can change the HR practices by reviewing a broad body of academic and industry literature [19].

Integration of Data Analytics in Strategic Human Resource Management

HRA is turning out to be a disruptive method of strategic talent management, allowing organizations to make evidence-based decisions during their recruitment, performance appraisal, retention and employee development. HRA offers information that can assist firms in matching human capital and business goals by combining data science methods with HR practices. It will review the development of HRA, its implication on evidence-based HR decisions, and its influence on organizational effectiveness [20].

The current business environment is highly dynamic and organizations are becoming more and more pressurized to streamline their workforce planning and succession management approaches. HRA has become an essential strategic resource helping organizations to use data-based knowledge to make knowledgeable decisions. It will discuss how HRA can help improve workforce planning and succession management through the examination of the trends in the workforce, how to predict future needs and which employees have high potential. Using data analytics, organizations can make proactive changes to their talent acquisition, growth, and maintenance strategies to match workforce potential with organizational objectives [21].

Predictive Analytics and AI-Driven Talent Optimization

Examines the transformational nature of predictive analytics within the Human Resource Information Systems (HRIS) with a focus on the strategic implications of this technology on predicting talent, optimizing the human resource, and making decisions in an organization. Based on the review of 155 peer-reviewed articles, the review indicates that predictive HRIS have transformed the processes of HR planning into reactive and spreadsheet-based to proactive and algorithm-driven forecasting tools. The results show that the internal mobility, attrition reduction, and accuracy in leadership succession planning increased in the organizations that applied predictive analytics [22].

A field in the HRM that has become highly significant in the success of the organization is found to be often problematic in adapting to new needs of a diverse and dynamic workforce. Thus, the integrative preference to Artificial Intelligence (AI, specifically, Deep Learning and Natural Language Processing (NLP) has been made, as required in the process of enhancing HR practices. It improved AI operated system of Sustainable Human Resource Management (SHRM) capitalizes on the application of the Deep Learning to score employee performance and employee turnover in predicting employee turnover, obtaining more than 90% success in predicting employee turnover [23].

Technological Advancements, Big Data, and Emerging Challenges in HRM

Discusses the use of the HR Analytics to make decisions in HRM that would result in a transformation using big data. The HR analytics can provide the answer by providing the actionable information to managing the workforce. To maximize the productivity and alignment of the human capital to the overall organizational goals by collecting, analyzing and interpreting large sets of employee data in a systematic way. The main theories included in the study are resource-based view and human capital theory, and such complex analytical tools as regression analysis, logistic regression to predict turnover and k-means clustering to segment workforce [24].

Discuss how artificial intelligence (AI) can be applied in HRM, especially under the recruitment, employee retention, and performance optimization. It will review numerous machine learning algorithms such as XGBoost, SVM, random forest, and linear regression in decision-making in employee-attrition prediction and talent management through a PRISMA based systematic literature review. The results indicate that the technologies may be used to automatize HR processes, minimize bias, and make the experience of employees more personal. The adoption of AI in HRM is not free of problems, with data privacy, the presence of bias in the algorithm, and resistance on the organizational level being among them [25].

Research Gap

Even though previous studies prioritize and highlight the importance of HR analytics, AI adoption, and predictive modeling, the majority of the research is dedicated to independent HR operations and functions, including recruitment, forecasting attrition, or performance management instead of risk assessment as a whole. There has been limited focus on individualized risk profiling of workforce as well as dynamic workforce risk profiling and optimization based intervention strategies. Also, not many models employ adaptive temporal risk scoring, or they use strategic alignment. Hence, the synergistic strategy that combines the predictive intelligence with tangible talent optimization has not been thoroughly investigated.

Table 1: Summary Of Related Works in Hr Analytics

Ref.	Study Focus	HR Analytics	Predictive Modeling	AI / ML Integration	Workforce Planning	Risk Profiling	Optimization Strategy
[18]	HR Analytics & DDDM Impact Study	✓	✓	✗	✓	✗	✗
[19]	Data-Driven HR Review	✓	✗	✗	✓	✗	✗
[20]	Strategic Human	✓	✓	✓	✓	✗	✗

	Resource Analytics						
[21]	Workforce Planning & Succession Analytics	✓	✓	✗	✓	✗	✗
[22]	Predictive Analytics in HRIS	✓	✓	✓	✓	✗	✗
[23]	AI-Based Sustainable HRM Framework	✓	✓	✓	✓	✓	✗
[24]	Big Data HR Analytics Models	✓	✓	✓	✓	✓	✗
[25]	AI in Recruitment & Retention	✓	✓	✓	✓	✓	✗

II. Proposed Method

AWIROM approach to data-driven HR risks assessment and talent management optimization. The model amalgamates multi-source employee data, sophisticated feature engineering, and ensemble predictive modeling and reinforcement-based optimization to study workforce dynamics. The suggested solution will allow recognizing risks associated with employees and ensuring better HR interventions to enhance the stability of the workforce. Organizational performance by addressing them proactively with predictive risk profiling and intelligent decision strategies.

Multi-Source Data Integration

The first step of the AWIROM model that is concerned with combining disparate HR data sources to build an analytical data structure. Structured databases (payroll and performance records, semi-structured engagement surveys, unstructured employee sentiment feedback), external market data are all structured databases to which the system gathers information.

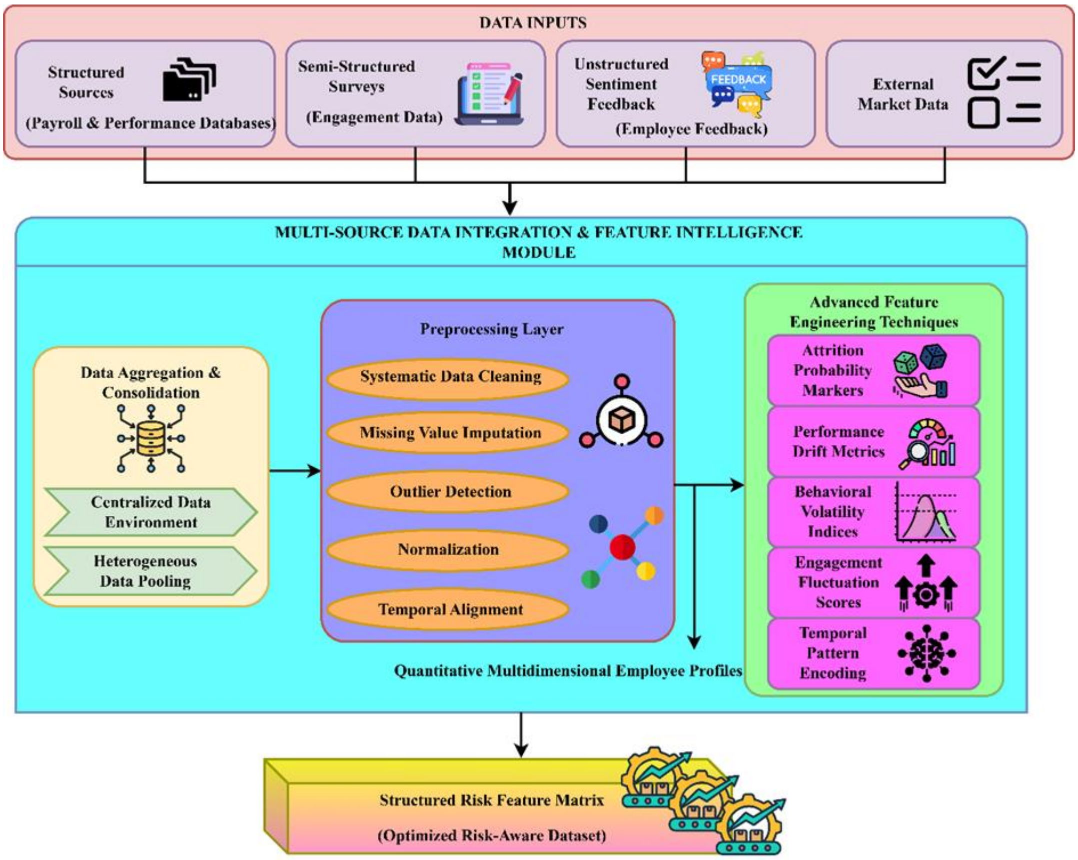

Fig 1: Multi-Source Data Integration and Feature Intelligence Module

Fig1 shows these inputs are centralized by the data aggregation layer which guarantees cross-source consistency. Systematic data cleaning, missing value imputation, outlier detection, normalization and temporal alignment is then done by a preprocessing module. After preprocessing, more sophisticated feature engineering models produce valuable risk signals, such as attrition probability signals, performance drift signals, behavioral volatility signals, engagement fluctuation signals, and encoding of temporal patterns. Engineered attributes generate quantitative multidimensional employee profiles, which are converted into a structured risk feature matrix. This streamlined dataset is used as the base input to the further predictive risk modelling and intelligent workforce analysis in the framework of AWIROM.

Feature construction and risk signal generation F_i processed using equation 1

$$\mathrm{F}_i = \phi\left(\mathcal{N}\left(\mathcal{P}\left(\mathrm{X}_i^{HR}, \mathrm{X}_i^{Perf}, \mathrm{X}_i^{Beh}, \mathrm{X}_i^{Temp}\right)\right)\right) \quad (1)$$

This equation represents the engineered feature vector for employee i. The variables X_i^{HR}, X_i^{Perf}, X_i^{Beh}, and X_i^{Temp} correspond respectively to structured HR records. The operator $\mathcal{P}$ represents preprocessing functions. The normalization function $\mathcal{N}$ standardizes scaled attributes to maintain comparability across dimensions.

Structured risk feature matrix construction R processed using equation 2

$$\mathrm{R} = \begin{bmatrix} \mathrm{F}_1 \\ \mathrm{F}_2 \\ \vdots \\ \mathrm{F}_N \end{bmatrix} - \left[r_{ij}\right]_{N\times M} \quad (2)$$

The matrix $\mathrm{R} \in \mathbb{R}^{N\times M}$ represents the aggregated risk intelligence dataset, where N denotes the total number of employees and M denotes the total number of engineered risk features. Each row F_i corresponds to the engineered feature vector of employee i. The element r_{ij} indicates the numerical value of the j-th risk feature for the i-th employee.

Predictive Risk Profiling and Dynamic Scoring Engine

The predictive intelligence aspect of AWIROM framework which estimates workforce risk. The risk feature matrix generated in the last step is structured and fed to a hybrid ensemble of learning architecture that consists of an array of parallel predictive models.

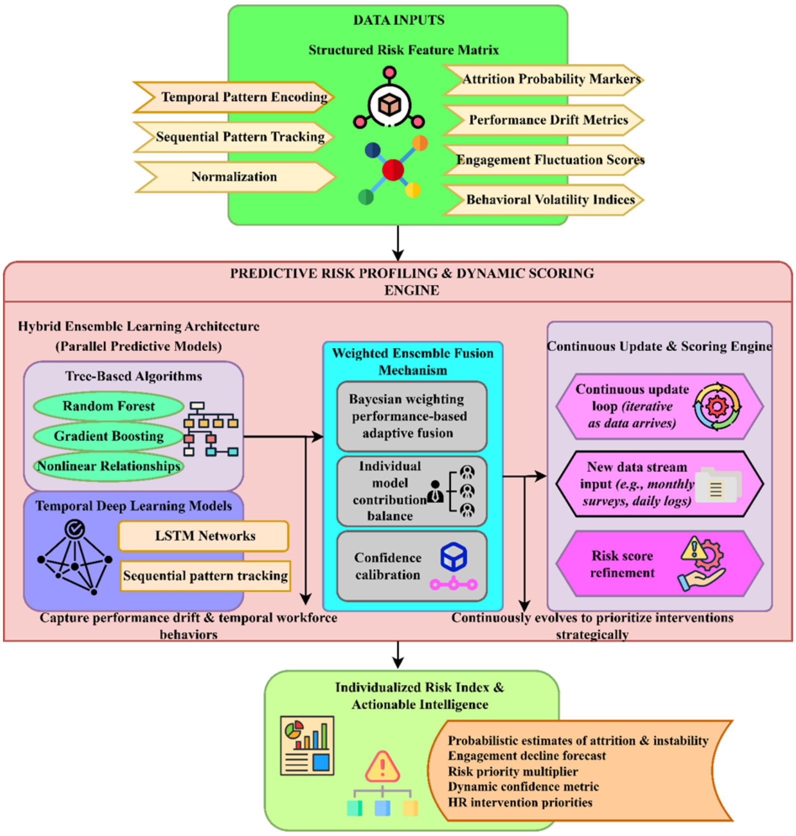

Fig 2: Predictive Risk Profiling and Dynamic Scoring Engine

Fig 2 gives Random Forest and Gradient Boosting are tree-based algorithms that can be used to examine nonlinear correlation between workforce factors and possible risk event. Simultaneously, sequential dynamics, performance trend, and changing behavioral trends in employee data are learned by temporal deep learning models, including Long Short-Term Memory (LSTM) networks. Predictive outputs of these models are combined through a weighted ensemble fusion mechanism according to Bayesian weighting, contribution balancing and confidence calibration to achieve high predictive reliability. An operational risk prediction flow is further optimized by a continuous update and scoring engine that takes new organizational data streams, including monthly surveys, operational logs, etc. The module eventually creates customized risk indexes and actionable intelligence towards pro-HR decision making.

Bayesian-weighted ensemble risk prediction $\hat{y}_i$ defined using equation 3

$$\hat{y}_i = \sum_{k=1}^{K} w_k^{(B)} \, f_k(\mathrm{F}_i) \quad (3)$$

The term $\hat{y}_i$denotes the final predicted risk score, which may correspond to attrition likelihood, performance degradation probability. The function $f_k(\mathrm{F}_i)$ represents the predictive output of the *k*-th model applied to the engineered feature vector F_i generated from the previous module. In this framework, f_k may correspond to tree-based models.

Dynamic risk score update with streaming data $S_i^{(t)}$ evaluated using equation 4

$$S_i^{(t)} = \lambda S_i^{(t-1)} + (1-\lambda)\, \hat{y}_i^{(t)} \quad (4)$$

The term λ represents the updated operational risk index for employee *i* at time period *t*, while $S_i^{(t-1)}$denotes the previous risk score. The value $\hat{y}_i^{(t)}$corresponds to the newly generated ensemble prediction derived.

Algorithm 1: Adaptive Workforce Intelligence and Risk Optimization Model (AWIROM)
Input: *Multi-source HR dataset* $D = \{X_s, X_{se}, X_u, X_e\}$, *feature matrix* $X \in \mathbb{R}^{n \times m}$, *target labels* y
Output: *Individual risk score* R_i*and optimized HR strategy* S_i
1. Initialize dataset $X^{(0)} \leftarrow merge(X_s, X_{se}, X_u, X_e)$
2. Preprocess data: $X^p \leftarrow clean(X^{(0)})$
3. For $i = 1$*to* n*do normalize* x_i*, impute missing values, detect outliers end for*
4. Construct feature matrix $F = [f_1, f_2, \ldots, f_k]$*using behavioral and performance metrics*
5. Initialize attention heads H*and weight matrices* W_h^Q, W_h^K, W_h^V
6. For $h = 1$*to* H*do*
7. $Q_h = FW_h^Q$, $K_h = FW_h^K$, $V_h = FW_h^V$
8. $A_h = softmax\left(\frac{Q_h K_h^T}{\sqrt{d_k}}\right)$
9. $Z_h = A_h V_h$
10. End for
11. Concatenate heads $Z = concat(Z_1, Z_2, \ldots, Z_H)$
12. Compute representation $Z^* = ZW^O$
13. Train ensemble models $M_1 = RF(Z^*), M_2 = GB(Z^*), M_3 = LSTM(Z^*)$
14. Predict probabilities p_1, p_2, p_3*from each model*
15. Compute risk score $R_i = \sum_{k=1}^{3} w_k\, p_k$
16. Update dynamic risk $R_i^{t+1} = \alpha R_i^t + (1-\alpha)\hat{R}_i$
17. Define state $s_t = (R_i, role_i, skill_i)$*and action set* $A = \{retain, train, reassign\}$
18. Select optimal action $a_t = arg\ max\ Q(s_t, a)$
19. Update reinforcement reward $Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \eta[r_t + \gamma max\ Q(s_{t+1}, a) - Q(s_t, a_t)]$
20. Output final risk score R_i*and optimized HR strategy* S_i

The AWIROM algorithm combines multiple source HR data and does preprocessing and normalization as well as feature engineering to build a structured risk feature table. The informative representations are obtained by a multi-head attention mechanism and then ensemble learning is implemented with the help of Random Forest, Gradient Boosting, and LSTM models to make predictions about the risk scores of employees. An optimization module of the reinforcement learning algorithm is then used to optimize the HR interventions by choosing the strategy that will result in the highest possible workforce stability and retention.

Reinforcement-Based Optimization

The last component of AWIROM framework is the conversion of predictive insights into optimal HR intervention strategies. Risk profiles created by the predictive engine at the individual level are used as input to a recursive-based optimisation module.

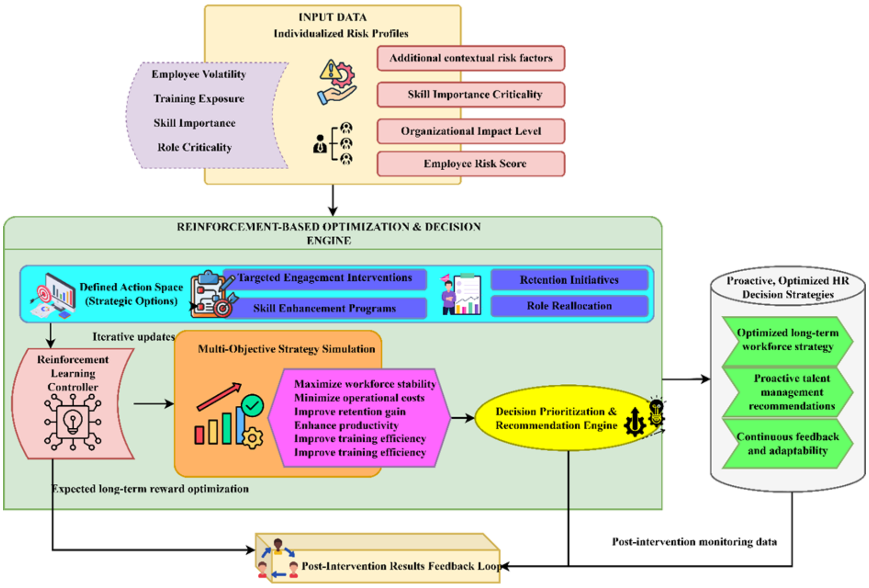

Fig 3: Reinforcement-Based Optimization and Decision Engine

Fig 3 shows the system measures the situational workforce variables, including employee volatility, training exposure, skill significance, role critical and level of organizational impact. As per these inputs, a specific action room is generated comprising of focused engagement activities, retention plans, skills development options, and restructuring of roles. A reinforcement learning controller is an iterative simulator that simulates decision policies and compares the results by means of multi-objective strategy optimization. The objective functions are going to focus on establishing workforce stability, retention gains, productivity and reducing costs of operations. The engine then suggests the best HR practices through a decision prioritization engine. Post intervention monitoring also provides continuous feedback that improves the decision model making it adaptable and sustainable to manage talent.

Multi-objective reward function R_t dealt using equation 5

$$R_t = \alpha_1 \, \Delta W_t + \alpha_2 \, \Delta Ret_t + \alpha_3 \, \Delta Prod_t - \alpha_4 \, C_t \quad (5)$$

The term $R_t$denotes the overall reward obtained after implementing a specific HR action. The variable ΔW_trepresents the measured improvement in workforce stability. The term ΔRet_tindicates retention gain, reflecting reductions in attrition probability or voluntary exits following targeted interventions. The variable $\Delta Prod_t$captures productivity improvement. The cost term $C_t$denotes the financial and operational expenditure. The coefficients $\alpha_1, \alpha_2, \alpha_3, \alpha_4$are strategic weighting parameters that balance competing organizational priorities.

Optimal policy learning via value function maximization $Q^*(s_t, a_t)$ processed using equation 6

$$Q^*(s_t, a_t) = \mathbb{E}\left[R_t + \gamma \max_{a_{t+1}} - Q^*(s_{t+1}, a_{t+1})\right] (6)$$

The term R_t denotes the optimal expected cumulative value $\mathbb{E}$ of taking action $a_t$in workforce state s_t. The state $s_t$is a structured representation of situational workforce a_{t+1} variables at time t, including employee volatility metrics γ.

III. Experimental Setup

Table 2: Description of HR Analytics Employee Attrition and Performance Dataset

Attribute	Description
Dataset Name	HR Analytics: Employee Attrition and Performance
Data Source	Organizational HR records (Kaggle public dataset)
Time Resolution	Employee-level static and periodic performance records
Duration	Multi-year employee records (historical workforce data)
Employee Parameters	Age, gender, job role, department, education, experience, salary, promotion history
Performance Parameters	Performance rating, job involvement, work-life balance, training hours
Engagement & Satisfaction Parameters	Job satisfaction, environment satisfaction, relationship satisfaction
Attrition Label	Employee Attrition (Yes/No classification target)
Data Level	Individual employee-level records
Applications	Attrition prediction, talent risk assessment, workforce analytics, retention strategy modeling, ML model training
Format	CSV

The table provides an organized summary of HR Analytics: Employee Attrition and Performance data set. It has employee demographics, performance measures, engagement measures, and attrition labels on the individual level. The dataset enables predictive modeling of attrition analysis, labor risk, and talent optimization, which is why it is applicable to machine learning-based HR decision support systems [26].

IV. Result And Discussion

The experimental study measures the effectiveness of the suggested AWIROM framework using several predictive and optimization measures. It is compared to the already available HR analytical models to evaluate the increase in the accuracy of prediction, ability to detect risks earlier, reduce false positives, strike a balance between precision and recall, risk stability, optimization efficiency, allocation of workforce and reliability of decisions. The findings confirm the uninterrupted superiority of AWIROM and prove its efficiency as a proactive, data-driven HR risks management and optimization of talents solution.

Prediction Accuracy Improvement

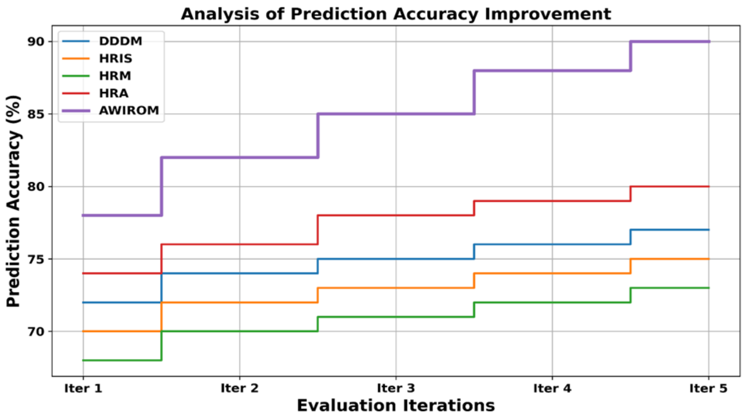

Fig 4: Analysis of Prediction Accuracy Improvement

Fig 4 is a comparison of prediction accuracy using five evaluation iterations. The proposed AWIROM model continues to beat the existing methods, increasing with 78% in the first iteration and 90% in the last iteration with 5. The best current model (HRA) takes the value of 80% at the fifth iteration. The continuous positive curve of the AWIROM shows better learning stability and generalization. The fact that its margin of improvement is around 10% - 15% over the baseline models raises the need to note that the model is more predictive and efficient in its workforce risk modeling.

Analysis of prediction accuracy improvement AI processed using equation 7

$$AI = \frac{Acc_{new} - Acc_{base}}{Acc_{base}} \times 100 \quad (7)$$

This equation measures the relative improvement in predictive accuracy after implementing the enhanced AWIROM framework. The variable Acc_{new} represents the classification accuracy achieved by the proposed predictive and optimization system, while Acc_{base} corresponds to the baseline model accuracy.

Early Risk Detection Lead Time

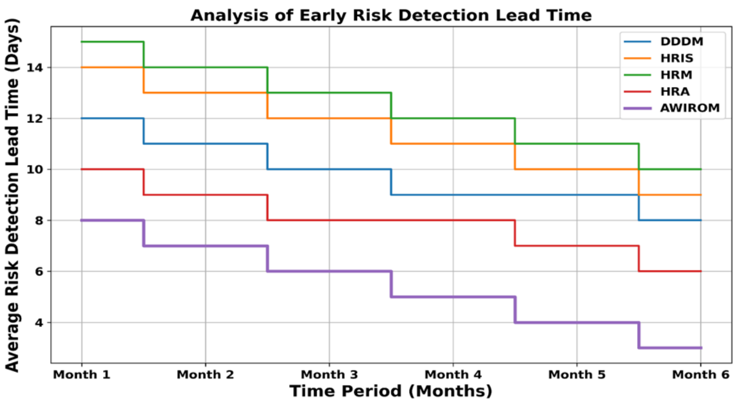

Fig 5: Analysis of Early Risk Detection Lead Time

Fig 5 is the evidence of the decreasing average risk detection lead-time within six months. AWIROM records the shortest detection time which is 8 days in Month 1 to 3 days in Month 6 with other existing models between 6-10 days. The trend of reduction is the same, which implies that risks on workforce were identified earlier. This early diagnosis is a benefit that provides intervention measures in advance. The minimized lead time shows that the time modeling and dynamic score of risk are better in AWIROM than the conventional HR analytics system.

Analysis of early risk detection lead time ELT processed using equation 8

$$ELT = \frac{1}{N}\sum_{i=1}^{N}(T_i^{event} - T_i^{detect}) \ (8)$$

This equation evaluates the average early detection advantage of the system. The variable N represents the total number of observed risk events. The value T_i^{event} indicates the actual occurrence time of risk event i, while T_i^{detect} denotes the time at which the model first flagged the employee as high risk.

False Positive Rate Reduction

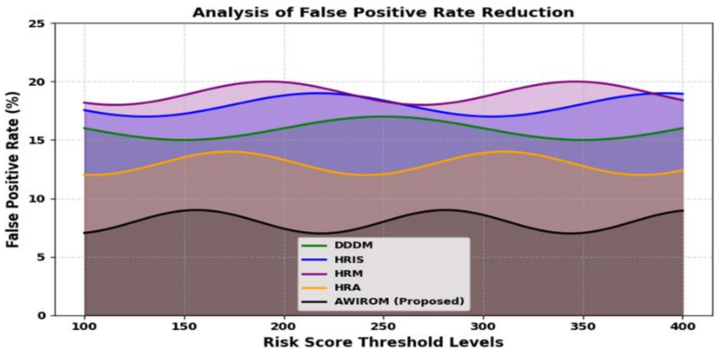

Fig 6: Analysis of False Positive Rate Reduction

Comparing false positive rates at different levels of risk score levels is assessed in Fig 6. The suggested AWIROM has the minimal false positive with the range of 7%-9%, as opposed to other models with 12%-20%. The lower error rate is an indicator of high classification accuracy and threshold sensitivity. The minimization of false risk alerts helps AWIROM to increase the reliability of decisions and minimize HR interventions. This shows good calibration and uncertainty management as compared to the current workforce prediction models.

Analysis of false positive rate reduction $FPRR$ evaluated using equation 9

$$FPRR = \frac{FPR_{base} - FPR_{new}}{FPR_{base}} \times 100 \ (9)$$

This equation measures the proportional reduction in false alarms. The baseline false positive rate FPR_{base} is computed as $\frac{FP}{FP+TN}$ under the traditional system, while FPR_{new} represents the same metric under the enhanced model.

Precision-Recall Enhancement

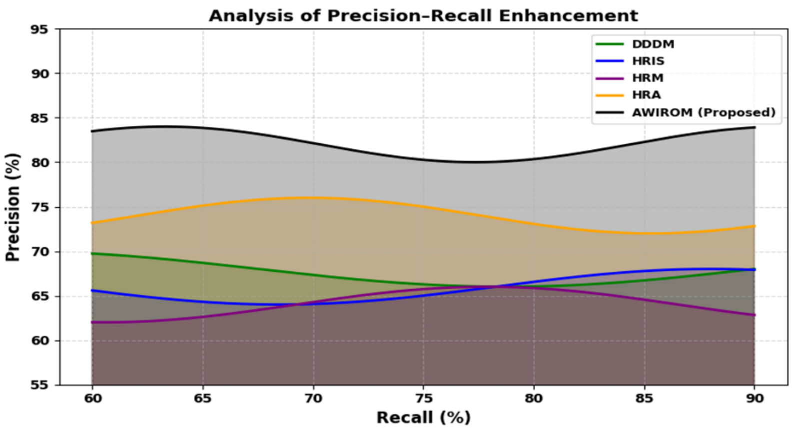

Fig 7: Analysis of Precision–Recall Enhancement

Fig 7 indicates the precision recall curve features classification effectiveness as recall level varies. The accuracy of AWIROM is extremely high (80%-84%) even at high recall (up to 90%). Current models have a range of between 62% and 76% accuracy. This high balance value implies that the discrimination ability is high and degradation of trade-off is lower. The consistent stability demonstrates the strength of AWIROM to deal with the situation of workforce risk imbalance and continue to provide accurate and reliable predictive results.

Analysis of precision–recall enhancement PRE valued using equation 10

$$PRE = \frac{2 \cdot (P_{new} \cdot R_{new})}{P_{new} + R_{new}} - \frac{2 \cdot (P_{base} \cdot R_{base})}{P_{base} + R_{base}} \quad (10)$$

This equation calculates the net improvement in the F1-score between the proposed and baseline systems. The variables P_{new} and R_{new} represent the precision and recall of the enhanced system, where precision is $\frac{TP}{TP+FP}$ and recall is $\frac{TP}{TP+FN}$. P_{base} and R_{base} correspond to the baseline metrics.

Risk Stratification Stability

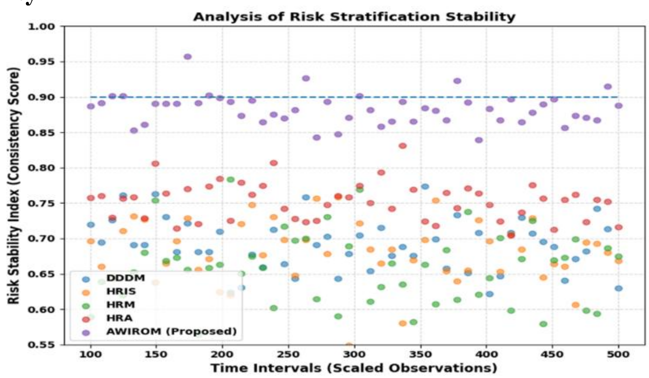

Fig 8: Analysis of Risk Stratification Stability

Fig 8 presents the assesses consistency of the stability over scaled time intervals. AWIROM exhibits the greatest stability index risk with values ranging between 0.88 and 0.92 as opposed to the current models that range between 0.60 and 0.78. The variance of workforce-related risks is decreased, which means that there is better consistency in categorizing workforce risk over time. The broken reference line around 0.90 points to the stable performance of AWIROM. This affirms the increased time-stability and decreased risk volatility in risk profiling as opposed to the conventional HR risk assessment tools.

Analysis of risk stratification stability RSS processed using equation 11

$$RSS = 1 - \frac{1}{N}\sum_{i=1}^{N} \mid S_i^{(t)} - S_i^{(t-1)} \mid \quad (11)$$

This equation quantifies the temporal consistency of employee risk categorization. The variable RSS denotes risk stratification stability. The term $S_i^{(t)}$ represents the normalized risk score for employee i at time t, while $S_i^{(t-1)}$ represents the previous score.

Optimization Efficiency Score

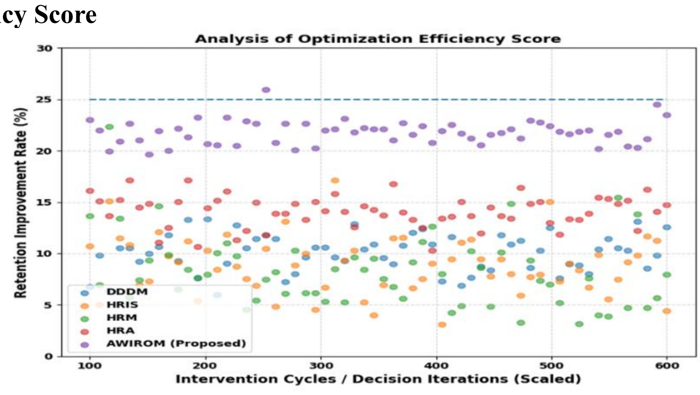

Fig 9: Analysis of Optimization Efficiency Score

Fig 9 presents the graph of the optimization efficiency which appraises the improvement rates of retention with the decision cycles. AWIROM has been proven to garner the highest retention gain which averages between 20%-26%, far exceeding that of other models which are 5%-16%. The high performance indicates the optimization of the strategy using reinforcers. The steady enhancement of the cycles justifies the capability of AWIROM to produce actionable and sustainable HR interventions with quantifiable workforce implications.

Analysis of optimization efficiency score OES dealt using equation 12

$$OES = 1 - \frac{\sum_{t=1}^{T} R_t}{\sum_{t=1}^{T} C_t} \quad (12)$$

This equation evaluates the efficiency of the reinforcement-based optimization engine. The term $R_t$represents the composite reward obtained at time step t , while $C_t$denotes the intervention cost at the same time step. The parameter Trepresents the total evaluation period.

Workforce Allocation Efficiency

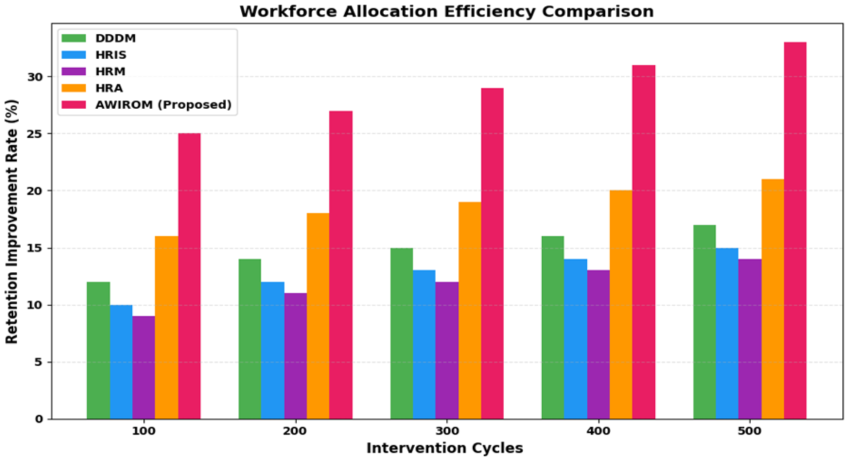

Fig 10: Workforce Allocation Efficiency Comparison

The bar graph in Fig 10 compares improvement in retention in various intervention cycles. AWIROM also demonstrates a constant rise in 25% to 33% at 100 and 500 cycles respectively compared to other competitive models at 21% or less. The increasing performance gap brings about the high efficiency in allocation and policies that optimize decisions. The unbroken upward trend proves the increased capability of AWIROM to act strategically and stabilize the workforce in the long term in relation to the conventional HR analytical methods.

Workforce allocation efficiency comparison WAE processed using equation 13

$$WAE = \frac{Prod_{opt}}{Res_{opt}} - \frac{Prod_{base}}{Res_{base}} \quad (13)$$

The variable $Prod_{opt}$represents productivity output under optimized allocation, while Res_{opt}denotes resources utilized. $Prod_{base}$and Res_{base}represent productivity and resource usage under baseline allocation methods.

Decision Reliability Index

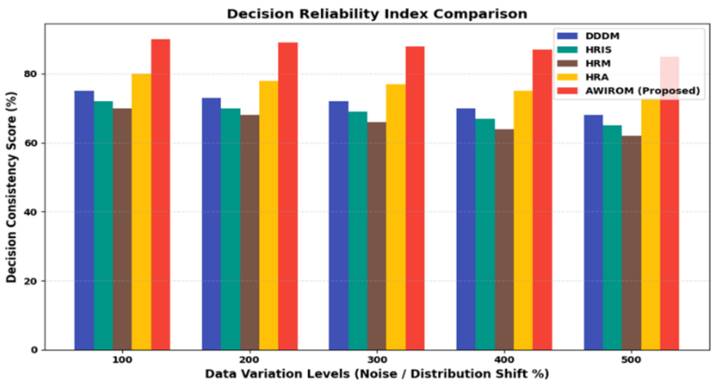

Fig 11: Decision Reliability Index Comparison

Fig 11 is a measure of the consistency of the decisions in the presence of an increasing level of data variation. AWIROM has a high reliability which declines marginally as variation increases to 90% at 100% variation and 85% at 500% variation but the existing models go lower to less than 75%. The fact that performance degradation is limited implies it has high strength against noise and distribution changes. The long-term high consistency indicates enhanced generalization, calibration and strength, justification of the reliability of AWIROM on dynamic, uncertain organizational settings.

Decision reliability index comparison DRI processed using equation 14

$$DRI = \frac{1}{M}\sum_{j=1}^{M} Con\,f_j \cdot Acc_j \quad (14)$$

This equation measures the aggregated reliability of decision recommendations. The parameter Mrepresents the number of decision scenarios evaluated. The term $Conf_j$denotes the calibrated confidence level associated with decision j, derived from ensemble probability calibration, while Acc_jrepresents whether the decision outcome was successful.

The general results indicate that AWIROM is much better in terms of accuracy, stability, efficiency of optimization, and reliability in comparison to traditional HR models. It has greater predictive accuracy, early risk identification, fewer false positives, and greater resistance to variation of data. These advancements make AWIROM a flexible and smart network of sustainable workforce risk management.

V. Conclusion

Launched the Adaptive Workforce Intelligence and Risk Optimization Model (AWIROM), which is an all-encompassing data-driven model that enables better HR risk evaluation and optimization of talent management. In the proposed model, multi-source data on employees, sophisticated feature engineering, ensemble machine learning, and reinforcement-based optimization are combined to allow taking proactive risk analysis of workforce. AWIROM forecasts employee departure and performance instability by integrating predictive intelligence, real-time risk scoring and model trend, which are used to create a customized risk profile. The experimental assessment based on HR analytics data revealed that the suggested framework is much more effective in terms of improving the accuracy of predictions, making false positive warnings less significant, and boosting the ability. To detect risks in their initial stages and increase the reliability of decisions taken in relation to standard HR analytic tools. The reinforcement-based optimization module is efficient in suggesting workforce intervention and retention plans, which in turn results in enhancing the workforce allocation efficiency and organizational stability. On the whole, AWIROM offers a predictive-based, scalable, and intelligent solution to present-day HR management. To allow an organization to utilize predictive analytics in workforce development to ensure sustainability and strategic optimization of talents.

Future Work

The future direction of work will be considered to be the incorporation of real-time HR streams of data, further sentiment analysis through natural language processing, and the explanation of the AI techniques to enhance the model transparency. The implementation of AWIROM into practice in real organizations and the further development of it with federated learning may improve the ability to scale and preserve privacy and provide cross-organizational workforce analytics.

Reference

[1]. Olayinka, Olalekan Hamed. "Leveraging Predictive Analytics And Machine Learning For Strategic Business Decision-Making And Competitive Advantage." International Journal Of Computer Applications Technology And Research 8.12 (2019): 473-486.

[2]. Al-Shammari, Minwir, Et Al. "Big Data And Predictive Analytics For Strategic Human Resource Management: A Systematic Literature Review." International Journal Of Computing And Digital Systems 17.1 (2024): 1-9.

[3]. Oladele, Oluwaseyi Kolawole. "Performance Management Analytics: Using AI To Analyze Employee Performance Data And Inform Development And Rewards Programs." 15 Aug. 2024,

[4]. Ezeafulukwe, Catherine, Chinenye Gbemisola Okatta, And Latifat Ayanponle. "Frameworks For Sustainable Human Resource Management: Integrating Ethics, CSR, And Data-Driven Insights." Journal Of Sustainable Management And Practices (2022).

[5]. Bonthu, Chandra. "Leveraging Predictive Analytics For Data-Driven Decision-Making In Enterprise Systems." Frontiers In Emerging Computer Science And Information Technology 1.01 (2024): 69-93.

[6]. Selvarajan, Guru. "Leveraging AI-Enhanced Analytics For Industry-Specific Optimization: A Strategic Approach To Transforming Data-Driven Decision-Making." International Journal Of Enhanced Research In Science Technology & Engineering 10.1 (2021): 78-84.

[7]. Kayusi, Fredrick, Et Al. "AI-Driven HR Analytics: Transforming Talent Management And Employee Engagement." Revista Multidisciplinaria Voces De América Y El Caribe:(REMUVAC) 2.1 (2025): 558-582.

[8]. Ali, Asif, And Nosheen Rafi. "Enhancing Human Resource Management Through Advanced Decision-Making Strategies: Harnessing The Power Of Artificial Intelligence For Strategic, Data-Driven, And Judicious Choices." Migration Letters 21.S8 (2024): 881-889.

[9]. Nwoke, J. "Harnessing Predictive Analytics, Machine Learning, And Scenario Modeling To Enhance Enterprise-Wide Strategic Decision-Making." International Journal Of Computer Applications Technology And Research 14.4 (2025): 123-136.

[10]. Rigamonti, Elia, Luca Gastaldi, And Mariano Corso. "Measuring HR Analytics Maturity: Supporting The Development Of A Roadmap For Data-Driven Human Resources Management." Management Decision 62.13 (2024): 243-282.
[11]. Abdelrahman, Hassan. "Artificial Intelligence In Human Resource Management: Advanced Computing Systems For Talent Analytics And Decision Making." Journal Of Advanced Computing Systems 3.6 (2023): 1-11.
[12]. Apeh, Charles Elachi, Et Al. "Advancing Workforce Analytics And Big Data For Decision-Making: Insights From HR And Pharmaceutical Supply Chain Management." International Journal Of Multidisciplinary Research And Growth Evaluation 5.1 (2024): 1217-1222.
[13]. Saling, Kristin. Data-Driven Talent Management: Using Analytics To Improve Employee Experience. Kogan Page Publishers, 2024.
[14]. Ndjama, Joelle Danielle Ngo. "Leveraging The Power Of Human Resource Analytics For Enhanced Decision Making: Opportunities And Challenges." International Journal Of Research In Business And Social Science 14.6 (2025): 53-68.
[15]. Sanjay, K., And Shweta Kaur Khalsa. "Talent Analytics For Workforce Forecasting, Fostering Employee Engagement, And Turnover Prediction." Harnessing Business Intelligence For Modern Talent Management (2025): 403-436.
[16]. Adesina, Abayomi Abraham, Toluwalase Vanessa Iyelolu, And Patience Okpeke Paul. "Leveraging Predictive Analytics For Strategic Decision-Making: Enhancing Business Performance Through Data-Driven Insights." World Journal Of Advanced Research And Reviews 22.3 (2024): 1927-1934.
[17]. Gonugunta, Krishna C., And Kornada Leo. "Role Of Data-Driven Decision Making In Enhancing Higher Education Performance: A Comprehensive Analysis Of Analytics In Institutional Management." International Journal Of Acta Informatica 3.1 (2024): 149-159.
[18]. Madhuri, A., And B. R. Kumar. "HR Analytics And Decision-Making: A Data-Driven Approach To Employee Performance Management." Journal Of Neonatal Surgery 14.7s (2025).
[19]. Okon, R. I. C. H. A. R. D., Chinekwu Somtochukwu Odionu, And B. E. R. N. A. D. E. T. T. E. Bristol-Alagbariya. "Integrating Data-Driven Analytics Into Human Resource Management To Improve Decision-Making And Organizational Effectiveness." Ire Journals 8.6 (2024): 574.
[20]. Khan, Ayesha, And Muhammad Rizwan. "HUMAN RESOURCE ANALYTICS: A DATA-DRIVEN APPROACH TO TALENT MANAGEMENT." Multidisciplinary Research In Computing Information Systems 5.8 (2025): 631-636.
[21]. Elugbaju, Wande Kasope, Nnenna Ijeoma Okeke, And Olufunke Anne Alabi. "Human Resource Analytics As A Strategic Tool For Workforce Planning And Succession Management." International Journal Of Engineering Research And Development 20.11 (2024): 744-756.
[22]. Hossain, Qaium, Md Zafor Ikbal, And Md Musfiqur Rahman. "A Meta Data-Driven Decision Support In Human Capital Management: Reviewing Hris And Predictive Analytics Integration." ASRC Procedia: Global Perspectives In Science And Scholarship 1.01 (2025): 215-246.
[23]. Miglani, Navjot Singh, And Nilesh Arora. "Optimizing Sustainable Human Resource Management Through Ai-Driven Predictive Analytics And Data-Driven Decision Models." 2025 3rd International Conference On Advancement In Computation & Computer Technologies (Incacct). IEEE, 2025.
[24]. Donthu, Somasekhar, Et Al. "HR Analytics: Leveraging Big Data To Drive Strategic Decision-Making In Human Resource Management." Journal Of Informatics Education And Research 4.1 (2024): 1541-1549.
[25]. Căvescu, Ana Maria, And Nirvana Popescu. "Predictive Analytics In Human Resources Management: Evaluating AIHR's Role In Talent Retention." Appliedmath 5.3 (2025): 99.
[26]. Https://Www.Kaggle.Com/Datasets/Mahmoudemadabdallah/Hr-Analytics-Employee-Attrition-And-Performance