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ORIGINAL

Enhancing Enterprise Human Resource Management Through Intelligent Strategies Using Hybrid Deep Learning Models

Mejorar la gestión de recursos humanos empresariales mediante estrategias inteligentes utilizando modelos híbridos de aprendizaje profundo

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ABSTRACT

Introduction: enterprise Human Resource Management (HRM), which tracks, evaluates, and improves employee performance, is essential to the expansion of a firm. However, conventional techniques like decision trees and linear regression frequently fall short in identifying intricate, non-linear relationships in employee data, which reduces their usefulness for making decisions in real time.
Objective: the research aims to develop an intelligent, accurate, and scalable model for forecasting employee performance using a hybrid Deep Learning (DL) approach called the Intelligent Water Drops Driven Dynamic Long Short-Term Network (IntWD-DynLSTN).
Method: a real-world HR dataset that includes employee information like task completion rates, training hours, attendance, and performance ratings is used to train the algorithm. Preprocessing included encoding categorical data, using Z-score normalization, and addressing missing values by imputation. High-level characteristics were extracted from the structured HR data using Convolutional Neural Networks (CNN). These attributes were subsequently fed into a Dynamic Long Short-Term Network (DynLSTN) to identify sequential patterns in monthly employee performance. Finally, model hyperparameters were adjusted using the Intelligent Water Drops (IntWD) technique to enhance generality and accuracy.
Results: experimental results show that the proposed IntWD-DynLSTN model achieves higher prediction accuracy (0,98), precision (0,97), recall (0,97), and F1-score (0,98) compared to traditional and baseline methods.
Conclusions: a scalable and dependable method for forecasting employee performance is provided by the suggested hybrid DL methodology. In dynamic organizational settings, it gives HR managers a strong tool for data-driven decision-making, facilitating quick interventions and efficient workforce management.

Keywords: Decision-Making; Employee Performance; Employee Data; Intelligent Water Drops Driven Dynamic Long Short-Term Network (IntWD-DynLSTN).

RESUMEN

Introducción: la gestión de recursos humanos (HRM) en la empresa, que realiza un seguimiento, evalúa y

mejora el rendimiento de los empleados, es esencial para la expansión de una empresa. Sin embargo, las técnicas convencionales, como los árboles de decisión y la regresión lineal, a menudo no logran identificar las relaciones complejas y no lineales en los datos de los empleados, lo que reduce su utilidad para la toma de decisiones en tiempo real.
Objetivo: la investigación tiene como objetivo desarrollar un modelo inteligente, preciso y escalable para pronosticar el rendimiento de los empleados utilizando un enfoque híbrido de aprendizaje profundo (DL) denominado Intelligent Water Drops Driven Dynamic Long Short-Term Network (IntWD-DynLSTN).
Método: para entrenar el algoritmo se utiliza un conjunto de datos de RR. HH. del mundo real que incluye información sobre los empleados, como las tasas de finalización de tareas, las horas de formación, la asistencia y las calificaciones de rendimiento. El preprocesamiento incluyó la codificación de datos categóricos, utilizando la normalización de la puntuación Z y abordando los valores perdidos mediante imputación. Se extrajeron características de alto nivel de los datos estructurados de RR. HH. utilizando redes neuronales convolucionales (CNN). Posteriormente, estos atributos se introdujeron en una red dinámica a corto y largo plazo (DynLSTN) para identificar patrones secuenciales en el rendimiento mensual de los empleados. Por último, se ajustaron los hiperparámetros del modelo utilizando la técnica Intelligent Water Drops (IntWD) para mejorar la generalidad y la precisión.
Resultados: los resultados experimentales muestran que el modelo IntWD-DynLSTN propuesto alcanza una mayor precisión de predicción (0,98), precisión (0,97), recuperación (0,97) y puntuación F1 (0,98) en comparación con los métodos tradicionales y de referencia.
Conclusiones: la metodología híbrida de aprendizaje profundo sugerida proporciona un método escalable y fiable para pronosticar el rendimiento de los empleados. En entornos organizativos dinámicos, ofrece a los responsables de recursos humanos una potente herramienta para la toma de decisiones basada en datos, lo que facilita intervenciones rápidas y una gestión eficiente de la plantilla.

Palabras clave: Toma de Decisiones; Rendimiento de los Empleados; Datos de los Empleados; Red Dinámica a Corto y Largo Plazo Impulsada por Intelligent Water Drops (IntWD-DynLSTN).

INTRODUCTION

The strategic approach to managing people in businesses to accomplish both individual and corporate goals is known as Human Resource Management (HRM).[1] To increase productivity and competitiveness, it encompasses hiring, training, development, and retention while coordinating worker performance with corporate goals. HRM encourages moral workplace conduct and makes sure labor rules are followed. It creates a motivated and effective workforce in the fast-paced world of today.[2,3,4] HRM began as clerical work but has now developed into a dynamic, data-driven field that focuses on leadership development, performance evaluation, and talent acquisition.[5,6,7]

Modern HRM systems monitor real-time performance metrics, attendance, and workforce trends, allowing organizations to respond quickly to change.[8,9,10] A strong HRM strategy encourages a positive work culture, diversity, satisfaction, and continuous learning.[9,11,12] Investments in employee training and fair practices support career growth and leadership development. HRM also improves collaboration, conflict resolution, and communication, serving as a vital driver of sustainability, innovation, and excellence in today's knowledge-based economy.[10,13,14]

The author recommended a hybrid model for enterprise Human Resource Management (HRM) risk prediction by integrating a Back Propagation Neural Network (BPNN) with an Improved Seagull Optimization Algorithm (ISOA) improved by the Whale Optimization Algorithm (WOA).[11,15,16] The work supported strategic HRM decision-making in power supply enterprises using a hybrid approach combining Recurrent Neural Network (RNN), BPNN, CNN, and a Bayesian model.[12] The research suggested improving employee performance evaluation using a Hybrid Intelligent Algorithm (HIA) integrating Cognitive Computing (CC) and DL.[13,17,18] Associated with Key Performance Indicators (KPI), Support Vector Machine (SVM), Random Forest (RF), and Decision Tree (DT), HIA improved accuracy, fairness, speed, and employee satisfaction across complex datasets.

The purpose of the research was to use the Placement-Assisted Resource Management Scheme (PRMS) to grow productivity and operational efficiency.[14] To maximize resource allocation, PRMS employed data-driven matching between employee expertise and business tasks.[19,20,21] The work suggested enhancing stress management by predicting employee stress using DL through a Stress Classification Model (SCM) and Stress Regression Model (SRM).[15] The work recommended improving HRM efficiency by developing a Salary Prediction Model (SPM) using BPNN and AI.[16,22,23] The author suggested improving risk prediction in digital HRM using AI by integrating Risk Event Chains (REC), Risk Event Graphs (REG), and an Attention Fusion Module (AFM).[17,24,25] The research developed an early warning model for HRM risks using BPNN. It involved index system design and risk factor analysis.[18,26,27,28]

The aim of this research is to develop an intelligent and scalable model for predicting employee performance accurately. It addresses the shortcomings of traditional techniques by effectively capturing complex, non-linear patterns in HR data. The proposed IntWD-DynLSTN hybrid model integrates DL and optimization techniques. This approach supports HR managers in making timely, data-driven workforce decisions.

METHOD

The methodology involves imputing missing values, applying Z-score normalization and label encoding, extracting features using CNN, modeling trends with DynLSTN, and optimizing hyperparameters using IntWD, as shown in figure 1.

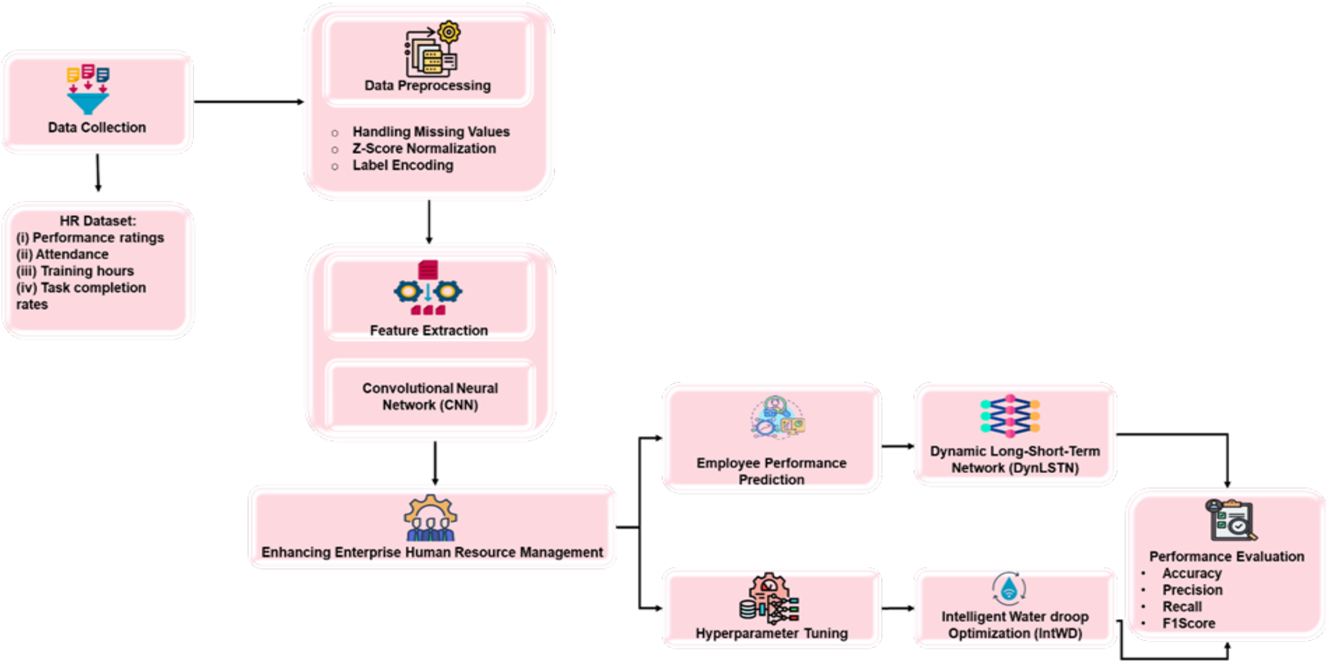


Figure 1. Framework for Intelligent Employee Performance Prediction Using IntWD-DynLSTN

Data collection

The data is collected from the Enterprise HR Performance Dataset from the Kaggle link.[19] The dataset contains time-series data on tasks, training hours, attendance, and evaluations, as well as monthly HR records for 100 employees during one year. Additionally, it includes demographic information such as department and pay range. To facilitate classification, trend analysis, and practical HR decision-making with missing numbers, employees are categorized according to their performance levels.

Data Preprocessing

Handling Missing Values

Managing missing variables was crucial to improving the precision and dependability of HRM analysis in that research. Imputation techniques like mean, mode substitution, forward filling, and interpolation were used to fill in the missing data in attributes like training hours, ratings, and attendance. Conflicting records in categorical variables were eliminated, and the most frequent value was used to maintain data integrity.

Z-Score Normalization

Z-score Normalization is a widely used preprocessing technique in data analysis and ML to standardize numerical features, according to the following equation (1).

$$v_i' = \frac{v_i - E}{std\,(E)} \quad (1)$$

Where v_i' is normalized to one value using the Z-score, vi is the row E value in the i^{th} column.

$$std(E) = \sqrt{\frac{1}{(n-1)}\sum_{i=1}^{n} \left(v_i - \underline{E}\right)^2}, \; \underline{E} = \frac{1}{n}\sum_{i=1}^{n} v_i$$

Or mean value. It transforms the data by rescaling the values so that they have a mean of 0 and a standard deviation of 1.

Label Encoding

Categorical variables were transformed into numerical form using label encoding to enable effective model training. To maintain ordinal linkages, it was applied to HR variables such as job type, department, and performance level. By guaranteeing compatibility with the IntWD-DynLSTN model, this improved learning performance and prediction accuracy while also strengthening the model's capacity to interpret categorical data.

Feature Extraction

Convolutional Neural Networks

CNNs were utilized to extract abstract features from HR data such as task completion, training hours, and attendance. By transforming inputs into an appropriate format, CNNs detected local patterns and relationships between performance metrics through convolutional layers that apply filters to produce informative feature maps. The outcome of a convolution process can be expressed mathematically in equations (2-3) as follows:

$$F_{i,j}^{(k)} = \sum_{m-1}^{M} \quad \sum_{n-1}^{N} \quad X_{i+m+j} \cdot K_{m,n}^{(k)} + b^{(k)} \qquad (2)$$

Where $F_{i,j}^{(k)}$ is the output feature map at position (i,j) for the K^{th} filter, X is the input data, K is the filter kernel, and b is the bias term. Activation functions like ReLU are applied after convolution to introduce non-linearity. Pooling layers are used to reduce dimensionality and retain dominant features. The resulting features serve as input to the DynLSTN model for learning temporal performance trends.

$$A_{i,j}^{(k)} - max(0, F_{i,j}^{(k)}). \qquad (3)$$

This step helps the model to learn complex patterns by zeroing out negative values. The resulting activated feature maps are then passed on to pooling layers and later to the DynLSTN model for capturing sequential performance trends over time.

Enhancing Human Resource Management with a Hybrid Deep Learning Model IntWD-DynLSTN Approach

The proposed research uses a hybrid DL framework combining CNN, DynLSTN, and the IntWD algorithm. CNN extracts high-level features from structured HR data, while DynLSTN captures sequential patterns in employee performance. IntWD optimizes hyperparameters to boost model accuracy, making the IntWD-DynLSTN approach effective and scalable for real-world HR applications.

Dynamic Long Short-Term Network

Employee performance data can be analyzed using DynLSTN to identify sequential patterns that show how past actions, such as task completion, training, and attendance, impact present and future results. For better temporal modeling, it improves on conventional LSTN by dynamically updating memory using the forget gate, input gate, and cell state.

Equation (4) represents the gate that determines which past information should be discarded from the memory. It is defined by the equation:

$$f_t =, \left(W_f \cdot [h_{t-1}, x_t] + \ b_t\right) \qquad (4)$$

Here, x_t denotes the input vector at time t, and h_{t-1} is the hidden state from the previous time step. The weight matrix W_f and bias b_t. Parameters are learned during training. The Softmax activation σ supports multiclass classification by producing output probabilities between 0 and 1 for performance levels like Excellent, Good, and Poor. Higher/Lower values indicate stronger/weaker confidence in assigning employees to specific performance categories.

Next, the input gate regulates what new information from the current input should be added to the memory. Equation (5) expressed as follows:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + \ b_i), \tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + \ b_C) \qquad (5)$$

The variable i_t acts as a filter for new data, and, $\tilde{C}_t$ represents the applicant values for informing the cell state, obtained through the hyperbolic tangent function, which allows both positive and negative influences to be learned. DynLSTN effectively captures both long-term trends and short-term changes in employee performance. This enhances HR decision-making by identifying consistent patterns and improving the model's overall accuracy and robustness.

Intelligent Water Drops (IntWD) optimization

The DynLSTN model's weights are tuned using a continuous optimization method adapted from the discrete IWD approach. A binary encoding scheme represents real-valued weights, with two probabilistic paths (0 and 1) at each decision node, enabling effective traversal and optimization in the neural network. The chance of choosing a path is calculated as follows:

$$P_i^{iwd}\left(e_{i,i+1}(k)\right) = \frac{f\left(soil\left(e_{i,i+1}(k)\right)\right)}{\sum_{l=0}^{1} \quad f\left(soil\left(e_{i,i+1}(l)\right)\right)} \qquad (6)$$

Equation (6) calculates the probability that an intelligent water drop (IWD) will select a particular path $e_{(i,i+1)}^{(k)}$ where k∈{0,1}. The function f(soil) reflects the desirability of a path based on the amount of "soil" on it. Paths with less soil are more likely to be chosen, simulating the natural erosion process.

Local soil is updated after each move to reflect learning:

$$soil\left(e_{i,i+1}(k)\right) = soil\left(e_{i,i+1}(k)\right) - 0{,}01 \times \triangle\, soil\left(e_{i,i+1}(k)\right) \qquad (7)$$

This equations (7-8) updates the soil level on a path after an IWD traverses it. A small portion of soil is removed, making the path more attractive in future iterations. The value 0,01 is a learning rate, and $\triangle soil(e_{i,i+1}^{(k)})$ is the soil removed per traversal, often defined by a fixed or adaptive rule.

After multiple iterations, global soil updating is applied to the best-performing solution path using:

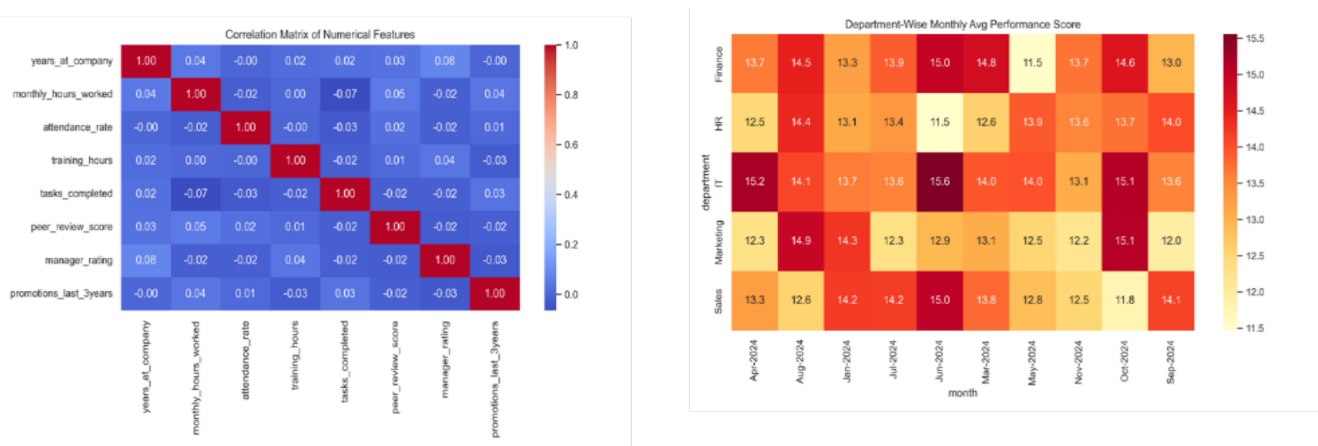
$$soil\left(e_{i,i+1}(k)\right) = min(max(TempSoil\ \left(e_{i,i+1}(k)\right), MinSoil, MaxSoil \qquad (8)$$

After all iterations are complete, the soil on paths in the best-performing solution (iteration-best path) is updated globally. This equation ensures the soil value stays within defined bounds [], preventing over-exploitation or neglect of any path. This step reinforces optimal paths while maintaining solution diversity.

RESULTS

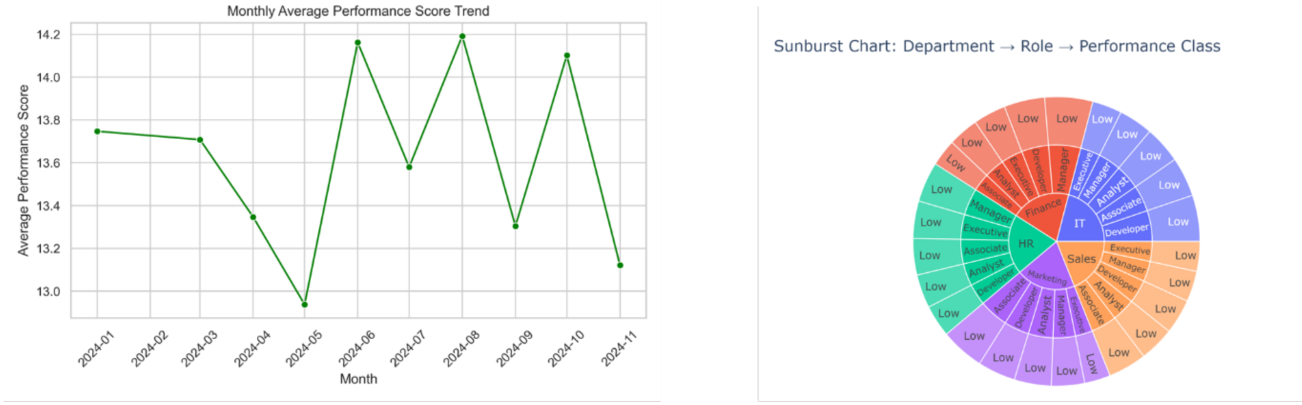
The performance of the suggested IntWD-DynLSTN model was evaluated and linked with traditional ML models, including Extra Trees and Gradient Boost using Python implementation. Metrics such as accuracy, precision, recall, and F1-score were used for benchmarking. The comparison highlights the superior predictive capability of the proposed hybrid model over existing methods.

Performance Analysis



(a) Feature Correlation Heatmap **(b) Department-wise Monthly**

Figure 2. Feature Correlation & Department-Wise Performance Trends in HR Metrics: (a) Feature Correlation Heatmap, (b) Department-wise Monthly



(a) Monthly Average Performance Score Trend

(b)Sunburst Chart; Department Role- Performance Class

Figure 3. Performance Trend Analysis and Departmental Role Mapping (a) Monthly Average Performance Score trend, (b) Sunburst Chart; Department Role-Performance Class

Comparison Analysis

Accuracy reflects the overall correctness of performance predictions, while precision shows how many of the predicted high performers were actually high performers. Recall identifies actual high performers, and the F1 Score balances both metrics, offering a reliable measure in imbalanced HR datasets.

The objective of this research is to develop an intelligent and accurate model for predicting employee performance using HR data. Figure 4 and table 1 illustrate the Comparison of Model Performance Metrics for HRM Prediction by demonstrating that the proposed IntWD-DynLSTN model achieves higher accuracy (0,98), precision (0,97), recall (0,97), and F1-score (0,98) than traditional models like Extra Trees and Gradient Boost.[20] These results validate the effectiveness of the proposed hybrid DL approach. It aligns with the research objective by offering a more reliable tool for data-driven HR decision-making.

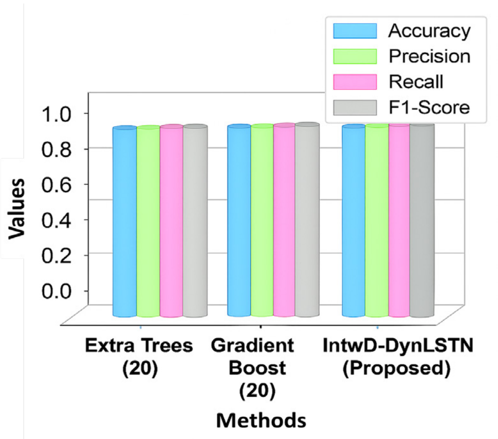


Figure 4. Comparison of Model Performance Metrics for HRM Prediction

Table 1. Performance Comparison of HRM Prediction Models Using Evaluation Metrics

Methods	Metrics			
	Accuracy	Precision	Recall	F1 Score
Extra Trees[20]	0,94	0,94	0,94	0,94
Gradient Boost[20]	096	096	096	096
IntWD-DynLSTN- [Proposed]	0,98	0,97	0,97	0,98

DISCUSSION

The intelligent, accurate, and scalable model was developed to predict employee performance by addressing the shortcomings of traditional ML techniques in managing complex, time-dependent HR data.[29,30,31] Methods

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such as Extra Trees[20] often failed to capture sequential patterns and were susceptible to overfitting without proper tuning, while Gradient Boosting[20] despite offering better accuracy, proved computationally intensive and unsuitable for real-time applications.[32,33,34] These limitations were addressed through the integration of CNN for feature extraction, DynLSTN for learning temporal dependencies, and IntWD for optimizing hyperparameters. The hybrid IntWD-DynLSTN model achieved improved generalization, higher predictive accuracy, and adaptability to evolving organizational needs.[35,36]

CONCLUSIONS

A sophisticated and accurate model was developed to forecast employee performance using HR data. The comparison showed that the proposed IntWD-DynLSTN model outperformed traditional models like Extra Trees and Gradient Boost in terms of accuracy (0,98), precision (0,97), recall (0,97), and F1-score (0,98), thereby supporting this objective. These results demonstrated the effectiveness of the hybrid DL approach. The model contributed to more reliable, data-driven HR decision-making. However, to address limitations in generalizing across different organizations, future research could explore cross-domain adaptation and real-time deployment.

BIBLIOGRAPHIC REFERENCES

1. Hamouche S. Human resource management and the COVID-19 crisis: Implications, challenges, opportunities, and future organizational directions. Journal of Management & Organization. 2023 Sep;29(5):799-814. https://doi.org/10.1017/jmo.2021.15

2. Akwei, C., & Nwachukwu, C. Contextual factors affecting strategy & HRM practices in Nigeria. International Journal of Human Resource Management. 2023; 34(16):3079–3122. https://doi.org/10.1080/09585192.2022.2104128

3. Knies E, Boselie P, Gould-Williams J, Vandenabeele W. Strategic human resource management and public sector performance: context matters. International journal of human resource management. 2024 Aug 5;35(14):2432-44. https://doi.org/10.1080/2432-44.

4. Kutieshat R, Farmanesh P. The impact of new human resource management practices on innovation performance during the COVID 19 crisis: A new perception on enhancing the educational sector. Sustainability. 2022 Mar 1;14(5):2872. https://doi.org/10.1108/S-02-2022-2872.

5. de Paúl AN, Farina P, Aranguren A, Portis A. Violence: manifestations in the health field. South Health and Policy. 2025; 4:230.

6. Nasser S, González H. Environmental Planning Strategies for the Sustainability of the Agricultural Sector. Environmental Research and Ecotoxicity. 2024; 3:114.

7. Aitken Gutierrez JH, Gamonal Torres CE, Ordoñez Mejia CA, Fernández Gastelo SX. Improving thermal comfort in educational environments: an innovative approach. Land and Architecture. 2024; 3:103.

8. Rocha C, Leitão L, Gonçalves A, Rodrigues C, Bento A filipa, Severino S, et al. Compassion fatigue, quality of care and clinical governance. Nursing Depths Series. 2025; 4:406.

9. Kim S, Vaiman V, Sanders K. Strategic human resource management in the era of environmental disruptions. Human Resource Management. 2022 May;61(3):283-93. https://doi.org/10.1002/hrm.22107

10. Wen J, Hussain H, Waheed J, Ali W, Jamil I. Pathway toward environmental sustainability: mediating role of corporate social responsibility in green human resource management practices in small and medium enterprises. International Journal of Manpower. 2022 Jul 19;43(3):701-18. https://doi.org/10.1108/IJM-01-2020-0013

11. Cahyadi A, Marwa T, Hágen I, Siraj MN, Santati P, Poór J, Szabó K. Leadership styles, high-involvement human resource management practices, and individual employee performance in small and medium enterprises in the digital era. Economies. 2022 Jul 5;10(7):162. https://doi.org/10.3390/economies10070162

12. Sypniewska B, Baran M, Kłos M. Work engagement and employee satisfaction in the practice of sustainable human resource management–based on the study of Polish employees. International Entrepreneurship and Management Journal. 2023 Sep;19(3):1069-100. https://doi.org/10.1007/s11365-023-00834-9

13. Edet Usoro I, Akhigbe RO, Promise Ogolodom M, Shuaibu A, Emeka Ezugwu E, Titi Oyegbata O, et al. Biointerfaces in sensors and medical devices: challenges, materials, and solutions for biological integration. eVitroKhem. 2025; 4:256.

14. Alejandro Gerlero M. Gamified web application with artificial intelligence for teaching programming in Spanish-speaking contexts. EthAIca. 2025; 2:55.

15. Estrada Meza RU, González Pérez MG. Analysis of public transport fares in Guadalajara, Mexico. Transport, Mobility & Society. 2023; 2:72.

16. Rodríguez-Portelles AC, Céspedes Rómulo AM. Infrared Thermography as a Diagnostic Tool in Podiatry: Advances, Applications, and Perspectives. Podiatry (Buenos Aires). 2025; 4:156.

17. Wang T, Li N, Li H. Design and development of human resource management computer system for enterprise employees. Plos one. 2021 Dec 17;16(12):e0261594. https://doi.org/10.1371/journal.pone.0261594

18. Yang Q, Tang Y. Big data-based human resource performance evaluation model using Bayesian network of deep learning. Applied Artificial Intelligence. 2023 Dec 31;37(1):2198897. https://doi.org/10.1080/08839514.2023.2198897

19. Ding M, Wu H. Risk prediction of enterprise human resource management based on deep learning. Human Systems Management. 2024 Nov 12;43(5):641-52. https://doi.org/10.3233/HSM-230064

20. Li X, Zhang L, Li D, Guo D. Construction and simulation of a strategic HR decision model based on recurrent neural network. Journal of Mathematics. 2022;2022(1):5390176. https://doi.org/10.1155/2022/5390176

21. Choque Ccanchi CA, Quintana Dragichevich CO, Meneses Claudio BA, Zapana Ruiz JA. Occupational Health and Safety Management: Impact on Work Performance and Risk Prevention. South Health and Policy. 2023; 2:62.

22. Mandelman T, Navas C. Strategies for sustainable growth in competitive environments. Environmental Research and Ecotoxicity. 2022; 1:20.

23. Almirón Cuentas JA, Bernedo-Moreira DH. Multisensory Design in Education: How Architecture Enhances the Learning Experience. Land and Architecture. 2024; 3:104.

24. Dias D, Reis J, Nunes N, Ruxa S, Severino S, Sousa L. Nurse leadership and the challenges of clinical governance in emergency settings: a theoretical and reflective analysis. Nursing Depths Series. 2025; 4:407.

25. Luo Z, Lu K. Application research and effectiveness evaluation mechanism of hybrid intelligent algorithm integrating cognitive computing and deep learning for dynamically adjusting employee performance evaluation in multi-scale organizational networks. Plos one. 2025 Dec;5(1):1-29. https://doi.org/10.1007/journal.Pone.-1-29

26. Zhao Y. Development of big data-assisted effective enterprise resource planning framework for smart human resource management. Plos one. 2024 May 20;19(5):e0303297. https://doi.org/10.1371/journal.pone.0303297

27. Zhang Y, Qi E. Happy work: Improving enterprise human resource management by predicting workers' stress using deep learning. Plos one. 2022 Apr 13;17(4):e0266373. https://doi.org/10.1371/journal.pone.0266373

28. Jiaping Y. [Retracted] Enterprise Human Resource Management Model by Artificial Intelligence Digital Technology. Economies. 2022;2022(1):6186811. https://doi.org/10.1155/2022/6186811

29. Miló Valdés CA, Pérez Acevedo LC, Vitón Castillo AA. Utility of immunoinformatics in epitope mapping for vaccine and therapeutic design. eVitroKhem. 2025; 4:152.

30. Matos Matos A. Algorithmic biases in mental health diagnoses and their impact on vulnerable populations: a documentary review of advances and challenges. EthAIca. 2022; 1:20.

31. Piñerez Díaz FJ, Sorrentino E, Caldera Molleja OA. Quality management system for Cardón Rent Car, C.A. Transport, Mobility & Society. 2025; 4:159.

32. Malagón Silva B. Trends in the use of artificial intelligence in the treatment of diabetic foot. Podiatry (Buenos Aires). 2025; 4:152.

33. Hu Y. Risk Prediction of Digital Human Resource Management Based on Artificial Intelligence. International Journal of Human Resource Management. 2022;30(1):23-33. https://doi.org/10.20532/cit.2022.1005456

34. Yan X, Deng X, Sun S. Analysis and simulation of the early warning model for human resource management risk based on the BP neural network. Complexity. 2022;2022(1):8838468. https://doi.org/10.1155/2022/8838468

35. Data Source: https://www.kaggle.com/datasets/ziya07/enterprise-hr-performance-dataset/data

36. Sinha H. Predicting Employee Performance in Business Environments Using Effective Machine Learning Models. IJNRD-Int. J. Nov. Res. Dev. 2024 Nov;9(9):a875-81. . https://doi.org/10.1155/2024/a875-81

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