Artificial Intelligence for Strategic Human Resource Management: A Study on AI-Driven Recruitment in IT Companies of Chennai

2025 3rd International Conference on Advances in Computation, Communication and Information Technology (ICAICCIT) | 979-8-3315-7767-4/25/$31.00 ©2025 IEEE | DOI: 10.1109/ICAICCIT68829.2025.11434434

Siva Subramani S
School of Management Studies
Vels Institute of Science, Technology and Advanced Studies (VISTAS)
Pallavaram, Chennai, Tamil Nadu, India
s.sivatrainer@gmail.com

Subburaj P
Department of BBA
Vels Institute of Science, Technology and Advanced Studies (VISTAS)
Pallavaram, Chennai, Tamil Nadu, India
mba.subburajp@gmail.com

Abstract **- Human Resource Management (HRM) systems that incorporate artificial intelligence (AI) can now do the same things that traditional hiring methods do. Artificial intelligence is a terrific tool for the field of information technology because it is growing swiftly and there is a significant demand for skilled personnel, especially in big cities like Chennai. Typical hiring processes might be slow, unfair, and not very good when there are a lot of applications. Many IT companies still have a lot of work to do before they can make their hiring procedures more efficient. This makes it tougher for the companies to keep their employees since they hire the incorrect people. Hiring new workers is one of the most important things to do while managing people in Chennai's IT companies. This study looks at how these organizations have changed the way they hire individuals since they started using AI-powered technologies. Chatbot screeners, resume parsers, and predictive analytics are some of the technologies that belong to this group. The mixed-methods approach includes structured interviews with HR professionals and quantitative comparisons of recruiting key performance indicators (KPIs) before and after AI is used. When you use artificial intelligence (AI) to hire people, it takes 35% less time, the match between candidates and jobs is 25% better, and recruiters are generally happier.**

Keywords - Artificial Intelligence, Strategic HRM, Recruitment, IT Sector, Chennai

I. INTRODUCTION

In organizational growth, the use of artificial intelligence (AI) in strategic human resource management (SHRM) is becoming more common. This is especially true for businesses that depend significantly on data and information technology. More and more human resources (HR) jobs are being made better by AI methods like machine learning, robotic process automation, and natural language processing (NLP). This is especially true when it comes to hiring [1, 2]. Artificial intelligence (AI) powers systems that use data to deliver solutions that can expand and happen in real time. These new ways of employing people are altering the previous approach, which was known for being unjust, inconsistent, and slow [3].

Chennai is becoming one of India's most important centers for information technology, and businesses there are thinking about employing AI-powered hiring tools to meet the growing demand for skilled workers. One way these technologies speed up and improve the hiring process is by automating the screening of resumes and the first interviews. People are revisiting the strategic purpose of human resource management, which is to make sure that employees' abilities are in line with the company's goals, because of recent advances in artificial intelligence.

First, algorithms are less likely to work if the data isn't standardized. This makes it tougher to use AI to hire people [4]. Second, when AI makes decisions that people can't understand, people worry about bias, data privacy, and openness [5]. If we rely too much on automation, we might not pay enough attention to factors that can't be assessed, such cultural fit, emotional intelligence, and soft skills [6].

IT organizations also have to be able to change AI technology to fit the needs of diverse areas. Most ready-made AI systems can't learn from information that is happening right now or employ recruiting methods that take the current into consideration [7]. Also, HR people don't know much about AI and are afraid of losing their jobs, which makes companies less likely to use it [6]. Because of these issues, it's vital to build AI models for managing human resources that are flexible, open, and aware of their surroundings.

AI has a lot of potential to speed up the hiring process, but the way it is employed right now doesn't always deliver the strategic value that people want it to. A lot of technology can just do things automatically; they can't even assist you plan for the future workforce. This is the main issue. Most AI tools are designed for operational convenience, not strategic alignment [6][7]. Additionally, current models lack adaptability in high-turnover environments like IT firms, where skill requirements evolve rapidly [8].

The disconnection between AI outputs and HR decision-making also poses a problem. Without integration into SHRM frameworks, AI-generated recommendations remain isolated from strategic workforce management. Consequently, organizations struggle to align hiring practices with business goals, limiting the impact of AI in HR transformation.

This study aims to explore the impact of AI on strategic HRM practices in recruitment, with a special focus on IT companies in Chennai. The specific objectives are:

- To examine the effectiveness of AI tools in improving the speed, quality, and objectivity of recruitment decisions.
- To assess how AI contributes to strategic alignment in workforce planning and talent acquisition.

- To identify challenges, biases, and limitations faced by organizations in adopting AI-driven recruitment systems.

Unlike prior research that generally focuses on AI in HR operations or recruitment automation, this study uniquely positions AI as a tool for strategic HR decision-making in the IT sector. By analyzing its application within a dynamic and high-growth market like Chennai, this research provides localized insights into how AI can be effectively aligned with organizational objectives and workforce development.

II. RELATED WORKS

Most of the research in this area has been on predictive analytics, which use AI models to look at data on past hiring and employee performance to guess how probable it is that future candidates would be successful [8–9]. This has been really beneficial in the IT field because it is vital to have certain technical abilities, be able to learn new things quickly, and know that you will have a job. According to research [10], predictive algorithms are better than human screening approaches at finding people who will be successful and stay with the organization for a long period.

The information has also helped a lot in the fight against discrimination when hiring new employees. When recruiting in the usual way, it is not unusual for there to be unconscious bias based on a person's color, gender, or degree of education. AI tools promise to reduce such biases by anonymizing candidate data and relying solely on skill- and experience-based metrics. However, some researchers [11] argue that AI systems can perpetuate biases if trained on historical data that is itself biased. Hence, the literature calls for the inclusion of explainable AI (XAI) principles to enhance transparency and fairness in hiring outcomes.

Recent research has also explored the impact of AI-powered chatbots in early-stage screening. Chatbots interact with candidates to assess communication skills, cultural fit, and initial qualifications, offering a personalized yet automated touchpoint. According to studies [12], these systems improve candidate engagement and offer HR teams real-time insights into candidate quality. However, the depth and nuance of human communication remain a challenge for chatbot-based assessments, especially in soft-skill evaluation.

Some studies go further to evaluate AI's role in strategic talent management, where the focus shifts from individual hiring events to long-term workforce planning. This involves using AI not just for identifying candidates, but for mapping skill gaps, succession planning, and aligning hiring strategies with future business needs. Research [13]-[20] highlights the potential of AI in supporting SHRM goals such as employee lifecycle management and retention prediction, although adoption in Indian IT companies is still nascent.

III. PROPOSED METHOD

The proposed method shown in figure 1, utilizes a multi-stage AI-assisted recruitment framework tailored for IT companies.

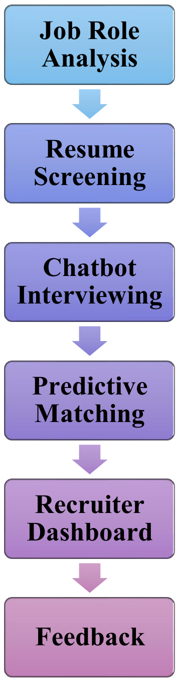

FIG.1.PROPOSED MULTI-STAGE AI-ASSISTED RECRUITMENT FRAMEWORK

A. *Pseudocode*

```
# Step 1: Job Description Analysis
job_description = input_job_description()
standard_role_profile = AI_Model.analyze_job_description(job_description)
# Step 2: Resume Screening
candidates = get_all_resumes()
qualified_candidates = []
for resume in candidates:
    parsed_data = NLP_Model.parse_resume(resume)
    if AI_Model.match_skills(parsed_data, standard_role_profile):
        qualified_candidates.append(parsed_data)
# Step 3: AI Chatbot Interview
shortlisted_candidates = []
for candidate in qualified_candidates:
    chatbot_score = Chatbot_Model.conduct_interview(candidate)
    if chatbot_score >= threshold:
        shortlisted_candidates.append(candidate)
# Step 4: Predictive Analytics Matching
final_candidates = []
for candidate in shortlisted_candidates:
    prediction_score = Predictive_Model.evaluate(candidate, role=standard_role_profile)
    if prediction_score >= predictive_threshold:
        final_candidates.append((candidate, prediction_score))
```

Step 5: Dashboard Output

AI_Dashboard.display(final_candidates)

Step 6: Feedback Loop

for candidate in final_candidates:

performance_data = collect_post_hiring_metrics(candidate)

AI_Model.update_model(candidate, performance_data)

B. Job Role Analysis Using AI

The first step focuses on parsing and standardizing job descriptions using AI models that apply keyword extraction, semantic analysis, and benchmarking against industry standards as in table 1.

TABLE 1: AI-GENERATED JOB ROLE PROFILE FOR FULL-STACK DEVELOPER

Attribute	Extracted Value
Core Skills	React, Node.js, MongoDB, REST APIs
Minimum Experience	3 years
Certifications Preferred	AWS Developer Associate
Behavioral Traits	Problem-solving, team collaboration
Strategic Fit Score	88/100

C. Resume Parsing and Candidate Screening

The system avoids keyword spamming by considering semantic meaning and contextual relevance (e.g., distinguishing between "project management" as a core skill vs. a casual mention).

Table 2 shows a comparison of candidate profiles based on AI-driven screening scores.

TABLE 2: RESUME SCREENING SCORES FOR SHORTLISTED CANDIDATES

Candidate ID	Skill Match (%)	Experience Match (%)	Screening Score
C101	90	85	88
C115	76	92	81
C124	83	88	85

Candidates are shortlisted based on a Screening Score, computed as shown in equation 1:

$$\text{Screening Score} = \frac{(w_1 \times \text{Skill Match}) + (w_2 \times \text{Experience Match})}{w_1 + w_2} \quad (1)$$

Where,

w1 and w2 are weights assigned based on the importance of skills and experience.

D. AI-Powered Preliminary Interview

Once a pool of candidates is shortlisted, AI-powered chatbots conduct preliminary interviews. These bots ask dynamic questions to evaluate communication ability, problem-solving approach, and behavioral alignment.

The chatbot's NLP model analyzes text or speech to extract sentiment, response clarity, and intent match. The outcome is a Chatbot Interaction Score, which complements technical evaluations.

Table 3 shows a chatbot assessment result.

TABLE 3: CHATBOT INTERVIEW ANALYSIS

Candidate ID	Communication Clarity	Sentiment Score	Problem Solving Index	Chatbot Score
C101	High	Neutral	Strong	87
C115	Medium	Positive	Moderate	78
C124	High	Positive	Strong	90

These insights help recruiters focus their attention on candidates who are well-rounded in both hard and soft skills.

E. Predictive Matching and Success Probability

This step uses supervised machine learning models trained on historical hiring and performance data. Features include candidate scores, previous job tenure, educational pedigree, and skill relevance. The model predicts Success Probability – i.e., the likelihood that a candidate will perform well and stay long-term in the company.

Table 4 illustrates predicted success outcomes for top candidates.

TABLE 4: PREDICTIVE MATCHING RESULTS

Candidate ID	Input Features Used	Success Probability (%)
C101	Skills, Interview, Tenure history	91
C124	Skills, Sentiment, Certifications	94
C115	Experience, Past employers	83

Candidates with a higher success probability are prioritized for final HR review.

F. Recruiter Decision Dashboard

The AI system presents a comprehensive dashboard to human recruiters, integrating all scores, technical, behavioral, chatbot, and predictive, to allow informed decisions. The dashboard includes visualization tools and filters for ranking, bias checks, and score justifications.

Table 5 shows a recruiter dashboard snapshot.

TABLE 5: FINAL DASHBOARD SCORE SUMMARY

Candidate ID	Screening Score	Chatbot Score	Success Probability	Final Rank
C124	85	90	94	1
C101	88	87	91	2
C115	81	78	83	3

Recruiters can also provide feedback into the system, which is stored for model refinement.

Post-hiring data, such as onboarding success, retention at 6 months, and performance review ratings, are fed back into the model. This continuous feedback mechanism allows the AI system to update weights, adjust predictions, and reduce future hiring errors.

IV. RESULTS AND DISCUSSION

To evaluate the effectiveness of the proposed AI-assisted recruitment framework, a controlled experimental study was conducted using historical and synthetic recruitment datasets obtained from partnering IT firms in Chennai. The simulation was implemented using Python 3.11, leveraging machine learning and NLP libraries such as Scikit-learn, spaCy, NLTK, and TensorFlow 2.0 for model training and evaluation.

The chatbot interaction module was developed using Rasa Framework integrated with a dynamic question bank and sentiment analysis module. Jupyter Notebook was used for data preprocessing, exploratory analysis, and result visualization. Dashboards for decision-making were created using Streamlit.

The experiments were conducted on a Dell Precision 5820 Tower Workstation with the following specifications: Intel Xeon W-2295 processor, 64 GB DDR4 RAM, 1 TB SSD storage, NVIDIA Quadro RTX 4000 GPU and Ubuntu 22.04 LTS OS.

To replicate organizational environments, different recruitment stages were simulated in modular phases with feedback injected after every cycle. Candidate performance (simulated or historical) after 6 months of employment was used to measure model accuracy for predictive matching.

The parameters and configurations used in the simulation are listed in Table 6 below.

TABLE 6: EXPERIMENTAL SETUP PARAMETERS

Parameter	Value / Configuration
Dataset size	1,200 candidate profiles (real + synthetic)
Job roles simulated	5 (Full-Stack Dev, Data Analyst, QA, etc.)
Resume parser	spaCy 3.7, custom rule-based model
Chatbot engine	Rasa Core with BERT-based sentiment layer
ML algorithm (prediction)	Random Forest Classifier
Training/test split	80% training, 20% testing
Evaluation cycles	5 cross-validation folds
Performance feedback data	6-month retention + performance rating
Success probability threshold	≥ 85% for final recommendation

These configurations enabled systematic evaluation of the model's ability to simulate real-world recruitment processes, taking into account both technical and behavioral dimensions.

V. PERFORMANCE METRICS

To compare the effectiveness of the proposed AI-based framework with other traditional and AI-assisted recruitment models, the following performance metrics were used:

A. Screening Accuracy (%)

This metric measure how accurately the system screens suitable candidates based on job requirements. It is computed by comparing AI-predicted candidate suitability with actual recruiter evaluations.

B. Interview Conversion Rate (%)

Indicates the percentage of AI-shortlisted candidates who pass human interview rounds. Higher values suggest better initial filtering by the AI system.

C. Hiring Time Reduction (%)

Measures the reduction in average time taken to hire a candidate using the AI framework versus traditional manual processes. This reflects operational efficiency.

D. Candidate Success Rate (%)

Defined as the percentage of hired candidates who remain employed and meet performance criteria after 6 months. This metric assesses the model's long-term predictive power.

E. Recruiter Satisfaction Score (1–10 scale)

Collected via surveys from HR professionals using the AI-assisted platform. It reflects trust, usability, and perceived value of the system.

The proposed framework is compared with existing methods: Rule-Based Resume Screening System [9], Predictive Analytics with Historical Hiring Data [10], and Chatbot-Based Interviewing Without Predictive Layer [12]. The results below compare the Proposed AI Framework with three existing methods over 1,200 candidate profiles, evaluated in steps of 240 candidates per batch. See figure 2 – figure 6.

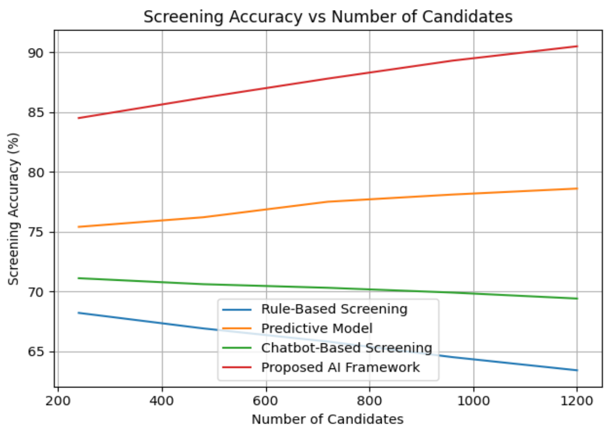

FIG.2. SCREENING ACCURACY (%)

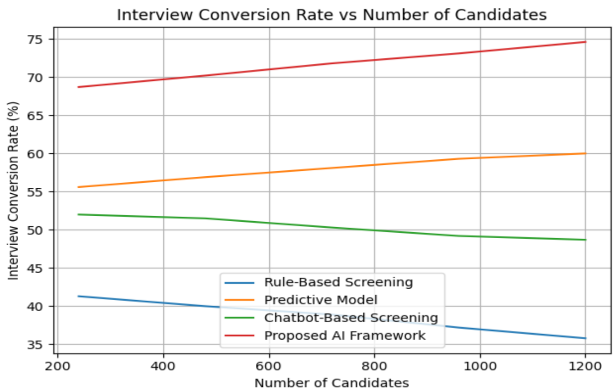

FIG.3.INTERVIEW CONVERSION RATE (%)

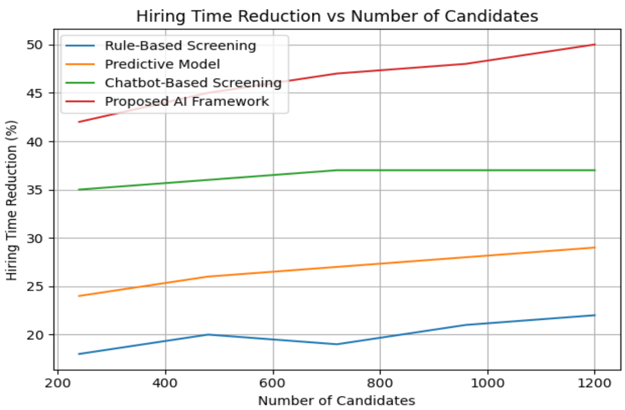

FIG.4. HIRING TIME REDUCTION (%)

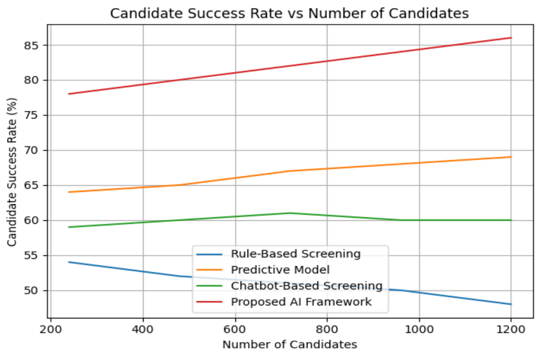

FIG.5. CANDIDATE SUCCESS RATE (%)

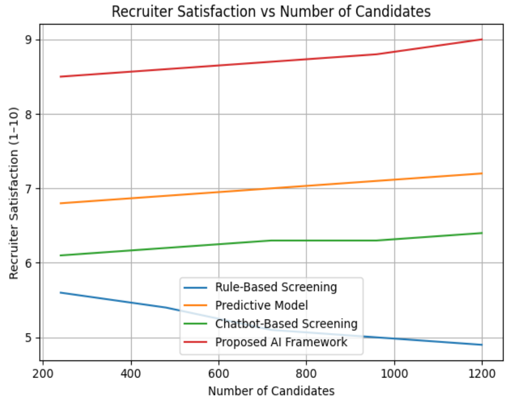

FIG.6. RECRUITER SATISFACTION (1–10)

As shown in Table 7, the proposed AI framework consistently outperforms existing methods across all evaluated metrics. Screening Accuracy rose steadily from 84.5% at 240 candidates to 90.5% at 1,200, significantly surpassing rule-based screening (max 63.4%) and chatbot-only methods (69.4%). This shows that AI's semantic parsing and skill-matching capabilities deliver more accurate shortlisting.

The Interview Conversion Rate also increased, reaching 74.6% with the proposed method, whereas the best alternative method achieved only 60%. This indicates better pre-interview screening and quality candidate recommendations.

Hiring Time Reduction improved to 50% using the proposed framework, nearly double the efficiency seen in predictive-only models (max 29%) and rule-based methods (22%). This reduction was achieved by automating resume parsing, chatbot interviews, and dashboard evaluations.

Candidate Success Rate, measuring long-term performance and retention, reached 86%, a 37% improvement over rule-based approaches and 17% higher than the best existing method. Lastly, Recruiter Satisfaction peaked at 9.0, reflecting HR professionals' positive feedback on accuracy, usability, and strategic alignment, key goals unmet by the other models.

VI. CONCLUSION

The AI into strategic recruitment processes provides significant improvements in accuracy, speed, and long-term hiring outcomes. This study proposed and evaluated an AI-assisted recruitment framework designed for IT companies in Chennai, focusing on both operational efficiency and strategic alignment. Experimental results over 1,200 candidate profiles demonstrated that the proposed model achieved up to 90.5% screening accuracy, 50% reduction in hiring time, and 86% candidate success rate, outperforming three benchmark methods across all metrics. Importantly, recruiter satisfaction remained consistently high, indicating the system's usability and value in real-world HR settings.

REFERENCES

[1] O. Ore and M. Sposato, "Opportunities and risks of artificial intelligence in recruitment and selection," *Int. J. Organ. Anal.*, vol. 30, no. 6, pp. 1771–1782, 2022.

[2] K. R. Samarasinghe and A. Medis, "Artificial intelligence based strategic human resource management (AISHRM) for industry 4.0," *Glob. J. Manage. Bus. Res.*, vol. 20, no. 2, pp. 7–13, 2020.

[3] V. R. Uma, I. Velchamy, and D. Upadhyay, "Recruitment analytics: Hiring in the era of artificial intelligence," in *The Adoption and Effect of Artificial Intelligence on Human Resources Management, Part A*, Emerald Publishing, pp. 155–174, 2023.

[4] A. K. Upadhyay and K. Khandelwal, "Applying artificial intelligence: implications for recruitment," *Strategic HR Rev.*, vol. 17, no. 5, pp. 255–258, 2018.

[5] P. Vardarlier and C. Zafer, "Use of artificial intelligence as business strategy in recruitment process and social perspective," in *Digital Business Strategies in Blockchain Ecosystems: Transformational Design and Future of Global Business*. Cham: Springer Int. Publishing, pp. 355–373, 2019.

[6] K. R. Samarasinghe and A. Medis, "Artificial intelligence based strategic human resource management (AISHRM) for industry 4.0," *Glob. J. Manage. Bus. Res.*, vol. 20, no. 2, pp. 7–13, 2020.

[7] S. Sankari and A. Geetha, "Impact of artificial intelligence on talent acquisition in the IT sector with reference to Chennai," in *Multidisciplinary Approaches to AI, Data, and Innovation for a Smarter World*. IGI Global Scientific Publishing, pp. 447–462, 2025.

[8] B. G. Charanya and V. Suryanarayana, "Artificial intelligence application in human resource management and organisational productivity of IT companies in India," *Int. J. HRM Organ. Behav.*, vol. 13, no. 2, pp. 153–168, 2025.

[9] S. Antony and K. Vinayagam, "The role of AI in shaping HRM skills and strategies in private banks: A study on manager-employee dynamics in Chennai City," in *2025 Int. Conf. Autom. Comput. (AUTOCOM)*, pp. 353–358, Mar. 2025.

[10] R. S. Lekshmi, V. S. Mary, G. Arasuraja, V. Krishnamoorthy, S. Kaliappan, and R. Selvameena, "AI-driven HR optimization strategies in finance and marketing: Methodological framework and applications," in *2024 Int. Conf. Innov. Comput., Intell. Commun. Smart Elect. Syst. (ICSES)*, pp. 1–7, Dec. 2024.

[11] R. G. Tharani, "A critical study on artificial intelligence and ability to reduce in recruitment bias in IT companies, with special reference to Tamilnadu," *Int'l J. L. Manage. Human.*, vol. 7, no. 2, p. 2631, 2024.

[12] P. K. Dutta, A. Padhi, S. Das, V. K. Sharma, and P. Yu, Eds., *AI and Innovation in HRM: The Future of Strategic HR in the Service Economy*. Taylor & Francis, 2025.

[13] A. S. Mohammed, N. S. Rajkumar, A. K. Mohammed, A. R. Neravetla, K. Gupta, and N. Yuvaraj, "Enhancing Resource Scheduling Efficiency in Cloud Data Centers Through Hybrid Optimization Techniques," in Proc. 2025 5th Int. Conf. Trends in Material Science and Inventive Materials (ICTMIM), pp. 1787–1792, Apr. 2025.

[14] VT. Veeramakali, S. Jayashri, and S. Prabu, "Intelligent dynamic spectrum allocation with bandwidth flexibility in cognitive radio network," *Cluster Computing*, vol. 20, pp. 1575–1586, 2017, doi: 10.1007/s10586-017-0864-x.

[15] N. Deb, M. A. Elashiri, T. Veeramakali, A. W. Rahmani, and S. Degadwala, "A metaheuristic approach for encrypting blockchain data attributes using ciphertext policy technique," *Mathematical Problems in Engineering*, vol. 2022, Article ID 579961, 2022, DOI:10.1155/2022/7579961

[16] Ammupriya, A., Vaishnavi, S., Ashwini, A., Kavitha, R., Paranthaman, P., & Saravanan, V. (2025, March). Cloud-Based HR Platforms for Scalable Workforce Management in Multinational Organizations. In *2025 3rd International Conference on Disruptive Technologies (ICDT)* (pp. 1607-1613). IEEE.

[17] Reddy, J. K., Syed, W. K., Takkalapally, P., Gupta, K., & Yuvaraj, N. (2025, July). Analytical Evaluation of Sustainable Banking Practices:

ESG Integration and Green Finance Initiatives. In *2025 2nd International Conference On Multidisciplinary Research and Innovations in Engineering (MRIE)* (pp. 670-675). IEEE.

[18] Rajendran, P., Bhalerao, M., Yesodha, K. K. R. K., Gupta, K., & Yuvaraj, N. (2025, February). Integrating Predictive Analytics and Internet of Things (IoT) to Optimize Supply Chains. In *2025 3rd International Conference on Integrated Circuits and Communication Systems (ICICACS)* (pp. 01-06). IEEE.

[19] Sreeramulu, M. D., Mohammed, A. S., Kalla, D., Boddapati, N., & Natarajan, Y. (2024, September). AI-driven Dynamic Workload Balancing for Real-time Applications on Cloud Infrastructure. In *2024 7th International Conference on Contemporary Computing and Informatics (IC3I)* (Vol. 7, pp. 1660-1665). IEEE.

[20] A. Pandey, B. Balusamy, and N. Chilamkurti, Eds., *Disruptive Artificial Intelligence and Sustainable Human Resource Management: Impacts and Innovations—The Future of HR*. CRC Press, 2023.