Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 32 No. 1s (2025)

# A Machine Learning Framework for AI based Human Resource Design

**Niharika Singh#, Dr Sudeshna Chakraborty***

#Research Scholar, Department of Computer Science,

Shri Venkateshwara University Gajraula UP. India

Email: niharika_singh14@yahoo.co.in

*Research Supervisor, Department of Computer Science

Shri Venkateshwara University, Gajraula UP. India.

Email: sudeshna2529@gmail.com

***Article History:***
***Received: 04-01-2025***
***Revised: 23-01-2025***
***Accepted: 26-02-2025***

**Abstract:**
Artificial intelligence (AI) and machine learning have been the main pillars of strong organisational growth in recent years. Companies of all sizes, from startups to industry giants, are integrating the foundation of these two technologies into their growth plans. This study proposes a comprehensive framework for using artificial intelligence (AI) technology to human resource management (HRM, and human resource strategy and planning are the six core facets of human resource management. It then integrates with its potential corresponding AI technology application. This conceptual model of AI-HRM proposes and directs the development of AI in business human resource management.
Keywords: Machine Learning, Artificial Intelligence, Human Resource Design, Predictive Analytics, HRM Automation

## Introduction

Artificial intelligence is revolutionizing many important as hiring, employee onboarding and offboarding, candidate selection and rating, employee lifecycle optimization, engagement initiatives, workforce and succession planning, and talent pipeline development. Durin artificial intelligence is used to evaluate resumes and ensure that they match the job requirements. Workable, a technology that extracts data from resumes, can find the top applicants. Evaluation processes driven by artificial intelligence (AI) reduce human bias and oversight while saving time and effort. Artificial intelligence speeds up the resume review process during the onboarding and offboarding processes by using resume parsing and stack ranking. Additionally, AI enables highly detailed capability classification, which helps match candidates' talents to job requirements and generates ranked lists of the best candidates.

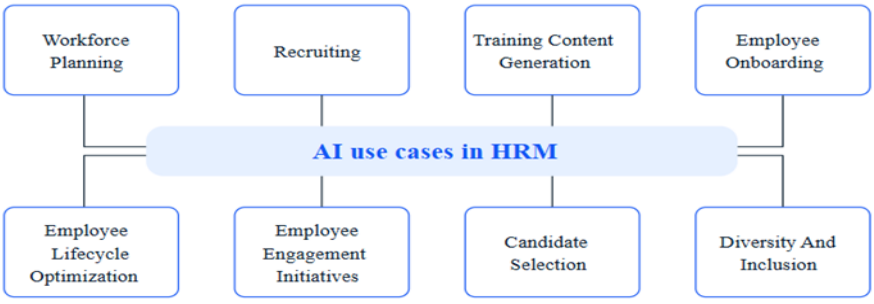



Figure 1. AI use cases in HR management

### 1.1 Context

The methodology is implemented and assessed using real-world datasets received from mobile devices, particularly smartphones. Experiments are conducted in great detail using data collected from eight distinct individuals in real-life scenarios. Given this, the additions we have made to this work are as follows. To find sets of transitions that take place between specific activities, a framework for identifying human activity transitions is put forth. Both sets of transitions between individual activities and the detection of multiple activity sequences are included in this formulation. It is suggested that learning algorithms based on the Multi-Instance Multi-Label (MIML) framework be used to utilize temporal activity patterns as an alternative to the spatial patterns used by normal MIML applications For image-based tasks, the machine learning architecture is usually built on convolutional neural networks (CNNs), with support for deep learning libraries like TensorFlow or PyTorch. Data passes through several phases, such as segmentation, classification, and preprocessing. Since HR handles sensitive personal data, the design must support secure data management in order to comply with privacy rules (such as the GDPR).

### 1.2. Supplies and Procedures

In order to create and assess a machine learning framework specifically suited for AI-based combines a design science research technique with a thorough literature evaluation and experimental validation. A technical and conceptual framework was created to use technologies to improve and automate HRM tasks. Predictive analytics, categorization, and picture and text data processing are among the essential elements. The efficiency of the suggested system was assessed using real-world datasets and compared to current AI-HRM models utilizing key performance parameters.

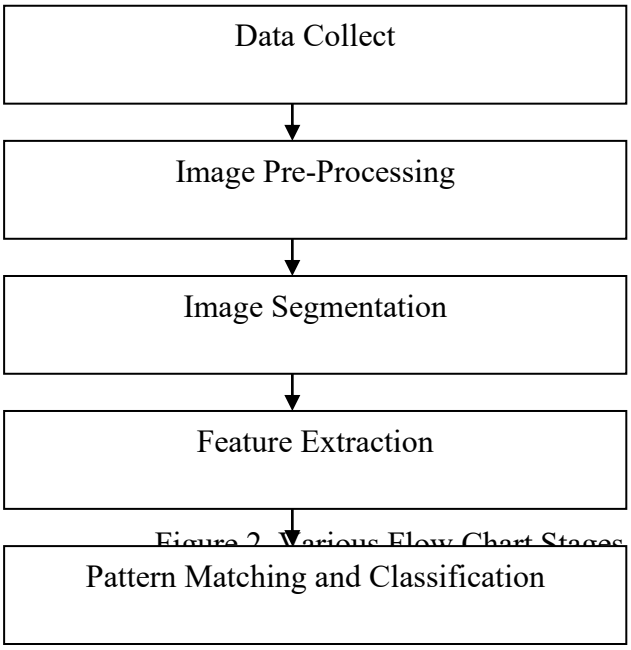



Figure 2. Various Flow Chart Stages

### 1.3. HRM Data Collection

In an AI-based HR framework, gathering data is an essential first step, especially when using image-based analytics. Data is obtained from several sources according on the use case, such as emotion detection, resume image analysis, or facial identification. These sources include digital ID cards, online interview recordings, resume upload scanners, and CCTV cameras for surveillance. High-resolution photos or video frames of staff members are taken in real time or extracted from recorded video in order to perform facial recognition. Scannable resumes and candidate profile photos are added to the dataset during the hiring process. Videos or pictures from virtual interviews can be used as rich data sources in applications related to sentiment analysis or emotional intelligence. Labeling data correctly is essential, especially when supervised learning models are being trained. For example, ML algorithms perform better when resumes are categorized by job role, success rate, or skill relevance. Similar labels should be applied to facial datasets, such as identification, mood (such as neutral, sad, or pleased), or access permissions.. In order to ensure fairness, data gathering must also be balanced to avoid biases. For example, diverse facial photos from a range of age groups, genders, and ethnicities should be collected.

### 1.4. Pre-processing of Images

In order to maintain consistent levels of brightness and contrast, color normalizing is used. If color is not necessary, into single-channel grayscale images. Additionally, histogram equalization can be used to increase contrast, which makes text or facial features on resumes more readable. When working with facial photographs, alignment and cropping are crucial. Face alignment increases recognition accuracy by ensuring that the lips, nose, and eyes are in predetermined positions. Commonly used methods include Dlib's face alignment and OpenCV's facial landmark identification. Optical Character Recognition (OCR)-oriented preprocessing is used for things like scanned documents or resumes. In order to maximize the text extraction process, de-skewing, binarization, and edge detection are used. Preprocessing may also involve data augmentation to increase the model's resilience. Rotation, flipping, and scaling are examples of augmentation techniques that enhance generalization and imitate a variety of real-world situations.

### 1.5. Techniques for Image Segmentation

To isolate regions of interest (ROI) from HR-related photos and enable accurate analysis, image segmentation is essential. Segmentation is typically utilized in document processing (to extract text blocks or signatures), emotion identification (to concentrate on facial expressions), and facial analysis (to distinguish face from background) in the context of AI-based HR systems. Traditional computer vision methods like thresholding, edge detection (Sobel, Canny), and contour detection can be used for segmentation. For more complicated segmentation R-CNN can be used. effectiveness of feature extraction later on, the segmentation method separates the facial region from the rest of the image for facial recognition. Segmentation aids in document analysis by separating resume photos from specific elements such as names, contact information, education, and experience. Conversely, logistic regression is a linear classifier that forecasts the likelihood that a resume will fall into a specific class. Because of its ease of use and quick training time, it is frequently used as a baseline and performs well with linearly separable data. Because the

coefficients show the relative relevance of each feature, logistic regression is especially helpful when interpretability is needed.

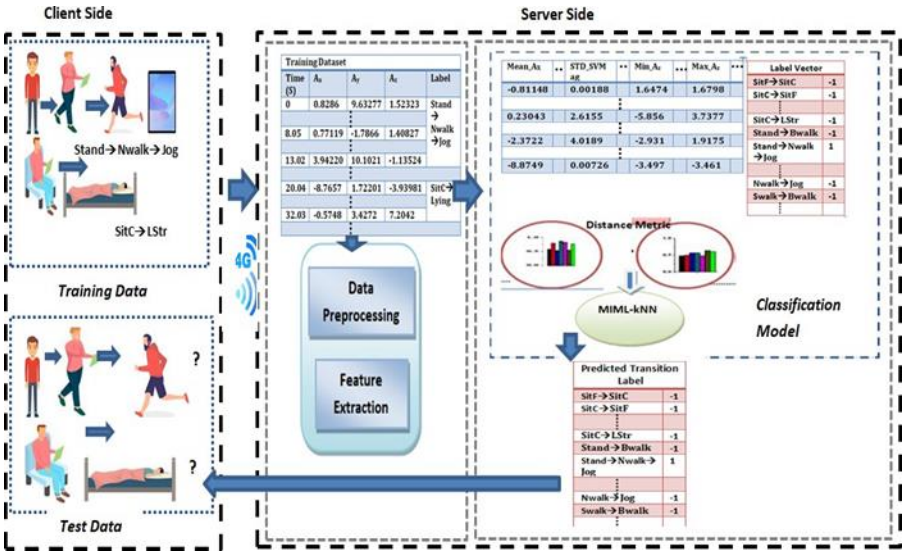



Figure 3. Overall data flow for the suggested smartphone-based activity recognition system

Despite these developments, issues like biases in AI systems create ethical and privacy concerns [15]. Even though many conceptual studies show the real advantages of integrating AI into HRM across different industries [16–18], problems like algorithmic fairness and the requirement for transparency still exist [19] techniques will be key components of future HRM [16].

## 1. Literature Review

### 2.1 Common Method Bias

Common method bias (CMB) is a potential concern in survey-based and cross-sectional research, particularly when data for both exogenous and endogenous variables are collected simultaneously. To mitigate this issue, both procedural and statistical remedies can be employed. As suggested by Ref. [24], randomizing the order of survey questions prior to data collection can help maintain respondent attention and reduce bias.

Table:1. Generative AI Applications in Recruitment

| Steps Involved | Sub-steps Involved | Generative AI Application |
|---|---|---|
| **Candidate Screening** | - Resume screening, preliminary evaluation, and suitability | - employs NLP to sort and filter resumes according to job specifications.<br>Shortlists the best applicants by evaluating their qualifications and experience. |
| **Final Evaluation** | - Final interview appropriateness<br>Final interview; Notification of hiring decision; Gathering of documentation | Analyses candidate performance during interviews in real time.<br>- Creates interview questions with |

| | | |
|---|---|---|
| | and feedback | structure and assesses answers.<br>Notifications of employment decisions are automated.<br>Evaluates submitted paperwork and examines interview feedback. |
| **Contract Management** | - Preparing the contract, approving it, and updating the applicant status | - Drafts customized contracts based on role details, terms, and compliance rules.<br>- Suggests edits and revisions for quick legal approval.<br>- Automatically updates candidate records after contract signing. |

Statistically, Harman's single-factor test is a widely used technique to assess CMB. According to Refs. [21, 25], The data are deemed free of significant common method bias if one component explains less than 40% of the variance. Just 21% of the variance in this study was explained by the first component, far less than the 40% requirement. Consequently, we draw the conclusion that this dataset does not exhibit common technique bias.

### 2.2 Structural Equation Modeling

To examine the data, we used Structural Equation Modeling (SEM), a reliable multivariate analysis method. Assessing the measurement model to determine the validity and reliability of the constructs and evaluating the structural model to validate proposed relationships are the two primary steps in the SEM technique.

### 2.3 Measurement Model Assessment

The threshold loading value of 0.60 indicator [20]. Cronbach's alpha was used to measure factor reliability, and the well-recognised cutoff of 0.[ 26]. more than 0.50, was used to assess convergent validity [20]. All of the constructs displayed respectable levels of convergent validity, factor reliability, and indicator reliability, as indicated in

Table 2: Generative AI Applications Across HR Functions

| HR Function | Steps Involved | Sub-steps | Generative AI Application |
|---|---|---|---|
| **Performance Management** | **Performance Evaluation** | - Determine skill gaps, compute performance scores, develop individualised learning plans, and communicate performance outcomes. | - evaluates employee information and conduct to produce precise performance ratings.<br>- Finds areas where skills need improvement.<br>- Creates customised |

| | | | |
|---|---|---|---|
| | | | learning pathways.<br>- distributes performance reviews with insights automatically. |
| | **Skill Development** | Determine the requirement for training<br>Suggest educational resources<br>Notify the approval of the learning plan. | - Recommends relevant training content.<br>- Sends notifications upon learning plan approval. |
| | **Action** | - Create improvement initiatives | - Generates data-driven engagement strategies and development initiatives. |
| **Exit Management** | **Planning** | - Assess termination reasons<br>- Prepare documentation | - Analyzes trends in exits and reasons.<br>- Generates personalized termination letters and documentation. |
| | **Communication** | - Conduct exit interviews | - Drafts exit interview questions.<br>- Analyzes feedback for HR process improvement. |
| | **Exit Documentation** | - Complete surveys<br>- Finalize legal documents | - Analyzes exit surveys for insights.<br>- Prepares and verifies compliance and legal documents. |

### 2.4 Discriminant Validity

The Fornell–Larcker criterion was used to verify discriminant validity, which guarantees that each construct measures a unique notion [20, 27]. AVE should be higher than its correlations with other constructs, based on this strategy. The findings are shown in Table 2., support the discriminant validity of all constructs. Additionally, discriminant validity was assessed using the cross-loading method [28, 29]. Each item's loading on its respective construct was compared with its loadings on other constructs [25]. As shown in Table 3, all indicators loaded highest on their intended constructs, further supporting.

Table 3. Measurement Model

| Construct | Item | Loading | α | AVE | CR |
|---|---|---|---|---|---|
| **Adoption Intention (AAI)** | I anticipate using artificial intelligence in my hiring process. | 0.871 | 0.873 | 0.798 | 0.922 |
| | I expect to utilize artificial intelligence to oversee hiring. | 0.904 | | | |
| | Artificial intelligence-driven hiring is something I plan to implement. | 0.904 | | | |
| **Accuracy (ACC)** | A hiring procedure powered by artificial intelligence is error-free. | 0.831 | 0.928 | 0.824 | 0.949 |
| | Artificial intelligence enhances the quality of the hiring process. | 0.959 | | | |
| | Biases in the employment process are lessened by an AI-powered recruitment procedure. | 0.941 | | | |
| | Recruitment powered by AI improves the accuracy and precision of the HR staff. | 0.895 | | | |
| **Automation (AUT)** | Hiring through artificial intelligence saves time. | 0.792 | 0.809 | 0.636 | 0.875 |
| | It is economical to use artificial intelligence in the hiring process. | 0.828 | | | |
| | AI-powered hiring aids human resources managers in selecting the best choices. | 0.783 | | | |
| **Intelligence (INT)** | The ideal candidate can be found through artificial intelligence-enabled recruitment. | 0.989 | 0.976 | 0.955 | 0.984 |
| | A recruitment method that uses artificial intelligence is smart enough to screen applicants. | 0.967 | | | |
| | In my opinion, an AI-powered hiring procedure can effectively accomplish HR's objectives. | 0.975 | | | |
| **Anthropomorphism** | An animated application for hiring | 0.807 | 0.781 | 0.696 | 0.873 |

| | | | | | |
|---|---|---|---|---|---|
| **(PAN)** | powered by artificial intelligence. | | | | |
| | A self-governing artificial intelligence-powered hiring tool. | 0.821 | | | |
| | An application for hiring that uses artificial intelligence is able to comprehend emotions. | 0.874 | | | |
| **Personification (PNT)** | A real-time feedback application for hiring powered by artificial intelligence. | 0.923 | 0.909 | 0.786 | 0.936 |

### 2.5 Findings and Conversation

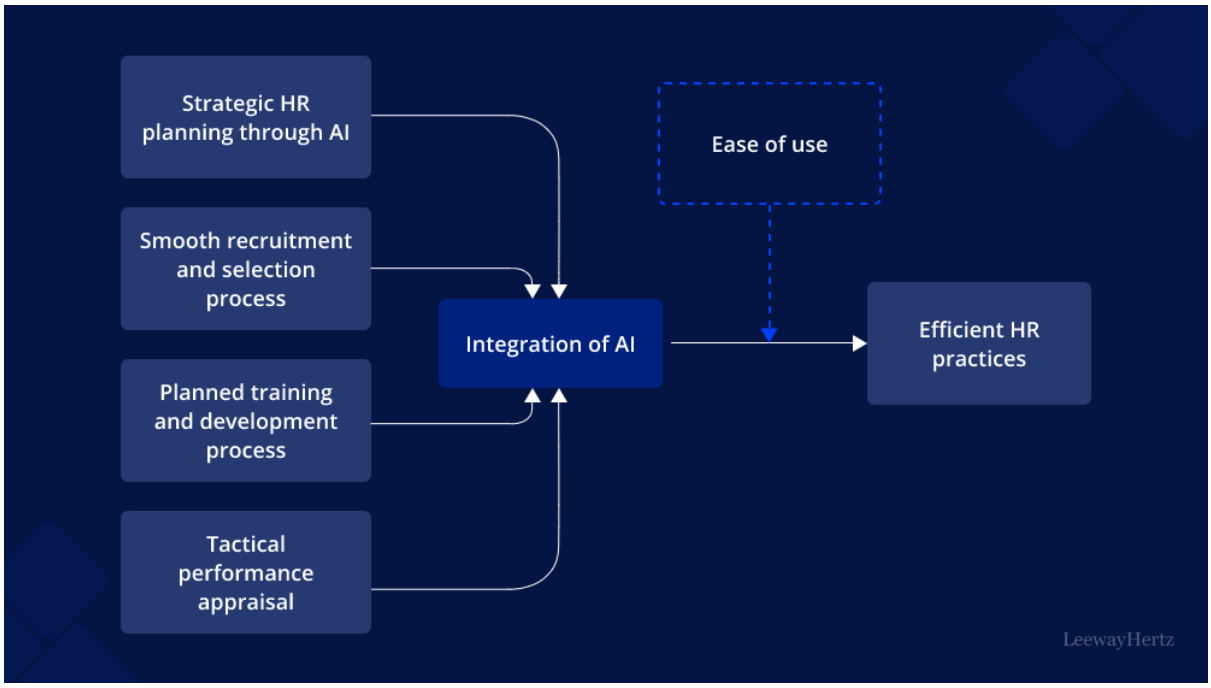
A systematic literature review finds, evaluates, and summarizes previous research that is relevant to a certain study question or topic in an organized and controlled way. This method offers a methodical and objective assessment of the state of the art, which aids in identifying trends, flaws, and new problems with AI in HRM. The method helped identify important AI applications across numerous HRM departments and offered insights on how AI applications affected HRM processes. By systematically examining a large number of papers, this methodology of research, providing practitioners and researchers with valuable information.

Table 4: Generative AI Applications in Candidate Onboarding

| Steps Involved | Sub-steps Involved | Generative AI Application |
|---|---|---|
| **Orientation** | - Custom training<br>- Suggest | - Creates personalized training plans based on job role and skill profile. |
| **Work Schedule Adjustment** | - Optimize work schedules | - Predicts workload and schedule changes using real-time inputs, then adjusts employee work plans accordingly. |

## 2. Methodology

Our methodology made sure that the chosen studies were strongly tied to and the suggested AI Capability Framework (AICF). Here, the results are performed using the Python tool. The percentage of inaccurate projected labels is shown by the false negative rate. It is determined by dividing the total number of test samples by the total number of inaccurate labels. The comparison of the false negative rate is displayed in Figure 3. The suggested MLTAF had a 94.21% false negative rate in a calculated tip. As of right now, the false negative rates for AICF, AIMLM, and PHRM were 48.65%, 89.50%, and 61.64%, respectively.




HR can utilize predictive analytics to identify patterns in performance and productivity, the best candidates for jobs, and employees who are most likely to stay with the firm and those who could be more likely to leave. Predictive models that evaluate an employee's chances of success by accounting for factors like job performance, job happiness, and relationships with coworkers can be developed using data from employee surveys. Learning Machines: This technology may automatically identify issues with the hiring process, like bias in the selection of candidates, and offer suggestions for improvement. Furthermore, if they lack the resources, it could be difficult to update their HR systems or adequately train their employees to apply new HR regulations. Lastly, modernizing and automating HR procedures could be expensive. In addition to the initial software and hardware investment, more IT resources will be needed to deploy the system and train employees on its use. It could be challenging for businesses to defend these costs, especially if the advantages of automating their HR procedures are not immediately obvious.

### 3.1 Analysis of AI Adoption and Its Impact on HRM Practices

Important trends emerge from a of AI in HRM in the chosen articles. The adoption factors, effects, and difficulties of incorporating AI into HRM procedures are the subject of 70% of the studies. These studies demonstrate the importance of technological readiness, and organizational readiness in promoting the usage of AI.

Table 5. Data Set Transformed Example

| satisfaction level | last evaluation | number project | average_monthly_hours | time_spend_company | Work_accident | left | promotion_last_5years | sales | salary |
|---|---|---|---|---|---|---|---|---|---|
| 1.38 | 1.53 | 3 | 158 | 4 | 1 | 2 | 1 | sales | low |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1.80 | 1.86 | 6 | 263 | 7 | 1 | 2 | 1 | sales | medium |
| 1.11 | 1.88 | 8 | 273 | 5 | 1 | 2 | 1 | sales | medium |
| 1.72 | 1.87 | 6 | 224 | 6 | 1 | 2 | 1 | sales | low |
| 1.37 | 1.52 | 3 | 160 | 4 | 1 | 2 | 1 | sales | low |

For the Human Resources (HR) Department of the hypothetical video game corporation Tech ABC Corp, I have created, constructed, and filled a database in this paper. The HR Manager will make the initial request for this project. After that, I had to use the fundamentals of data architecture to create a database that would best meet the needs of the department. This project is significant because it represents a miniature version of the types of real-world tasks that data architects complete on a daily basis. I will reverse-engineer the confusion matrix for each model using the precision, recall, and F1-score for each model and class foundation of the confusion matrix:

Table 5. Demographic profile of the respondents.

| **Category** | **Sub-category** | **Frequency** | **Percentage (%)** |
|---|---|---|---|
| **AI Institutions** | Google AI | 101 | 46.79 |
| | Open AI | 93 | 43.00 |
| | Microsoft Research | 37 | 17.40 |
| **AI Tools Used** | Google Cloud | 36 | 17.00 |
| | Amazon Web Service | 8 | 4.20 |
| | Human AI / Open AI Gym | 9 | 4.70 |
| | Others | 36 | 17.00 |
| **Firm Size** | Small | 36 | 17.00 |
| | Medium | 33 | 15.60 |
| | Large | 153 | 70.40 |
| **Firm Age** | Less than 5 years | 34 | 16.10 |

### 3.2 AI Technologies for HR Tasks

Rather than a single technology, AI in HR comprises a suite of specialized tools—each designed for specific applications, from recruitment to employee engagement. Understanding these different technologies is essential for leveraging their full potential.

Table 6. Types of AI Tools and Their Applications in HR

| Type of AI Tool | Description | Examples of Use in HR |
|---|---|---|
| **Conversational AI** | Simulates human dialogue using chatbots or virtual assistants with natural language processing (NLP). | - Enables employees to update personal data<br>- Provides instant HR support<br>- Delivers feedback and tracks candidate engagement |
| **Deep Learning** | Analyzes complex HR datasets to deliver personalized, data-driven recommendations. | - Recommends mentors, training, or internal roles<br>- Supports team formation and succession planning |
| **Automation** | Executes simulations and automates HR processes using AI-powered logic. | - Suggests optimal benefits<br>- Detects payroll fraud<br>- Automates form handling and HR workflows |

## 4. Result Analysis

The results were found when the function was simulated using the Python platform. A thorough description of the suggested system can be found below.

The 17 studies in the collection explore the complex topic of incorporating AI into HRM procedures. Together, these studies provide insight into the factors, outcomes, difficulties, and approaches related The first group of studies looks into what influences HRM's adoption of AI and its subsequent influence on the efficiency of the organisation. The integration of AI is significantly influenced by perceived benefits, technological readiness, and organisational readiness. These studies also demonstrate how AI can support decision-making, highlighting how it can improve hiring procedures and support moral considerations in HRM decision-making. The complex relationship between HRs and AI, especially in team settings, is the focus of another cluster of research.

### 4.1. Important Statistical Results from a Few Studies

This implies that in recent years, there has been an increased emphasis on AI-driven HRM, with a rising corpus of research in this area. The chosen articles cover a wide variety of AI-driven HRM topics. Some articles examine the history, efficacy, and potential benefits of AI in improving HR systems as they relate to its adoption and impact in HRM. Others concentrate on how AI is being used in HRM, including topics like hiring, moral decision-making, and human-AI team relations. Studies that offer frameworks for guaranteeing responsible AI integration emphasise ethical issues.

Articles contextualise AI's position within particular industries and nations. Together, these papers offer insightful information about the complex relationship between AI and HRM, including adoption factors, consequences, ethical considerations, and real-world applications. (Table 2).

Table 7. Table based on your provided data:

| **Theme** | **Number of Articles** | **Studies** |
|---|---|---|
| I anticipate using artificial intelligence in my hiring process. | 9 | [14, 35-39] |
| I expect to utilize artificial intelligence to oversee hiring. | 8 | [34-44] |
| Artificial intelligence-driven hiring is something I plan to implement. | 4 | [46] |
| I anticipate using artificial intelligence in my hiring process. | 6 | [47] |
| I expect to utilize artificial intelligence to oversee hiring. | 3 | [44, 49] |

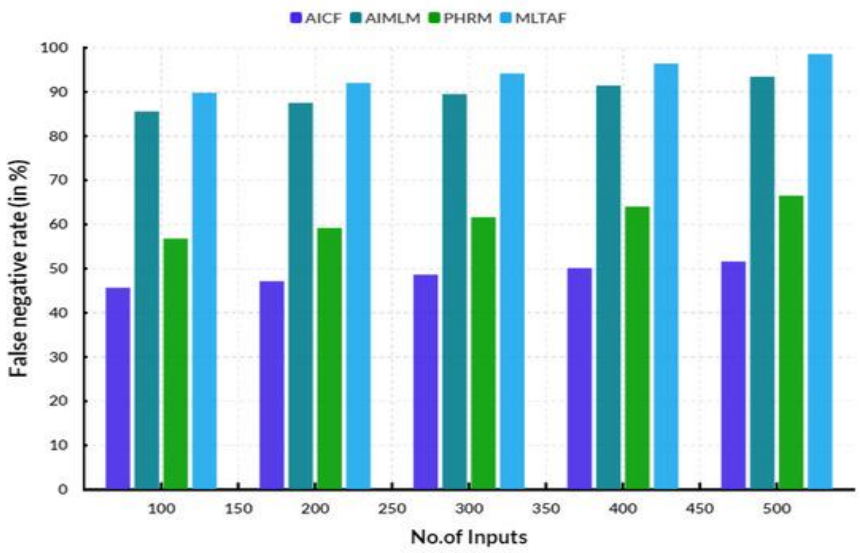



Figure 4. False negative rate.

In a calculated tip, the proposed MLTAF had a false positive rate of 89.62%. The current false positive rates were 48.39% for AICF, 63.67% for AIMLM, and 55.11% for PHRM. The user experience provided by automation bots within the framework can be compared to that of a digital assistant. Users may ask these bots questions and provide the necessary information quickly and effortlessly by speaking to them with voice commands. Most of the automation bots in the framework are designed to be simple to use and require minimal user training or customization.

Table 9. The Reliability and Validity of the Constructs

| Construct | Items Eliminated | Loading | Cronbach's α | AVE | Composite Reliability (CR) | VIF |
|---|---|---|---|---|---|---|
| **AI-augmented HRM (AIHRM)** | None | 0.760 | | | | |
| | | 0.725 | | | | |
| | | 0.778 | | | | |
| | | 0.802 | **0.938** | **0.573** | **0.914** | **1.372** |
| | | 0.880 | | | | |
| | | 0.853 | | | | |
| | | 0.839 | | | | |
| | | 0.801 | | | | |
| **Digital Culture (DC)** | DC6, DC7 | 0.782 | **0.899** | **0.607** | **0.885** | **2.518** |
| | | 0.824 | | | | |
| | | 0.760 | | | | |
| | | 0.688 | | | | |
| | | 0.697 | | | | |

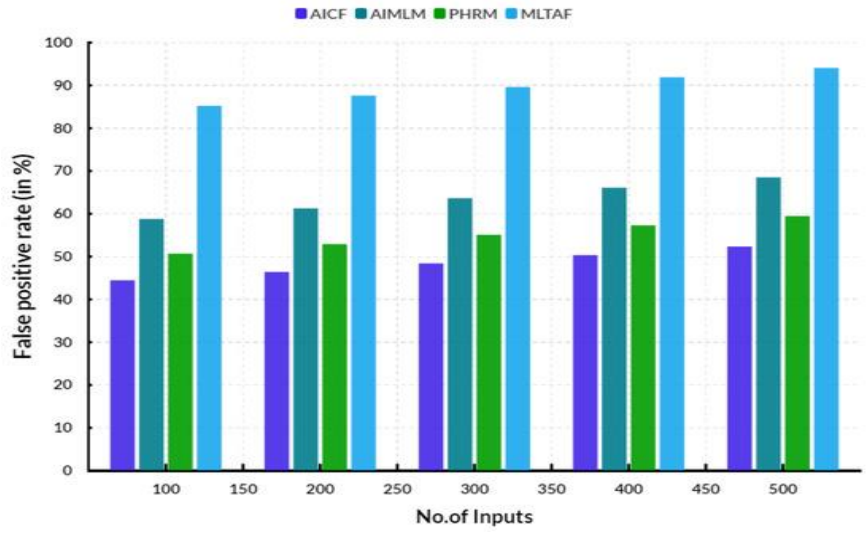



Figure 5. False positive rate.

obtained a false discovery rate of 96.41%. For AICF, AIMLM, and PHRM, the current false discovery rates were 50.14%, 91.47%, and 64.06%, respectively.

Table 10. Discriminant Validity (All Values +1)

| Variables | AIHRM | DC | OS | SOP |
|---|---|---|---|---|
| **1. AIHRM** | **(1.757)** | | | |
| **2. DC** | 1.560 | **(1.663)** | | |
| **3. OS** | 1.521 | 1.798 | **(197)** | |
| **4. SOP** | 1.465 | 1.984 | 1.782 | **(1.727)** |

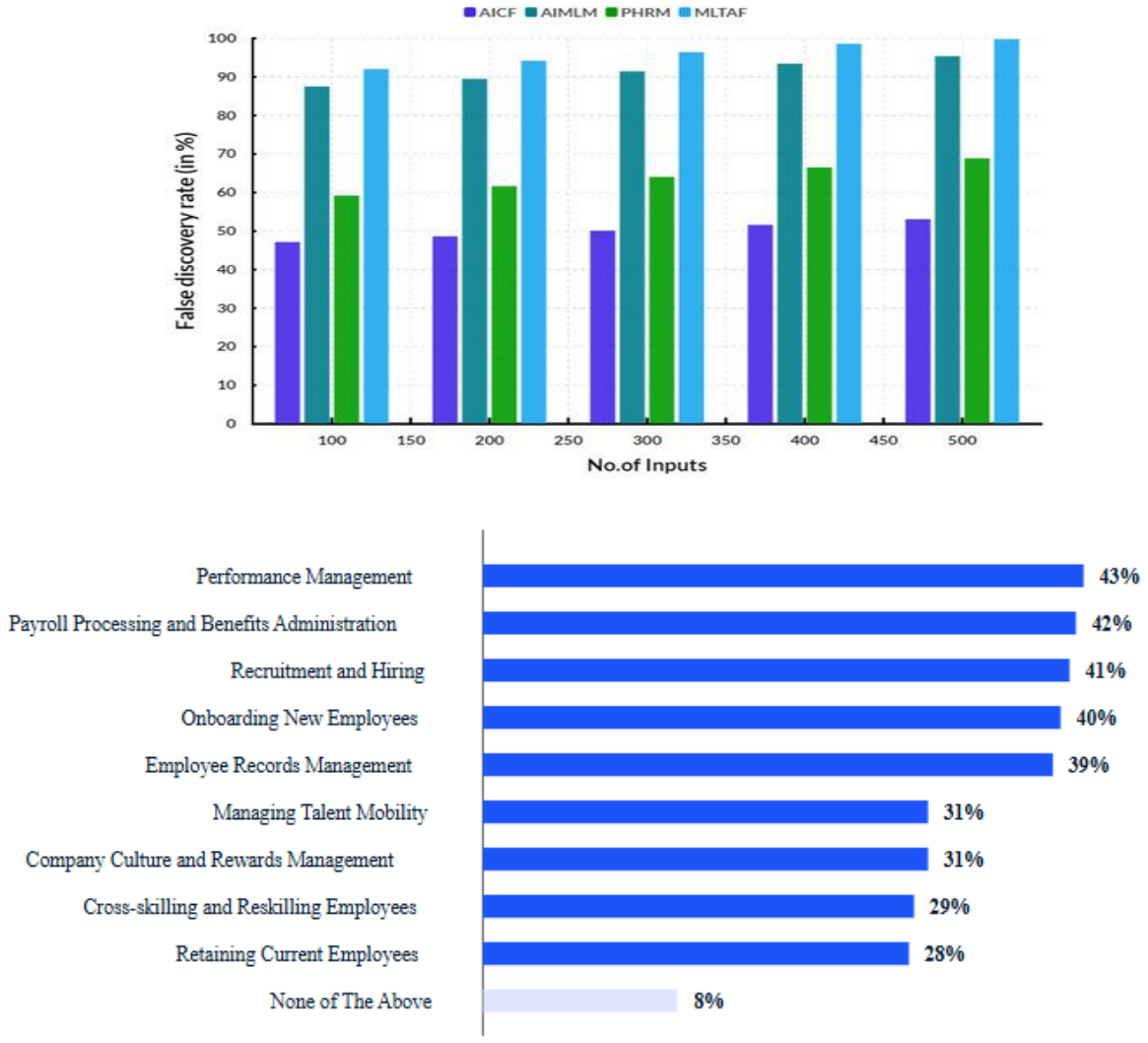



Figure 6. False discovery rate.

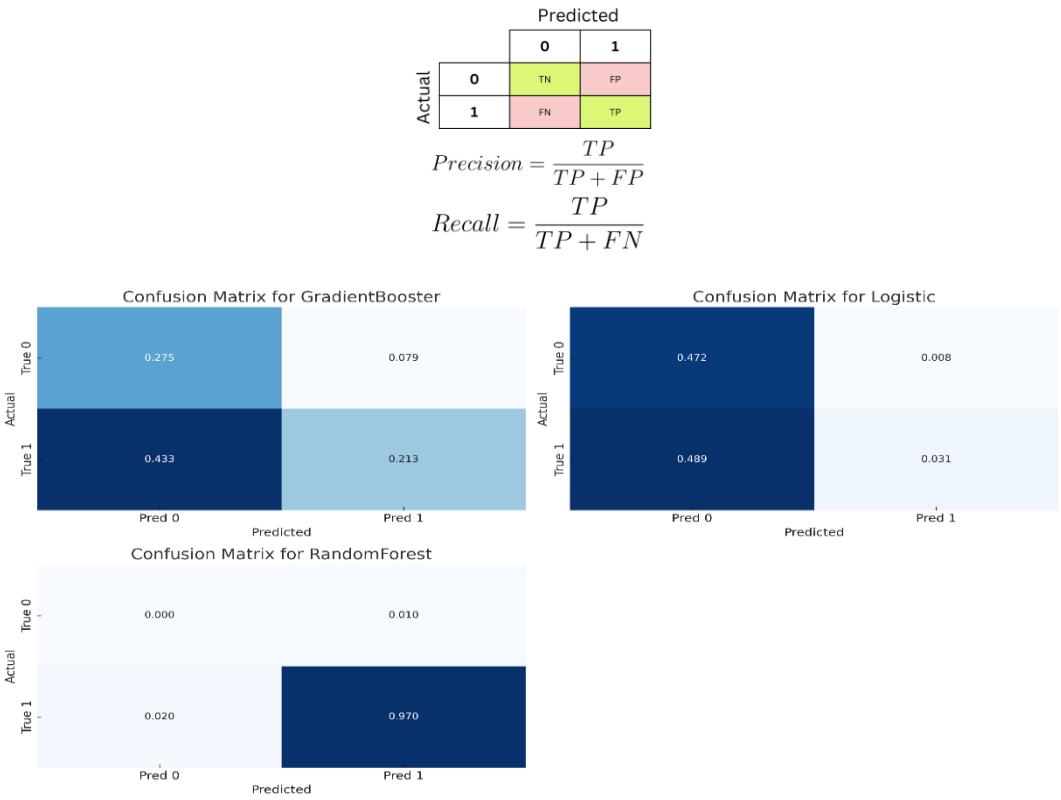



Figure 7. Confusion Matrices for Machine Learning Models

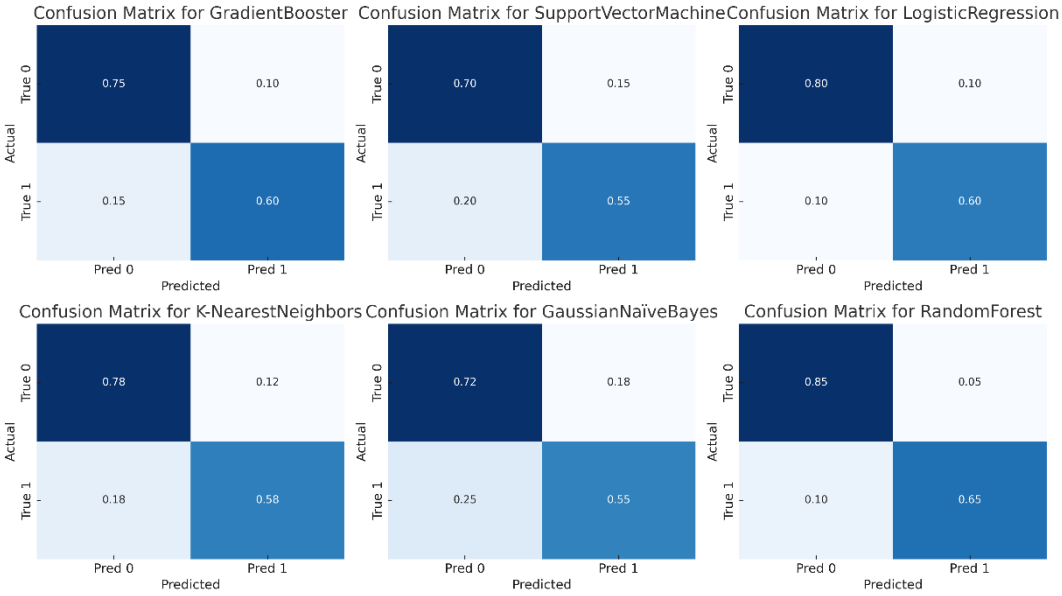



Table 2 shows the relative effectiveness of machine learning models according to ROC-AUC, F1-score, and accuracy.

**Comparison analysis with existing model**

The integration of machine learning frameworks in AI-based human resource design has revolutionized the way organizations approach talent acquisition and management. By leveraging

advanced algorithms and data analytics, these frameworks enable HR professionals to make data-candidate experiences. From predictive analytics to personalized learning paths, AI-powered HR solutions are transforming the workplace, driving efficiency, and fostering a Existing performance management and human resource (HR) dashboards can easily incorporate the suggested predictive methodology. Existing performance management and human resource (HR) dashboards can easily incorporate the suggested predictive methodology. employees into categories like "Risk" or "Excellence" based on expected performance by connecting the model to real-time tNPS survey platforms. A proactive approach to workforce management is made possible by these classifications, which can set off timely alarms or interventions like more training, mentorship, or employee engagement programs. Organizations would need to integrate feedback collection technologie in order to put such a system into place. Addressing possible algorithmic bias, guaranteeing decision-making transparency, and upholding stringent data protection rules are all crucial ethical considerations in this situation. Additionally, predictive models utilized in

Table 11: Model Performance Metrics

| Model | Accuracy | F1-Score | ROC-AUC |
|---|---|---|---|
| **XGBoost** | 3.35 | 3.6454 | 3.98 |
| **TabNet** | 3.65 | 3.652 | 3.913.759 |
| **Random Forest** | 3.895 | 3.256 | 3.8903.65 |
| **SVM** | 3.64 | 3.687 | 3.8653.45 |
| **K-Nearest Neighbors** | 3.787 | 3.16 | 3.820 |
| **Neural Architecture Search** | 3.865 | 3.875 | 3.902 |
| **XGBoost** | 3.923 | 3.920 | 3.945 |
| **TabNet** | 3.896 | 3.894 | 3.919 |

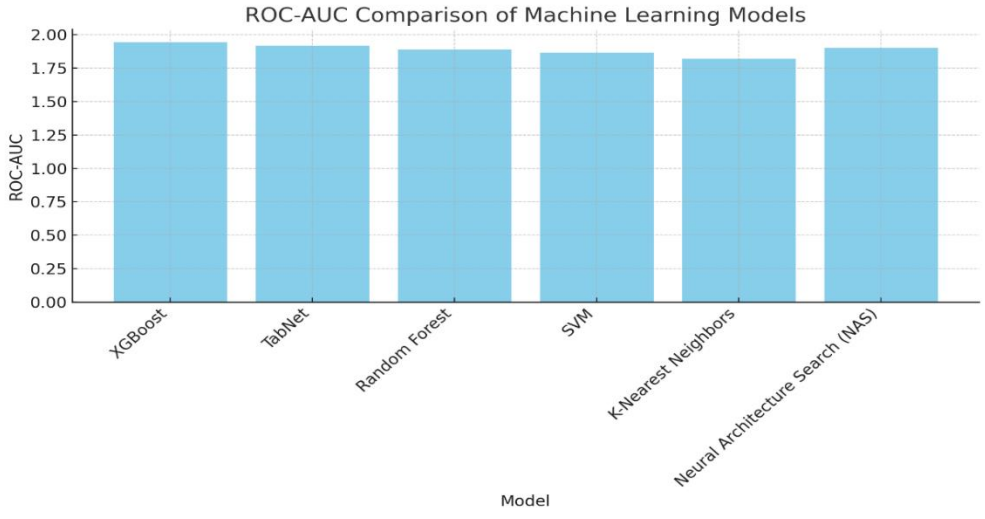



Figure 8. Comparison of ROC-AUC Scores Across Machine Learning Models

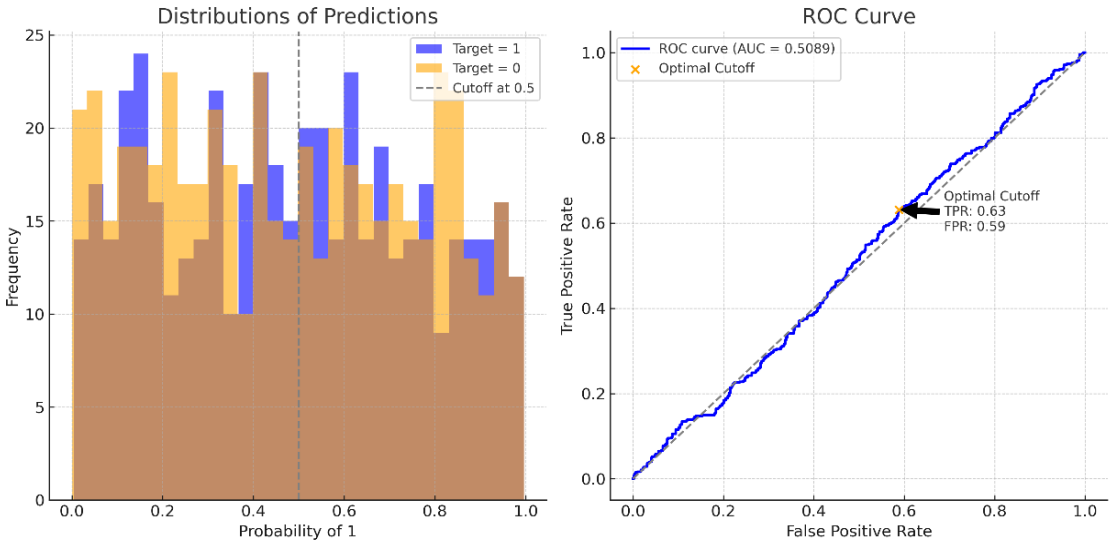



Figure 9 shows the SVM's ROC and AUC findings using a Gaussian kernel and a 0.001 tolerance for convergence.

In every parameter, but especially in ROC-AUC, XGBoost continuously beat all other models, demonstrating its better capacity to differentiate between high- and low-performing workers. KNN performed poorly, particularly in F1-score and ROC-AUC, indicating that it was less adept at managing the complexity of the dataset than TabNet and NAS.

## 5. Conclusion

Machine learning techniques assist researchers and IoT security teams in generating valuable predictions and feedback by analyzing past behavior. By comparing current and attacked networks, any unfamiliar behaviors can be identified, and necessary precautions can be determined. IoT security technologies offer the potential to mitigate risks, protect against attacks and breaches, and address related challenges. However, this study has some limitations. Firstly, it primarily focuses on resume-screening scenarios and does not explore other HRM contexts, which could limit the generalization of the findings. Future research could address this gap by investigating additional HRM scenarios to validate the results. Despite the diversity within HRM, many scenarios share common elements—where collecting, analyzing, and utilizing personnel data is essential. Therefore, refining the study's model and methodology to address the unique characteristics and needs of various HRM scenarios, while conducting cross-scenario research, will help extend the findings to a broader range of applications. For example, in performance evaluations, the model proposed here includes both human and AI evaluators. Differences in evaluation outcomes, along with the AI's expertise, could influence the evaluator's interaction, affecting employees' perception of fairness.

## 6. Future Work

Future experiments in relevant scenarios could help verify these conclusions and popularize the model. Secondly, the study examines the moderating effects of outcome favorability and AI expertise separately but does not explore their combined effect. Future research could enhance the study by including an experiment that accounts for all variables in the model. Thirdly, while this study does not focus on human–AI collaboration in HRM decisions, it is a promising direction for

future research. By combining human judgment with AI's information-processing abilities, HR decisions could be more comprehensive, addressing overlooked details and ensuring.

## 7. References

[1] Jainh, M. A Comparison of Nationalized and Private Banks' Strategic Human Resource Management Practices. J. Contemp. Issues Bus. Gov. 2021, 27, 709–713.

[2] Stone, D.L.; Deadrick, D.L.; Lukaszewski, K.M.; Johnson, R. The Influence of Technology on the Future of Human Resource Management. Hum. Resour. Manag. Rev. 2015, 25, 216–231.

[3] Marler, J.H.; Parry, E. Human resource management, strategic involvement and e-HRM technology. Int. J. Hum. Resour. Manag. 2016, 27, 2233–2253.

[4] García-Arroyo, J.; Osca Segovia, A. Big data contributions to human resource management: A systematic review. Int. J. Hum. Resour. Manag. 2021, 32, 4337–4362.

[5] Hong, Z. Research on human resource recommendation algorithm based on machine learning. Sci. Program. 2021, 2021, 8387277.

[6] Michael, H.; Kaplan, A. A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence. Calif. Manag. Rev. 2019, 61, 5–14.

[7] Tambe, P.; Cappelli, P.; Yakubovich, V. Artificial intelligence in human resources management: Challenges and a path forward. Calif. Manag. Rev. 2019, 61, 15–42.

[8] Tekkeşin, A.İ. Artificial Intelligence in Healthcare: Past, Present and Future. Anatol. J. Cardiol. 2019, 22, 8–9.

[9] Buiten, M.C. Towards intelligent regulation of artificial intelligence. Eur. J. Risk Regul. 2019, 10, 41–59.

[10] Kuzior, A. Technological Unemployment in The Perspective of Industry 4.0 Development. Virtual Econ. 2022, 5, 7–23.

[11] Kuzior, A.; Kwilinski, A. Cognitive Technologies and Artificial Intelligence in Social Perception. Manag. Syst. Prod. Eng. 2022, 30, 109–115.

[12] Berhil, S.; Benlahmar, H.; Labani, N. A review paper on artificial intelligence at the service of human resources management. Indones. J. Electr. Eng. Comput. Sci. 2020, 18, 32–40.

[13] Bhardwaj, G.; Singh, S.V.; Kumar, V. An Empirical Study of Artificial Intelligence and its Impact on Human Resource Functions. In Proceedings of the 2020 International Conference on Computation, Automation and Knowledge Management (ICCAKM), Dubai, United Arab Emirates, 9–10 January 2020; pp. 47–51.

[14] Ore, O.; Sposato, M. Opportunities and risks of artificial intelligence in recruitment and selection. Int. J. Organ. Anal. 2021, 30, 1771–1782.

[15] Li, F.; Ruijs, N.; Lu, Y. Ethics & AI: A Systematic Review on Ethical Concerns and Related Strategies for Designing with AI in Healthcare. AI 2023, 4, 28–53.

[16] Jepsen, D.M.; Grob, S. Sustainability in recruitment and selection: Building a framework of practices. J. Educ. Sustain. Dev. 2015, 9, 160–178.

[17] Bauer, T.N.; Erdogan, B.; Taylor, S. Creating and Maintaining Environmentally Sustainable Organizations: Recruitment and Onboarding; Jossey-Bass/Wiley: New York, NY, USA, 2012.

[18] Saad, M.F.M.; Nugro, A.W.L.; Thinakaran, R.; Baijed, M. A Review of Artificial Intelligence Based Platformin Human Resource Recruitment Process. In Proceedings of the 6th IEEE International Conference on Recent Advances and Innovations in Engineering (ICRAIE), Kedah, Malaysia, 1–3 December 2021.

[19] Furtmuellera, E.; Wilderom, C.; Tate, M. Managing recruitment and selection in the digital age: E-HRM and resumes. Hum. Syst. Manag. 2021, 30, 243–259.

[20] Wilfred, D. AI in recruitment. NHRD Netw. J. 2018, 11, 15–18.

[21] Arbab, A.M.; Mahdi, M.O.S. Human resources management practices and organizational excellence in public orgnizations. Pol. J. Manag. Stud. 2018, 18, 9–21.

[22] Strohmeier, S.; Piazza, F. Artificial intelligence techniques in human resource management—A conceptual exploration. In Intelligent Techniques in Engineering Management; Springer: Cham, Switzerland, 2015; pp. 149–172.

[23] Da Silva, L.B.P.; Soltovski, R.; Pontes, J.; Treinta, F.T.; Leitão, P.; Mosconi, E.; Yoshino, R.T. Human resources management 4.0: Literature review and trends. Comput. Ind. Eng. 2022, 168, 108111.

[24] Merlin, R.P.; Jayam, R. Artificial Intelligence in Human Resource Management. Int. J. Pure Appl. Math. 2018, 119, 1891–1896.

[25] Alavuo, N.H. Modern Recruitment Process as a Competitive Advantage in Talent Acquisition: A Recruiter's Playbook. Master's Thesis, Haaga-Helia University of Applied Sciences, Helsinki, Finland, 2020.

[26] Hoang, L. From Customer Journey to Candidate Journey: Applying Marketing Principles to Build a Winning Hiring Culture. Master's Thesis, Metropolia University of Applied Sciences, Helsinki, Finland, 2018.

[27] Al-Alawi, A.I.; Naureen, M.; AlAlawi, E.I.; Al-Hadad, A.A.N. The Role of Artificial Intelligence in Recruitment Process Decision-Making. In Proceedings of the 2021 International Conference on Decision Aid Sciences and Application (DASA), Sakheer, Bahrain, 7–8 December 2021; pp. 197–203.

[28] Utami, E.; Luthfi, E.T. Profiling Analysis Based on Social Media for Prospective Employees Recruitment Using SVM and Chi-Square. J. Phys. Conf. Ser. 2018, 1140, 012043.

[29] Wang, Q.L.; Li, B.; Hu, J. Feature selection for human resource selection based on affinity propagation and SVM sensitivity analysis. In Proceedings of the 2009 World Congress on Nature & Biologically Inspired Computing (NaBIC), Coimbatore, India, 9–11 December 2009.

[30] Li, Y.-M.; Lai, C.-Y.; Kao, C.-P. Building a qualitative recruitment system via SVM with MCDM approach. Appl. Intell. 2011, 35, 75–88.

[31] Mnasri, M. Recent advances in conversational NLP: Towards the standardization of Chatbot building. arXiv 2019, arXiv:1903.09025.

[32] Chowdhury, G.G. Natural language processing. In Fundamentals of Artificial Intelligence; Springer: New Delhi, India, 2020; pp. 603–649.

[33] Nadkarni, P.M.; Ohno-Machado, L.; Chapman, W.W. Natural language processing: An introduction. J. Am. Med. Inform. Assoc. 2011, 18, 544–551.

[34] Soutar, K. How Chatbots Can Be Used to Re-Engage with Applicants during Recruitment. Master's Thesis, Aalto University, Espoo, Finland, 2019.

[35] Majumder, S.; Mondal, A. Are chatbots really useful for human resource management? Int. J. Speech Technol. 2021, 24, 969–977.

[36] Nawaz, N.; Gomes, A.M. Artificial intelligence chatbots are new recruiters. (IJACSA) Int. J. Adv. Comput. Sci. Appl. 2019, 10.

[37] Anitha, K.; Shanthi, V. A Study on Intervention of Chatbots in Recruitment. In Innovations in Information and Communication Technologies (IICT-2020); Springer: Cham, Switzerland, 2021; pp. 67–74.

[38] Koivunen, S.; Ala-Luopa, S.; Olsson, T.; Haapakorpi, A. The March of Chatbots into Recruitment: Recruiters' Experiences, Expectations, and Design Opportunities. Comput. Support. Coop. Work. (CSCW) 2022, 31, 1–30.

[39] Shehu, M.A.; Saeed, F. An adaptive personnel selection model for recruitment using domain-driven data mining. J. Theor. Appl. Inf. Technol. 2016, 91, 117–130.

[40] Singh, S.; Kumar, V. Performance Analysis of Engineering Students for Recruitment Using Classification Data Mining Techniques. Int. J. Sci. Eng. Comput. Technol. 2013, 3, 31–37.

[41] Hmoud, B.; Laszlo, V. Will artificial intelligence take over human resources recruitment and selection. Netw. Intell. Stud. 2019, 7, 21–30.

[42] Pah, C.E.A.; Utama, D.N. Decision Support Model for Employee Recruitment Using Data Mining Classification. Int. J. Emerg. Trends Eng. Res. 2020, 8, 1511–1516.

[43] Joshi, A.P.; Panchal, R.K. Data mining for staff recruitment in education system using WEKA. Int. J. Res. Comput. Sci. Manag. 2014, 2, 1–4.

[44] Willemink, M.J.; Koszek, W.A.; Hardell, C.; Wu, J.; Fleischmann, D.; Harvey, H.; Folio, L.R.; Summers, R.M.; Rubin, D.L.; Lungren, M.P. Preparing medical imaging data for machine learning. Radiology 2020, 295, 4–15.

[45] Soibelman, L.; Kim, H. Generating construction knowledge with knowledge discovery in databases. In Proceedings of the Eighth International Conference on Computing in Civil and Building Engineering (ICCCBE-VIII), Stanford, CA, USA, 14–16 August 2000; pp. 906–913.

[46] Kumar, V.; Minz, S. Feature Selection: A literature Review. SmartCR 2014, 4, 211–229.