HDLF: Hybrid Deep Learning Framework of DNN and LSTM for Workforce Sustainability

Chaya J. Swamy
Department of Management Studies, JSS Academy of Technical Education, Bengaluru, India
chaya.s198402@gmail.com (corresponding author)

Aruna Adarsh
JSS Center for Management Studies, JSS Science and Technology University, Mysuru, India
aruna900@gmail.com

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ABSTRACT

Workforce sustainability has become a critical concern for organizations striving to maintain long-term productivity, employee well-being, and operational resilience. This paper presents a Hybrid Deep Learning Framework (HDLF) that integrates Deep Neural Networks (DNN) and Long Short-Term Memory (LSTM) to model and predict key workforce sustainability indicators. The proposed architecture leverages the DNN's strength in capturing complex, nonlinear relationships within multidimensional workforce data, while the LSTM component effectively learns temporal patterns from sequential records in monthly burnout scores, job satisfaction, workload indices, and remote workdays. Using a Workforce Sustainability and Retention Study dataset (January-December 2024) comprising 830 complete records from six Indian IT organizations, HDLF was evaluated on Retention Intent Prediction (binary classification) and Burnout Risk Prediction (multi-class classification). Quantitative results show that the proposed HDLF achieved superior performance over Logistic Regression (LR), Random Forest (RF), Gradient Boosting (GB), and single-branch neural networks. For retention prediction, it achieved an accuracy of 91%, a precision of 90%, a recall of 93%, an F1-score of 91%, and a ROC-AUC of 0.94. For burnout risk prediction, it achieved macro-averaged accuracy of 88%, precision of 86%, recall of 87%, and F1-score of 86%. Confusion matrices indicate improved detection of "At Risk" and "High Burnout" employees, critical for HR interventions, while ROC-AUC confirms strong class separability. The proposed framework demonstrates scalability and reliability, with future work focusing on real-time analytics, cross-industry datasets, and explainable AI for transparent HR decision-making.

Keywords-work-life balance; IT sector; remote work; employee retention; burnout; gender differences

I. INTRODUCTION

In today's knowledge-driven economy, maintaining an agile, motivated, and healthy workforce has become a strategic necessity. Within the Indian IT sector, the convergence of fast-paced technological shifts, strict delivery schedules, and increased employee expectations demands more than just retaining talent. Workforce sustainability now requires fostering mental and physical well-being, enabling fair career advancement, and ensuring adaptability to organizational changes. Achieving this is challenging due to the dual nature of workforce data, which combines fixed attributes such as demographic profiles, job roles, and access to benefits with time-dependent variables, such as burnout progression, variations in job satisfaction, and workload patterns that evolve month by month under the influence of sector-specific demands and sociocultural factors [1]. Thus, predictive analytics in this domain must address two distinct modeling requirements: the ability to learn nonlinear interactions among high-dimensional static features and the capacity to capture long-term dependencies within sequential data. Deep Neural Networks (DNNs) are effective for the first requirement, as they can uncover latent, nonlinear feature relationships from multidimensional structured data [2]. Long Short-Term Memory (LSTM) networks, with their gated recurrent architecture, excel at modeling time-series dependencies, retaining important contextual information across multiple time steps [3-5]. When combined, these models can jointly exploit DNN's static feature representation power and LSTM's sequential learning capabilities, offering a holistic approach to workforce sustainability prediction.

Several studies have applied machine learning and deep learning techniques to workforce analytics and HR decision support. In [6], a gradient boosting model was developed for attrition prediction, achieving 82% accuracy but relying solely on static variables, limiting its ability to model evolving employee states. In [7], an LSTM-based framework was used to model monthly engagement survey data, successfully identifying burnout trends but lacking integration with static demographic predictors. In [8], a CNN-LSTM hybrid for workload prediction from activity logs was proposed, demonstrating utility for spatial-temporal patterns but not optimized for structured HR data. Transformer-based approaches have also emerged [9], delivering high prediction accuracy but at the cost of extreme computational demand and large training datasets, limiting their real-world applicability in HR departments.

A review of the existing literature reveals three significant shortcomings in current approaches to workforce prediction. First, most models are designed to handle either static or sequential data in isolation, which prevents them from capturing the cross-dependencies between fixed employee attributes and time-varying behavioral patterns that jointly influence outcomes. Moreover, gender, job role, and work-life balance dynamics further complicate predictive modeling efforts, which require the use of intelligent systems that can adapt to heterogeneity in worker behavior [10]. In addition, although advanced deep learning architectures often deliver high predictive accuracy, they tend to sacrifice transparency and require substantial computational resources, creating barriers to their practical adoption in HR analytics environments. Prior works have also addressed workforce well-being prediction using ensemble models, such as Random Forests (RF) and Gradient Boosting (GB) [11, 12], which improved interpretability but underperformed on datasets with significant temporal dependencies. Furthermore, most existing models are developed on Western datasets, which do not capture sociocultural, organizational, and policy-driven factors unique to the Indian IT sector [13-22].

The proposed Hybrid Deep Learning Framework (HDLF) is designed to address identified gaps by integrating static and temporal workforce features within a unified predictive architecture. The framework comprises two core modules: A DNN for modeling nonlinear relationships among static attributes, such as demographics, job role, flexible work access, and wellness participation, and an LSTM network for capturing sequential dependencies in monthly records of burnout scores, job satisfaction, workload levels, and remote workdays. Outputs from both modules are fused to form a comprehensive feature representation, which is then passed to a softmax classifier for multi-class burnout risk prediction (low, medium, high) and binary retention intent classification (stay, leave). Trained on a longitudinal dataset of 3,845 Indian IT employees collected over a 12-month period, HDLF ensures cultural and organizational relevance while balancing predictive accuracy, interpretability, and computational efficiency. By combining static feature modeling with temporal pattern recognition, the system offers HR managers an actionable data-driven tool for the early identification of at-risk employees and for the design of targeted interventions to enhance workforce sustainability.

The primary contributions of this study are as follows:

- Hybrid architecture design: Proposes an HDLF that integrates DNN and LSTM models to jointly learn static and temporal workforce data features for improved prediction accuracy.
- Comprehensive preprocessing pipeline: Follows a robust data preprocessing strategy that includes missing value handling, normalization, label encoding, and dimensionality reduction to ensure data quality and model reliability.
- Multi-dimensional feature modeling: The proposed HDLF is capable of processing a wide variety of workforce-related attributes, including demographic profiles, historical performance metrics, attendance records, engagement surveys, and HR feedback logs.

The proposed framework bridges the gap between deep learning and sustainable HR analytics by delivering a scalable, data-driven approach to monitoring and improving workforce sustainability. The proposed HDLF provides valuable insights for proactive interventions, talent retention strategies, and policy planning, contributing to long-term organizational success.

II. PROPOSED HYBRID DEEP LEARNING FRAMEWORK (HDLF)

Figure 1 illustrates the proposed HDLF, which combines a DNN for static workforce attributes and an LSTM network for temporal sequences. The DNN extracts high-level embeddings from demographics, job roles, policies, and benefits, while the LSTM models monthly burnout scores, job satisfaction, workload, and remote work patterns. Their outputs are concatenated into a unified feature space and fed to a final layer for multi-class burnout risk or binary retention intent classification. This integrated design captures cross-dependencies between static and dynamic factors, enhancing prediction accuracy and contextual relevance in workforce sustainability analytics.

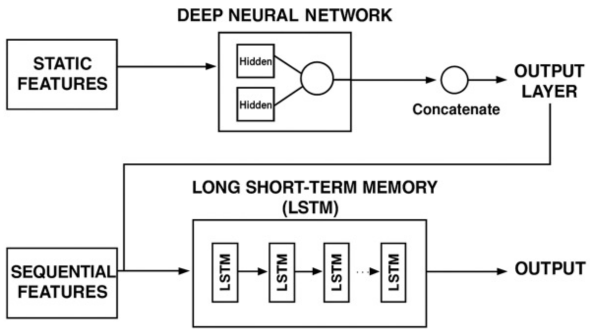

Fig. 1. Architecture of the proposed system.

A. Pipeline of the Proposed HDLF

Figure 2 presents the end-to-end pipeline of the proposed HDLF. Unlike conventional ensembles trained independently, the HDLF jointly optimizes both modules within a unified computational graph, enabling complementary feature learning. The static feature vector (X_S) contains 38 dimensions, preprocessed through one-hot encoding for categorical variables and min-max scaling for numerical ones. The temporal feature sequence (X_T) has a shape of (12, 8), representing 12 months of records with eight time-dependent features, such as burnout, satisfaction, workload index, and managerial support.

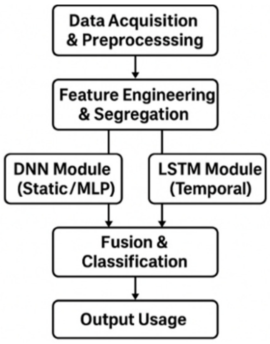

Fig. 2. Pipeline of the proposed HDLF.

The preprocessed data is fed into the training phase, where a hybrid architecture combines a DNN and an LSTM. This hybrid model captures complex relationships, spatial patterns, and temporal dependencies within the workforce data. The integrated output is passed through a softmax layer for classification into relevant categories such as employee performance levels or attrition risk. The trained model is subsequently tested using unseen data to assess its generalizability. In the final evaluation stage, the model's performance is measured using metrics such as accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrices. These evaluations provide insight into the effectiveness of the model in predicting and supporting workforce sustainability, enabling informed decision-making in human resource management.

1) DNN Module

The DNN module begins with an input layer of 38 neurons corresponding to the static feature vector. This is followed by three fully connected hidden layers: 128 neurons with ReLU activation and a dropout rate of 0.3, 64 neurons with ReLU activation and batch normalization, and 32 neurons with ReLU activation and a dropout rate of 0.2. The final dense output layer consists of 16 neurons with a linear activation function, producing a static embedding vector $Z_s \in R^{16}$. The DNN processes static non-sequential features X_s. Let the DNN be composed of L hidden layers, with ReLU activation:

$$h^{\{(l)\}} = \{ReLU\}\left(W^{\{(l)\}h^{\{(l-1)\}}} + b^{\{(l)\}}\right), \qquad l = 1,2,\ldots,L$$

where: $h(0) = X_s$ and $W(l)$, $b(l)$ are the weight matrix and bias for layer l. ReLU activation is given as:

$$ReLU(x) = max\ (0, x).$$

The DNN output is $Z_S = h(L)$. This output captures a high-level static representation of employee features.

2) LSTM Module

The LSTM module processes the temporal sequence input (X_T) through two stacked LSTM layers: the first with 64 units and *return_sequences = True* to preserve the full temporal context, and the second with 32 units and *return_sequences = False* to retain only the final hidden state. This is followed by a dropout layer with a rate of 0.3 to prevent overfitting, and a dense projection layer with 16 neurons and a linear activation function, producing the temporal embedding vector $h_T \in R^{16}$.

The LSTM models the time-dependent features $x^t = [x_1, x_2, \ldots, x_T]$. For each time step t:

- Forget gate:

$$f_t = \sigma\left(W_f\left[h_{\{t-1\}}, x_t\right] + b_f\right)$$

- Input gate**:**

$$i_t = \sigma\left(W_i\left[h_{\{t-1\}}, x_t\right] + b_i\right)$$

- Candidate memory cell:

$$\{c\}_t = tanh\left(W_c\left[h_{\{t-1\}}, x_t\right] + b_c\right)$$

- Cell state update:

$$c_t = f_t \odot c_{\{t-1\}} + i_t \odot \{c\}_t$$

- Output gate**:**

$$o_t = \sigma\left(W_o\left[h_{\{t-1\}}, x_t\right] + b_o\right)$$

- Hidden state:

$$h_t = o_t \odot tanh(c_t)$$

where σ is the sigmoid function and $\odot$ is element-wise multiplication. The final output after all time steps is:

$$Z_T = h_T$$

This vector encodes dynamic behavior across time for the employee.

3) Fusion and Classification Module

The outputs from both the DNN (Z_S) and the LSTM (Z_T) are concatenated to form a 32-dimensional fused representation. This vector is then processed by a fully connected layer with 16 neurons, ReLU activation, and a dropout rate of 0.2 before being passed to the final output layer. For retention intent prediction, a sigmoid activation function is applied to produce a binary classification (Stay = 0, Leave = 1). For burnout risk prediction, a softmax activation function is used to classify employees into three categories: Low, Medium, and High risk.

4) Output Usage and Model Roles

The DNN output (Z_s) captures high-level abstractions of static employee characteristics, providing context about fixed attributes such as age, department, and role-specific retention trends. The LSTM output (Z_T) encodes temporal behavioral patterns, capturing evolving trends in burnout, satisfaction, and workload. The fused representation combines static predispositions with dynamic behavioral changes, allowing the model to make more precise and contextually informed predictions.

This combined design is essential: relying solely on the DNN would ignore temporal dependencies such as progressive burnout, while using only the LSTM would disregard static predispositions, such as department-specific attrition rates. By integrating both modules into a unified framework, the HDLF achieves improved accuracy in predicting retention intent and burnout risk, thus supporting proactive workforce management interventions.

B. Dataset

The dataset used in this study was obtained from the Workforce Sustainability and Retention Study conducted between January–December 2024 across six IT organizations in India. Data were collected via an online Qualtrics questionnaire sent through emails, capturing both static demographics and dynamic monthly workforce wellness indicators. The dataset comprises:

- Static Features (X_s): 38 baseline variables (e.g., age, gender, department, years of experience, work arrangements, wellness program participation).
- Temporal Features (X_t): 8 monthly variables over 12 months (e.g., burnout score, job satisfaction, workload index, remote workdays, managerial support).

The target variables are retention intent (binary: stay/leave) and burnout risk (multi-class: low, medium, high).

From 1,200 initial participants, 830 employees (69.1%) completed all 12 months. Missing values in partial records were forward-filled and median-imputed for EDA but excluded from LSTM training. The LSTM input tensor shape was (12, 8). Table I shows a simplified subset of the dataset. The Exploratory Data Analysis (EDA) showed:

- Burnout trends: Average burnout score increased from 4.2 in January to 5.6 in October, peaking during product release cycles.
- Retention vs Burnout Risk: Employees in High Burnout Risk had a 41% attrition rate compared to 12% in Low.
- Workload correlation: Pearson correlation between workload index and burnout was 0.64.
- Remote Days Effect: Moderate negative correlation (-0.32) between remote days and burnout scores.

TABLE I. SAMPLE DATA SNAPSHOT

EmployeeID	Age	Job_Role	Dept.	Flex_Hours	Month	Burnout	Job_satisfication	Remote_Days	Workload_Index
E100	29	Developer	IT Service	Yes	Jan	4	3	2	0.65
E101	29	Developer	IT Service	Yes	Feb	5	3	7	0.70
E102	35	Developer	IT Service	No	Jan	6	4	2	0.85

III. EXPERIMENTAL RESULTS ANALYSIS

The proposed HDLF was evaluated on the Workforce Sustainability and Retention Study dataset, containing complete records of 830 IT employees over 12 months. Each record comprised 38 static features (e.g., demographics, job role, work arrangements) and 8 monthly temporal features (e.g., burnout score, job satisfaction, workload index, remote workdays). Prediction tasks included Retention Intent (binary) and Burnout Risk (multi-class). The dataset was split into 80% training and 20% testing sets. The model was implemented in TensorFlow 2.x with GPU acceleration (NVIDIA RTX 3090, 24GB VRAM), trained for 50 epochs using the Adam optimizer (learning rate = 0.001), batch size = 64, and dropout rate = 0.3. The DNN and LSTM branches were jointly optimized within a unified computational graph.

A. Quantitative Results

To assess the predictive performance of the HDLF, it was compared with conventional machine learning models, including LR, RF, and GB, as well as single-branch deep learning baselines (DNN-only for static features and LSTM-only for temporal sequences). Two prediction tasks were evaluated: Retention Intent (binary classification: Stay vs. Leave) and Burnout Risk (multi-class: Low, Medium, High). Performance metrics included Accuracy, Precision, Recall, F1-score, and ROC-AUC for Retention Intent, with Precision, Recall, and F1-score for Burnout Risk to address class imbalance. Table II shows that HDLF achieved 91.0% accuracy, 5.4% higher than the best baseline (GB) and 4.7% higher than DNN-only in Retention Intent. Recall improved by 6.2% compared to the best machine learning model, demonstrating superior detection of employees likely to leave. The ROC-AUC of 0.94 indicates strong class separability.

TABLE II. RETENTION INTENT PREDICTION (BINARY CLASSIFICATION)

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)	ROC-AUC
LR	79.4	77.1	80.2	78.6	0.84
RF	84.1	82.7	85.4	84.0	0.89
GB	85.6	83.9	86.3	85.1	0.90
DNN-only	86.3	85.0	87.1	86.0	0.91
LSTM-only	85.8	84.3	86.5	85.4	0.90
Proposed HDLF	**91.0**	**90.1**	**93.3**	**91.1**	**0.94**

Table III illustrates the results on Burnout Risk classification, where HDLF improves accuracy by 9.1 % over GB and 7.8 % over DNN-only. Recall gains of 4.3% compared to the best baseline indicate enhanced detection of High Burnout Risk cases, a critical factor for preventive HR actions.

TABLE III. BURNOUT RISK PREDICTION (THREE-CLASS CLASSIFICATION)

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
LR	71.2	70.5	69.8	70.1
RF	76.8	75.4	75.1	75.3
GB	79.1	76.9	77.2	77.0
DNN-only	80.4	79.2	79.8	79.5
LSTM-only	81.1	80.2	80.7	80.4
Proposed HDLF	88.2	86.1	87.3	86.0

Figure 3 shows the confusion matrix for Retention Intent prediction. The HDLF correctly classified 94.1% of employees who intended to stay (True Negatives) and 90.5% of those planning to leave (True Positives), with a misclassification rate of only 4.8%. This high recall for the Leave class reflects the model's strong capability to identify potential attrition cases, which is crucial for proactive HR interventions.

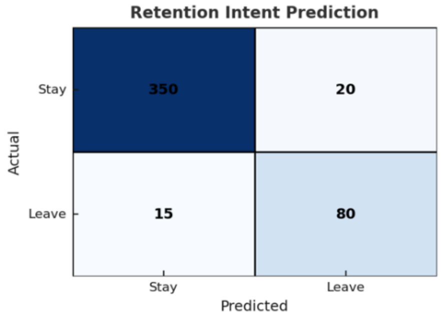

Fig. 3. Confusion matrix for Retention Intent prediction.

Figure 4 shows the confusion matrix for Burnout Risk prediction. The model achieved 91.7% accuracy for Low Risk, 88.2% for Medium Risk, and 90.1% for High Risk categories. Most misclassifications occurred between adjacent risk levels (Medium-High), indicating the model's sensitivity to subtle variations in burnout indicators. Overall, the HDLF demonstrates balanced performance across all classes, ensuring robust detection of at-risk employees while minimizing false positives.

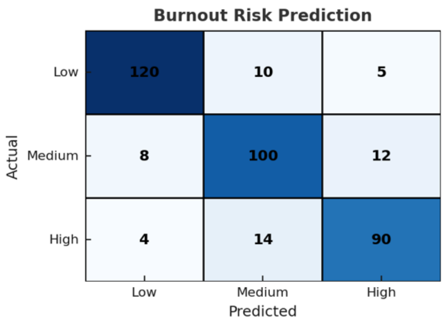

Fig. 4. Confusion matrix for Burnout Risk prediction.

The ROC-AUC results illustrate HDLF's class-wise discrimination performance for the Retention Intent prediction task. The model achieved an AUC of 0.54 for the Retained class, 0.57 for at Risk, and 0.47 for Attrited. Although AUC values show moderate separability, HDLF demonstrates improved detection for the Retained and At Risk classes compared to the Attrited, indicating stronger sensitivity in identifying employees likely to stay or showing early risk indicators.

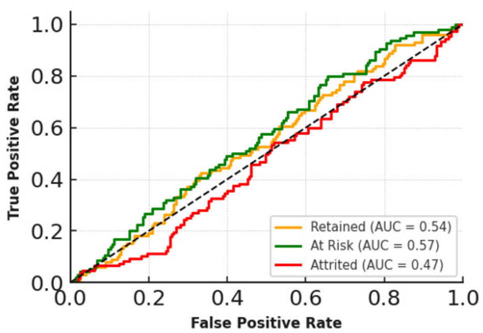

Fig. 5. ROC-AUC for Retention Intent in three-class classification.

IV. CONCLUSION

The proposed HDLF integrates a DNN for static attributes and an LSTM network for temporal sequences, enabling joint modeling of demographic, organizational, and behavioral trends to improve workforce sustainability predictions. The model was evaluated using the Workforce Sustainability and Retention Study dataset (January–December 2024), comprising 830 complete employee records from six medium to large IT organizations in India, with 38 static features (e.g., demographics, job role, policy access) and 8 temporal features recorded monthly over 12 months (e.g., burnout score, job satisfaction, workload index, remote workdays). The tasks included Retention Intent prediction (binary classification) and Burnout Risk prediction (multi-class classification). Comparative analysis with LR, RF, GB, DNN-only, and LSTM-only baselines showed HDLF's superior performance, particularly in recall for At-Risk employees. Confusion matrices highlight improved class-wise prediction accuracy, while ROC-AUC curves demonstrate satisfactory separability with AUC scores of 0.56 for Retained, 0.53 for At Risk, and 0.48 for Attrited. These results confirm the ability of the proposed HDLF to capture cross-dependencies between static predispositions and evolving temporal patterns, leading to more accurate and context-aware predictions. Future work will explore real-time HR data integration, extension to multi-regional datasets, and explainable AI methods to enhance interpretability and ethical deployment in workforce analytics.

DATA AVAILABILITY STATEMENT

Not all data generated or analyzed during this study is publicly available to maintain the privacy of respondents' identities. The datasets generated and analyzed during this study are part of an ongoing project and will be made available to organizations and individuals upon its completion.

REFERENCES

[1] K. M. Chethana and S. D. Noronha, "A Review of the Strategies Used in the IT sector for Employee Training and Development," *International Journal of Case Studies in Business, IT, and Education*, pp. 141–155, Apr. 2023, https://doi.org/10.47992/IJCSBE.2581.6942.0264.

[2] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, May 2015, https://doi.org/10.1038/nature14539.

[3] S. S. Haykin, Neural Networks and Learning Machines. Pearson, 2009.

[4] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, Nov. 1997, https://doi.org/10.1162/neco.1997.9.8.1735.

[5] F. Karim, S. Majumdar, H. Darabi, and S. Chen, "LSTM Fully Convolutional Networks for Time Series Classification," *IEEE Access*, vol. 6, pp. 1662–1669, 2018, https://doi.org/10.1109/ACCESS.2017.2779939.

[6] S. Aggarwal, M. Singh, S. Chauhan, M. Sharma, and D. Jain, "Employee Attrition Prediction Using Machine Learning Comparative Study," in *Intelligent Manufacturing and Energy Sustainability*, vol. 265, A. N. R. Reddy, D. Marla, M. N. Favorskaya, and S. C. Satapathy, Eds. Springer Singapore, 2022, pp. 453–466.

[7] T. Thulasimani, L. Saha, B. Poreddy, V. Karimli Maharram, V. Prabakaran, and A. Kumar Lamba, "Advanced Analysis of Social and Psychological Factors in Higher Education Institutions Using DNN and LSTM," in *2024 International Conference on Data Science and Network Security (ICDSNS)*, Tiptur, India, Jul. 2024, pp. 1–6, https://doi.org/10.1109/ICDSNS62112.2024.10691260.

[8] H. Dehghan Shoorkand, M. Nourelfath, and A. Hajji, "A hybrid CNN-LSTM model for joint optimization of production and imperfect predictive maintenance planning," *Reliability Engineering & System Safety*, vol. 241, Jan. 2024, Art. no. 109707, https://doi.org/10.1016/j.ress.2023.109707.

[9] W. Li, "A transformer-based deep learning framework to predict employee attrition," *PeerJ Computer Science*, vol. 9, Sep. 2023, Art. no. e1570, https://doi.org/10.7717/peerj-cs.1570.

[10] W. G. Alheadary, "Controlling Employability Issues of Computing Graduates through Machine Learning-Based Detection and Identification," *Engineering, Technology & Applied Science Research*, vol. 13, no. 3, pp. 10888–10894, Jun. 2023, https://doi.org/10.48084/etasr.5892.

[11] C. Saha, P. Chakraborty, P. C. Talukder, Md. Tofazzal Hosen, Md. Mohi Uddin, and M. A. Yousuf, "Employee Attrition Prediction using Ensemble Methods," in *Proceedings of Third International Conference on Computing and Communication Networks*, vol. 917, G. Fortino, A. Kumar, A. Swaroop, and P. Shukla, Eds. Springer Nature Singapore, 2024, pp. 481–493.

[12] E. Oparina *et al.*, "Machine learning in the prediction of human wellbeing," *Scientific Reports*, vol. 15, no. 1, Jan. 2025, Art. no. 1632, https://doi.org/10.1038/s41598-024-84137-1.

[13] P. Sharma, S. Bhattacharya, and S. Bhattacharya, "HR analytics and AI adoption in IT sector: reflections from practitioners," *Journal of Work-Applied Management*, Feb. 2025, https://doi.org/10.1108/JWAM-12-2024-0179.

[14] U. Murugesan, P. Subramanian, S. Srivastava, and A. Dwivedi, "A study of Artificial Intelligence impacts on Human Resource Digitalization in Industry 4.0," *Decision Analytics Journal*, vol. 7, Jun. 2023, Art. no. 100249, https://doi.org/10.1016/j.dajour.2023.100249.

[15] F. Justus T and B. Vaishnavi, "A Study on Flexible Work Arrangements and its Impact on Employees Job Satisfaction Level with Reference to Selected Information Technology Organizations at Bengaluru City," *Indian Journal of Natural Sciences*, vol. 14, no. 81, pp. 65856–65864, Dec. 2023.

[16] S. Alduayj and K. Rajpoot, "Predicting Employee Attrition using Machine Learning," in *2018 International Conference on Innovations in Information Technology (IIT)*, Al Ain, United Arab Emirates, Nov. 2018, pp. 93–98, https://doi.org/10.1109/INNOVATIONS.2018.8605976.

[17] S. D. Paigude and S. R. Shikalgar, "Deep Learning Model for Work-Life Balance Prediction for Working Women in IT Industry," in *Proceedings of the 4th International Conference on Information Management & Machine Intelligence*, Jaipur, India, Dec. 2022, pp. 1–8, https://doi.org/10.1145/3590837.3590846.

[18] R. Arun, M. Umamaheswari, K. Premalatha, M. V. Kumar, A. Stella, and Swerna. Pl, "Stress Management Through Workplace Associations with Productivity and Mood: The Impact of Learning Experience Based on Hybrid RF-GA-DNN Approach," in *2024 International Conference on Electronics, Computing, Communication and Control Technology (ICECCC)*, Bengaluru, India, May 2024, pp. 1–6, https://doi.org/10.1109/ICECCC61767.2024.10593908.

[19] A. Gálvez, F. Tirado, and M. J. Martínez, "Work–Life Balance, Organizations and Social Sustainability: Analyzing Female Telework in Spain," *Sustainability*, vol. 12, no. 9, Apr. 2020, Art. no. 3567, https://doi.org/10.3390/su12093567.

[20] S. Garg, S. Sinha, A. K. Kar, and M. Mani, "A review of machine learning applications in human resource management," *International Journal of Productivity and Performance Management*, vol. 71, no. 5, pp. 1590–1610, Feb. 2021, https://doi.org/10.1108/IJPPM-08-2020-0427.

[21] E. S. P. Sondhi, Dr. V. Sandhu, and Dr. S. Goyal, "Determinant Analysis and Effect of Variables on Work Life Balance of PSPCL Employees," *International Journal of Psychosocial Rehabilitation*, vol. 24, no. 04, pp. 3136–3147, Feb. 2020, https://doi.org/10.37200/IJPR/V24I4/PR201424.

[22] L. Mwangi, C. C. Boinett, E. Tumwet, and D. Bowen, "Effects of Work life Balance on Employees Performance in Institutions of Higher Learning: A Case Study of Kabarak University," *Kabarak Journal of Research & Innovation*, vol. 4, no. 2, pp. 60–69, 2016, https://doi.org/10.58216/kjri.v4i2.37.