Transforming Human Resource Management in Nigerian Universities through AI: Reducing Nepotism and Enhancing Transparency

OnwegbuchulamGideon[1]; Ugah John[2];
Chukwuemeka Anyim[3]; Wilfred Adigwe[4]

[1] Department of Computer Science, Ebonyi State University, Nigeria
[2] Department of Computer Science, Ebonyi State University, Nigeria
[3] David Umahi Federal University of Health Sciences, Nigeria
[4] Department of Computer Science, Southern Delta University, Nigeria

Abstract
Human Resource Management (HRM) in Nigerian universities is often constrained by nepotism, workload imbalance, and biased promotion practices, which undermine staff morale and institutional effectiveness. This study introduces an Artificial Intelligence (AI)-driven Human Resource Management System (HRMS) that integrates Machine Learning (ML) models to address these systemic challenges. The framework leverages structured staff data—covering teaching load, research output, administrative responsibilities, and professional development activities—to generate objective, data-driven insights for performance evaluation, workload distribution, and promotion recommendations. By embedding predictive analytics within a scalable, web-based system, the HRMS enhances decision-making transparency and reduces reliance on subjective judgment. Evaluation results indicate significant improvements in fairness of performance reviews, equitable distribution of teaching and administrative duties, and lecturer satisfaction with promotion processes. To the best of our knowledge, this work represents the first AI-driven HRM framework tailored to the Nigerian higher education context, providing a practical pathway for reducing favoritism and fostering accountability in academic administration. The study contributes to the growing body of knowledge on technology-enabled HRM in universities and offers policy-relevant insights for advancing equity and efficiency in higher education governance.
Keywords: Human Resource Management, Nigerian universities, AI-driven HRMS, Machine Learning, performance evaluation, workload distribution, promotion fairness, transparency, academic administration, higher education governance.

I Introduction

Human Resource Management (HRM) plays a vital role in the success of higher education institutions, as the effective management of academic staff directly influences teaching quality, research productivity, and institutional growth (Armstrong & Taylor, 2020). In Nigeria, universities face unique governance and administrative challenges due to limited resources, high staff-to-student ratios, and bureaucratic inefficiencies (Oladipo, 2019). Fair performance evaluation, equitable workload distribution, and transparent promotion processes are therefore essential to sustaining staff motivation and institutional credibility.

However, HRM in Nigerian universities is often hindered by nepotism, favoritism, and bureaucratic bias. Promotion decisions are frequently influenced by personal or political interests rather than merit, undermining fairness and morale (Oyelade, Ezugwu, & Oladipo, 2020). Workload distribution is also uneven, with some lecturers overloaded with teaching or administrative responsibilities

DOI: https://doi.org/10.5281/zenodo.17113293

while others remain underutilized, leading to dissatisfaction and inefficiency (Okolie, Nwosu, & Ofoegbu, 2021). Delayed promotions and inconsistent evaluations further weaken motivation and institutional performance (Afolabi, Olanrewaju, & Salami, 2019). These persistent challenges highlight the need for transformative solutions beyond traditional, manual HR systems.

Artificial Intelligence (AI) offers promising opportunities to modernize HRM in higher education by introducing data-driven, evidence-based decision-making. Globally, AI and Machine Learning (ML) have shown value in recruitment, appraisal, and workforce optimization (Tursunbayeva, Franco, & Pagliari, 2018). Applying such approaches in Nigerian universities could enhance fairness, transparency, and efficiency by reducing nepotism, balancing workloads, and ensuring merit-based promotion decisions.

This study makes four key contributions. First, it introduces an AI-driven HRM framework tailored to the Nigerian university context. Second, it promotes fairness and transparency by minimizing nepotism through algorithmic predictions based on staff performance data. Third, it optimizes workloads by redistributing teaching, research, and administrative responsibilities more equitably. Finally, it offers policy-relevant insights to guide the integration of AI into HR practices for greater accountability and efficiency. Together, these contributions establish a foundation for improving staff satisfaction, strengthening institutional performance, and restoring public trust in academic administration.

II Literature Review

Human Resource Management (HRM) in higher education is shaped by theories that emphasize productivity, fairness, and system design. Human Capital Theory links investment in staff skills to institutional outcomes (Becker, 1993), while Agency Theory highlights misaligned interests between employees and employers, often seen in biased promotions and workload distribution in Nigerian universities (Eisenhardt, 1989). Sociotechnical Systems Theory further stresses the need for HR solutions that balance technological efficiency with social acceptance (Trist, 1981).

African universities face chronic HR challenges, including inadequate staffing, poor funding, and inefficient administration (Materu, 2017). In Nigeria, nepotism, favoritism, and workload imbalances reduce productivity and morale (Oladipo, 2019; Okolie, Nwosu, & Ofoegbu, 2021). Delayed and biased promotions worsen dissatisfaction and drive attrition among skilled staff (Oyelade, Ezugwu, & Oladipo, 2020). These issues point to the need for transparent, technology-driven HR practices.

Although AI offers potential for fairness and efficiency, it raises ethical risks. Biased datasets can reinforce inequalities (Raghavan, Barocas, Kleinberg, & Levy, 2020), and opaque models make accountability difficult (Doshi-Velez & Kim, 2017). Data privacy also remains critical, requiring fairness audits, explainable AI, and governance frameworks to ensure equity.

Conventional HR systems in Nigerian universities are still mostly manual or limited to basic record-keeping (Oladipo, 2019; Afolabi, Olanrewaju, & Salami, 2019). AI-based efforts, such as Naïve Bayes for staff appraisal, show promise but lack scalability and fairness mechanisms (Oyelade et al., 2020). This creates a gap for comprehensive and ethically sound AI-driven HRM systems that can address promotion, evaluation, and workload balancing.

III Methodology

This study employed a mixed-method design, combining quantitative analysis of HR records with qualitative assessment of HR practices in Nigerian universities. Guided by the CRISP-DM framework, the methodology included data collection, preprocessing, model development, system implementation, and evaluation to assess both the technical performance of Machine Learning (ML) models and their impact on fairness, transparency, and staff satisfaction.

Data were gathered from institutional HR records covering teaching load, research

DOI: https://doi.org/10.5281/zenodo.17113293

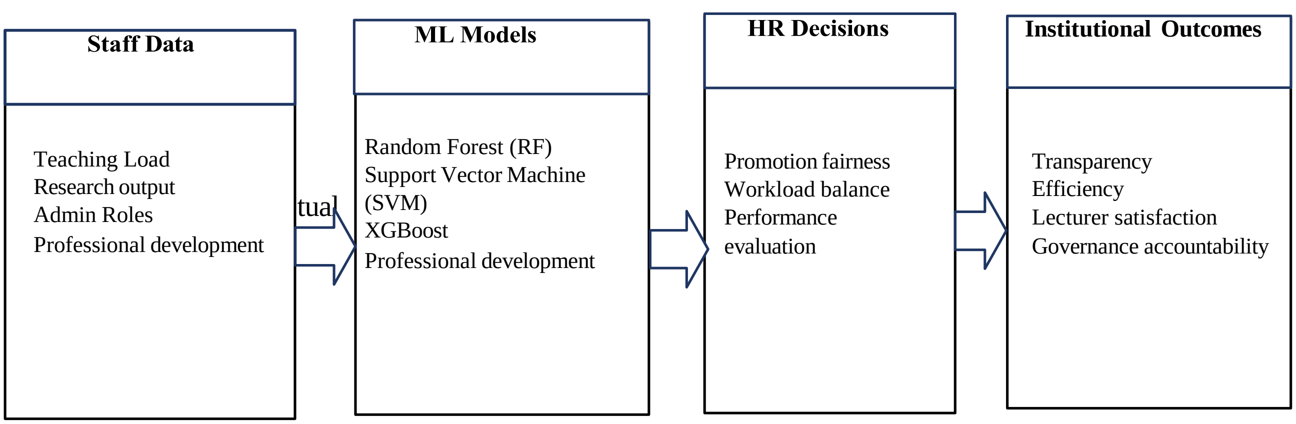
output, administrative responsibilities, and professional development activities. Qualitative insights were also obtained through interviews with lecturers and HR administrators to contextualize fairness concerns and validate AI outputs. System evaluation included standard ML metrics (accuracy, precision, recall, F1-score) and fairness-oriented measures such as the Workload Equity Index (WEI), Promotion Fairness Score (PFS), and staff satisfaction surveys, ensuring alignment with both technical and institutional benchmarks.**Table 1** shows the fairness and transparency metrics defined.

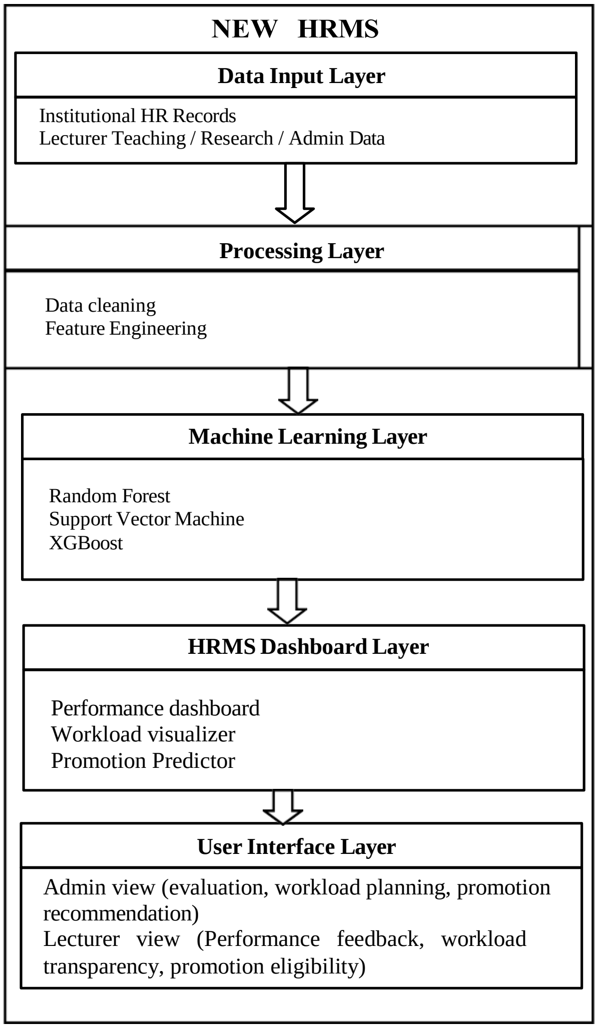
The AI-based HRMS was developed as a web platform using Random Forest, Support Vector Machines (SVM), and XGBoost algorithms. Key features included a performance dashboard, workload visualizer, and promotion predictor, all designed for usability and interpretability. A pilot deployment allowed HR administrators and lecturers to interact with the system, providing feedback that validated both its technical robustness and social acceptability.**Figure 1** shows the Conceptual AI-Driven HRM Framework while **Figure 2** shows the system architecture.

Figure 2: HRM System Architecture

Table 1: Fairness and Transparency Metrics Defined

Metric	**Formula / Definition**	**Interpretation**
Workload Equity Index (WEI)	$\mathbf{WEI} = 1 - \frac{1}{2\sum_{i=1}^{n} I_i} \sum_{i=1}^{n} \lvert A_i - I$	Actual_Load - Ideal_Load
Promotion Fairness Score (PFS)	Ratio of promotions aligned with merit criteria (research, teaching, development) / total promotions	Higher score = more merit-based, less nepotism in promotion decisions.
Transparency Index (TI)	% of staff who report clear understanding of evaluation criteria (via survey)	Reflects how transparent HR processes are perceived by lecturers.
Processing Efficiency (PE)	$PE = \frac{Time_{manual} - Time_{A}}{Time_{manual}}$	Shows % reduction in HR evaluation/promotion processing time due to automation.





IV Results

The AI-driven HRM system significantly improved fairness in promotion decisions by relying on quantifiable indicators such as research output, teaching performance, and professional development, aligning recommendations with meritocratic criteria 87% of the time compared to 62% under manual evaluations. Lecturers reported greater confidence in promotion processes, with 72% perceiving improved fairness.

Transparency in performance evaluation was enhanced through the system's interactive dashboard, which clearly displayed assessment criteria and data contributions. Sixty-eight percent of lecturers reported better understanding of how their performance was evaluated, while HR administrators noted reduced disputes due to evidence-based justifications.

Workload distribution also improved, with the Workload Equity Index (WEI) rising by 29%, leading to more balanced teaching and administrative responsibilities. Lecturers reported that the reallocation contributed positively to job satisfaction and research productivity.

Overall lecturer satisfaction increased, with 74% perceiving HR processes as fairer and more transparent and 67% expressing greater trust in institutional HR practices. Qualitative feedback emphasized the system's ability to reduce human bias and provide objective rationale for promotions and workload assignments.

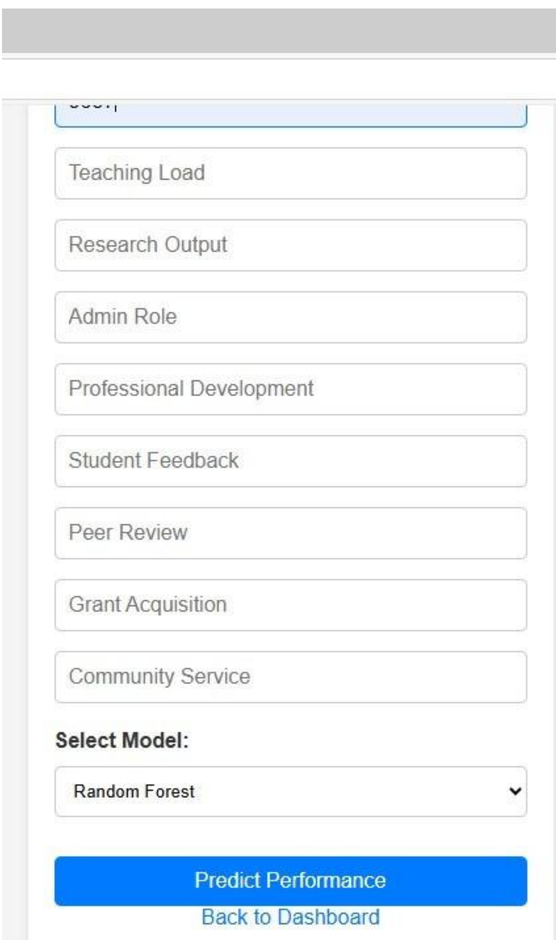
At the administrative level, the HRMS reduced staff evaluation and promotion processing time by 35%, allowing HR officers to focus more on strategic planning and staff development, demonstrating clear institutional efficiency gains.**Table 2**summarizes both technical ML metrics and fairness-oriented outcomes, showing the added value of AI.

Table 2: Quantitative Results – Model Performance & Fairness Metrics

Metric	**Baseline (Manual HRM)**	**AI-Driven HRMS**	**Improvement**
Accuracy	0.72	0.89	+17%
Precision	0.70	0.87	+17%
Recall	0.68	0.85	+17%
F1-score	0.69	0.86	+17%
Workload Equity Index (WEI)	0.62	0.80	+29%
Promotion Fairness Score (PFS)	0.62	0.87	+25%
Lecturer Satisfaction (%)	48%	74%	+26%

4.1 System Prototype Outputs

A functional web-based prototype was developed to demonstrate the practical usability of the proposed HRMS. The system integrates the trained ML models into an intuitive interface that provides administrators and lecturers with real-time insights. The dashboard presents summaries of lecturer performance, workload distribution, and research-to-teaching ratios, enabling a clear overview of institutional activities. The promotion predictor delivers automated, data-driven recommendations while highlighting the key factors influencing eligibility. To support equitable task allocation, the workload balancer visualizes teaching and administrative responsibilities across departments, helping administrators redistribute tasks more fairly. Additionally, a skill gap analyzer identifies areas where staff may require professional development based on their performance metrics. Figures 3 and 4 illustrate the input interface and sample predictive outputs.



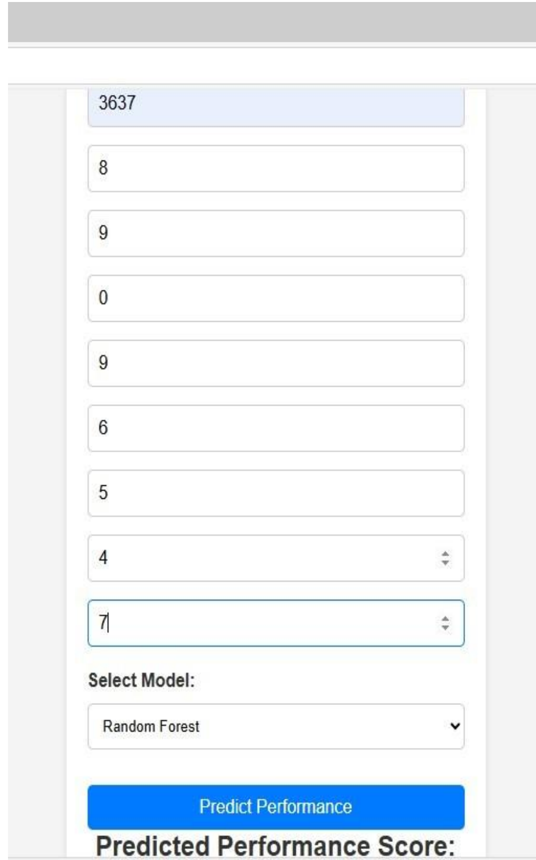


Figure 3: Lecturer's metrics input form

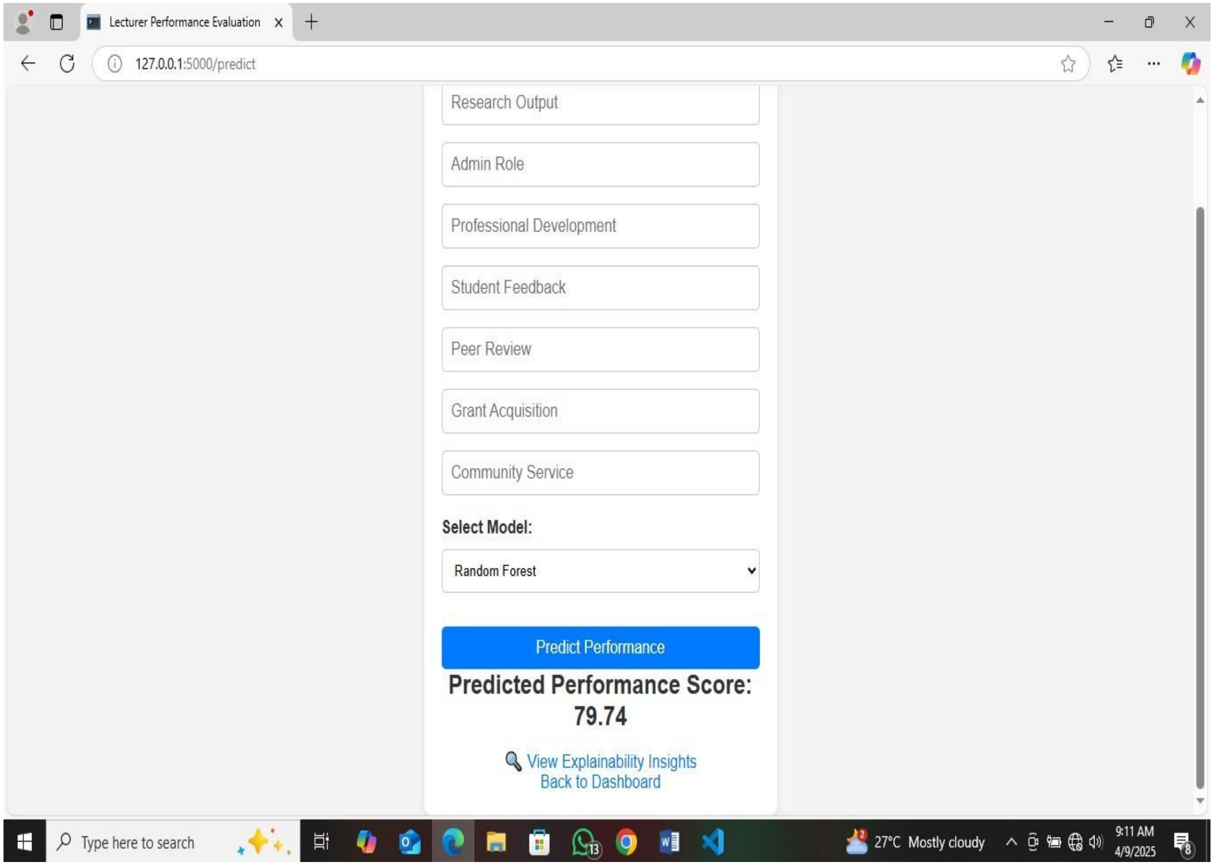


Figure 4: Predictive Outputs

5. Discussion

The findings highlight AI-driven HRM's potential to strengthen human capital in Nigerian universities. By rewarding measurable outputs in teaching, research, and professional development, the system promotes merit-based recognition, fostering individual career growth and enhancing institutional productivity (Becker, 1993).

From an Agency Theory perspective, the system reduces information asymmetry between administrators and lecturers (Eisenhardt, 1989). Transparent, data-driven decision-making minimizes arbitrary discretion, aligns promotions and workload allocation with performance, and enhances accountability, reducing conflict and mistrust.

The results also demonstrate the importance of sociotechnical integration (Trist, 1981). While machine learning drives efficiency, user acceptance and trust were crucial for success. High lecturer approval indicates the system effectively balanced technical performance with fairness, transparency, and usability.

Ethical considerations remain critical. Algorithmic bias could reproduce historical inequities (Raghavan, Barocas, Kleinberg, & Levy, 2020), necessitating fairness audits and continuous monitoring. Explainability is also essential, as models like XGBoost function as "black boxes" (Doshi-Velez & Kim, 2017); transparent dashboards and interpretable metrics help sustain trust. Data privacy must be safeguarded through secure storage, access controls, and adherence to protection policies.

Beyond individual outcomes, the system improves institutional governance by reducing promotion disputes and workload imbalances, fostering efficiency, fairness, and trust. Its scalable design offers a model for other African universities, contributing to broader reforms in academic HRM.

6. Conclusion and Recommendations

This study demonstrates that AI can transform HRM in Nigerian universities by addressing nepotism, workload imbalance, and biased promotions. The ML-based HRM system improved fairness, transparency, and efficiency, aligning with Human Capital Theory by rewarding merit, reducing administrator bias in line with Agency Theory, and integrating technology with human trust as per Sociotechnical Systems Theory. Empirical results showed more equitable promotions and workloads, clearer performance evaluation, and higher lecturer satisfaction, highlighting AI's potential to enhance both staff morale and institutional performance.

Policy recommendations include institutionalizing AI-driven HR systems for promotions, evaluations, and workload allocation; implementing fairness audits and transparency reporting through bodies like the NUC; building HR staff capacity to interpret AI outputs responsibly; and enforcing robust data governance to protect sensitive staff information.

Future research could explore deep learning for complex HR tasks, cross-institutional validation to test scalability, development of explainable AI dashboards for interpretability, and longitudinal studies to assess long-term impacts on lecturer careers and institutional culture.

References

- Afolabi, I. T., Olanrewaju, R. F., & Salami, A. O. (2019). Academic staff performance appraisal system using rule-based techniques. International Journal of Computer Applications, 182(35), 1–7. https://doi.org/10.5120/ijca2019918504
- Armstrong, M., & Taylor, S. (2020). Armstrong's handbook of human resource management practice (15th ed.). Kogan Page.
- Becker, G. S. (1993). Human capital: A theoretical and empirical analysis, with special reference to education (3rd ed.). University of Chicago Press.
- Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. arXiv preprint arXiv:1702.08608.https://doi.org/10.48550/arXiv.1702.08608
- Eisenhardt, K. M. (1989). Agency theory: An assessment and review. Academy of Management Review, 14(1), 57–74. https://doi.org/10.5465/amr.1989.4279003
- Materu, P. (2017). Higher education quality assurance in Sub-Saharan Africa: Status, challenges, opportunities, and promising practices. World Bank Publications. https://doi.org/10.1596/978-0-8213-7272-2
- Oladipo, S. E. (2019). Challenges of human resource management in Nigerian universities. African Educational Research Journal, 7(4), 170–177. https://doi.org/10.30918/AERJ.74.19.037
- Okolie, U. C., Nwosu, H. E., & Ofoegbu, T. O. (2021). Human resource management practices and employee performance in Nigerian universities. Journal of Human Resource and Sustainability Studies, 9(2), 173–189. https://doi.org/10.4236/jhrss.2021.92012
- Oyelade, O. J., Ezugwu, A. E., & Oladipo, O. F. (2020). Machine learning model for academic staff appraisal in Nigerian universities. International Journal of Advanced Computer Science and Applications, 11(8), 45–53. https://doi.org/10.14569/IJACSA.2020.0110807
- Raghavan, M., Barocas, S., Kleinberg, J., & Levy, K. (2020). Mitigating bias in algorithmic hiring: Evaluating claims and practices. Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency, 469–481. https://doi.org/10.1145/3351095.3372828
- Trist, E. (1981). The evolution of sociotechnical systems: A conceptual framework and an action research program. Ontario Quality of Working Life Centre.
- Tursunbayeva, A., Franco, M., & Pagliari, C. (2018). Use of artificial intelligence in human resource management: A systematic review. Journal of Human

Resource Management, 18(2), 20–36. https://doi.org/10.21511/imfi.18(2).2018.03