International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 11 | Nov - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

Transitioning From Algorithmic Decision-Making to Human-Centered Workplaces: A Governance Framework for Responsible AI in Human Resource Management

Rama Singh[1], Prof. (Dr.) Pramod Kumar[2], Dr. Niraj Srivastava[3]

[1]Research Scholar, Department of Commerce, M.G.K.V.P. Varanasi
[2]Principal, Govt. P.G. College, Obra, Sonbhadra
[3]Principal, Krishna College of Education and Management, Lucknow
Email: rama38854@gmail.com

Abstract

Artificial intelligence (AI) is transforming Human Resource Management (HRM) through algorithm-based recruitment, selection, performance management, workforce planning, learning and development, and workforce monitoring. Such applications may improve their utilisation, speed and analytics, and consistency in processing worker data. At the same time, the use of these applications for decisions in the employment context presents a rising set of challenges including algorithmic bias, opacity, privacy, responsibility, employee autonomy, trust, and worker well-being. This study explores the transformation of algorithmic decision-making in human-centred workplaces and suggests a conceptual governance framework for the responsible adoption of AI in HRM. The paper distils six interrelated themes from the literature matrix for the study: (1) digital transformation of HRM, (2) implementing algorithms in HR functions, (3) ethical questions and responsibilities, (4) human-algorithmic interplay and trust, (5) algorithmic management and employee well-being, and (6) strategic capabilities for responsible adoption. The approach incorporates five governance pillars: (1) Openness and Explainability; (2) fairness and non-discrimination; (3) meaningful human supervision and responsibility; (4) employee involvement, privacy, and well-being; and (5) ongoing evaluation and organisational learning. Potential human-centred consequences of these pillars might include trust, organisational fairness, autonomy, employee engagement and well-being, hence contributing to sustainable organisational performance. Seven propositions are suggested for future empirical research. It provides a holistic, lifelong perspective on AI as a decision assistant and enriching mechanism rather than an isolated judge of high-stakes employment outcomes. The paper ends with implications for management and policy and a future research agenda for empirical validation.

Keywords: Human Resource Management; Algorithmic Decision-Making; Responsible AI; Human-Centered Workplaces, AI Governance; Employee Well-Being; Human–AI Collaboration.

Introduction

AI as a driver of transformational change in a business strategically. For instance, Human Resource Management is also harnessing AI-enabled applications and automated analytics programs used to source and screen candidates, offer employee services, perform workforce analytics and apply in the management of talent and employee performance appraisal, human capital and workforce management, workforce planning and learning and development, and employee monitoring. These types of apps will help firms to examine enormous volumes of data to spot trends and automate repetitive operations and generate predictive insights for decision-making. Thus, HRM is transitioning from the traditional administrative job to a more analytical and strategically aligned position.

Digitalization in HRM has evolved via a series of stages, from electronic HRM to digital HR platforms, HR analytics, and AI-supported workflows. For example, Bondarouk and Brewster (2016) discuss the digital future of HRM, while Strohmeier (2020) treats digital HRM as a new topic for critical elaboration. And the promise is further apparent in the evidence-based HR analytics (Marler & Boudreau, 2017) and in AI's opportunities and challenges for HRM (Tambe, Cappelli, & Yakubovich, 2019). In this literature there are sympathetic signs that the instruments of HR

departments and the knowledge, power, and responsibility in enterprises are currently being changed by technology but AI in HRM is not only about technology or efficiency.

Decisions regarding people determine access to work and income, career progression, identity, dignity, and livelihood. When these decisions are taken by means of algorithmic systems, issues are raised regarding data quality and representativeness, fairness of the output/model, explanation of the decision, protection of employee information, and the scope for meaningful oversight by humans. Even a well-designed system may provide unsatisfactory or damaging output (such as embodying historical biases in the data, ignoring mitigating factors, and not affording employees the opportunity to challenge the results).

So the question is not whether businesses should accept or even shun AI in toto. Rather, it's about the kinds of AI governance organizations can take on to complement human judgment and design work that is just, inclusive, and sustainable. Jarrahi (2018) uses on the human-AI symbiosis, interfacing computing technologies and human decision-makers in businesses and their beneficial complementarity. Leicht-Deobald et al. (2019) present consequences of decision-making algorithms for personal integrity; Kellogg et al. (2020) discuss working in the era of algorithms.

In this regard, the article presents a conceptual governance framework for responsible AI adoption, namely, 'Human-Centred Responsible AI Governance Framework for HRM. 'Responsible AI adoption: An extended typology of ethical, management, employee, and organizational issues. It is not a substitute but an enabler in any critical employee decision such as recruitment/selection, appraisal, promotion, remuneration, discipline, and termination.

1.1 Research problem

Works are underway to utilise AI for particular HR tasks, as well as to separate biases, privacy, transparency, trust, autonomy, and even employee well-being. However, these themes are usually discussed in isolation. It needs to be governed in organisations in a manner that combines principles (e.g. fairness, explainability) and mechanisms (e.g. human review, consulting employees, audit, accountability, continuous improvement). The research problem that we tackle in this article is that there is no integrated conceptual account (in the surveyed research literature) of how these governance mechanisms can come together to enable the transition from algorithmic decision making to human-centred workplaces.

1.2 Research objectives

1. To look at what AI looks like and how it is used in modern HRM.

2. To identify and analyse the key organizational, ethical and labour algorithmic HR issues.

3. Review of literature on human-AI interaction, trust, autonomy and wellbeing at work.

4. Robust governance framework for effective AI adoption in the HR function.

5. Implications for policy, future research, and management.

2. Review of Literature

2.1 Digitalization and AI as a Driver of the Transformation of HRM.

Digitalization and Data-Based Management, a Sub-Trend of Artificial Intelligence and Human Resource Management. Bondarouk and Brewster (2016) address the relevance of digital technologies to e-HRM and the future of digital HRM, as well as how they might enable and contribute to the strategy of several HR roles. Strohmeier (2020) delivers a strong criticism of digital HRM and establishes a research agenda at the convergence of HR functions and digital technology. Kshetri, N. Big data and human resources management analytics (2018). Marler, J., & Boudreau, B. (2017). Human resource analytics: A new field to map and address the data to decisions pipeline. Sivathanu, K., Pillai, P., & Marler, J.H. (2019). Sivathanu, M. & Pillai, P. (2018). Smart HR 4.0-How tech-enabled HR practices work. These sources demonstrate that, while artificial intelligence can boost the analytical potential of HR managers, the success of this undertaking is based on the data's purity, the suitability of the AI solutions, the degree of the organisational preparation, and the competence in interpreting the results. Therefore, the adoption of AI should be treated as an organizational change and should not only be the installation of software.

2.2. Algorithmic applications across HR functions

Use of AI in Human Resource operations Multiple human resource operations apply algorithms. AI in recruitment and selection not only finds, screens, and matches potential applicants but also contacts the candidates and, in certain cases, even schedules the prospects. Upadhyay and Khandelwal (2018) review the application of AI in recruitment and selection; van etch et al. (2019) try to classify recruitment automation with its organizational issues. Chat bots for recruitment and HR: the candidate experience and process efficiency (Suen et al., 2019) Tarabasz, P., & Kowalki, T. (2022). Chatbot utilisations in on-boarding and recruitment: A survey. Other AI applications include talent development, performance appraisal, workforce planning, and talent management. For example, Ai-talent management solutions were examined by Fernandez & Gallardo-Gallardo (2021). Agarwal, Gautham, & Sinha (2022) studied AI and customised instruction for skills gaps, and Yadav (2024) researched AI in talent analytics and workforce planning. Ghosh (2020) examined AI in performance appraisals, noting its promise for objectivity but also its inability to perceive context. These are some of the extents of AI-enhanced human resource management. However, not all tasks can be automated. While many jobs like as basic administrative work are great candidates for automation, decisions that involve employee rights or complex interpersonal situations or major career implications require greater human contact. Rather than asking, "What do we automate in HR?" Instead ask, "Where should we bring smart human judgement and oversight into HR?"

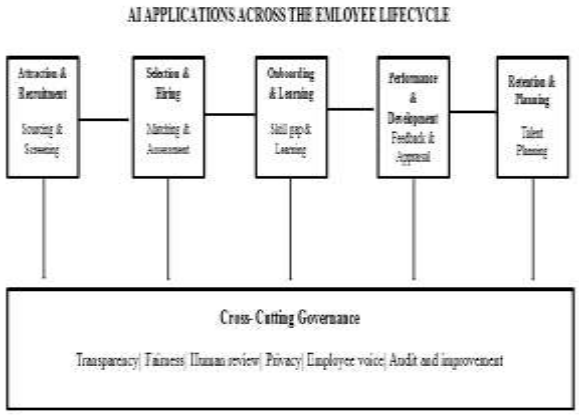


Figure 1: AI applications across the employee lifecycle and cross-cutting governance safeguards.

2.3 Ethical challenges: bias, transparency, privacy, and accountability

Algorithmic systems can also reveal or reproduce yesterday's data patterns. For instance, a system training off samples or reports of practice treating certain people unequally for hiring or promotions can learn poor models of certain people. For instance, Amazon was forced to scrap an experimental AI recruiting tool that displayed signs of gender bias (Dastin, 2018). At least in that it shows how meet can exploit automation to perpetuate, rather than remedy, historic imbalances (this, of course, is a recorded case, not a regulated academic exercise). Regarding the integrity of a human individual, Leicht-Deobald et al. (2019) explore problems with efficiency from the point of view of the technical approach and the challenges of making algorithmic HR decisions. Ajunwa (2020) discusses the ethics or legality of automating hiring labor, reviewing the paradox of automation in HR. Meijerink, Bondarouk, & Lepak (2021). Algorithmic HRM: Changing the Meaning of Work, Autonomy, Fairness, and Governance through Automation. This literature review emphasizes the need to evaluate artificial intelligence (AI) systems not only for their predictive accuracy but also for their implications for fundamental rights and equality and dignity of man, viewed from the perspective of law. Providing explanations and clarity is necessary to guaranty that employee and supervisors understand the basis and limitations of AI-assisted recommendations. Also, the division of duties within an organization (system selection, data verification, model validation, decision making, damage response, etc.) must also be clear. Systematized approaches should be developed for ethical review, monitoring, evaluation, and AI challenge.

2.4 Human–AI collaboration, trust, and decision quality

The literature is beginning to attend to AI as an augmentation. Jarrahi (2018) discusses symbiosis in human-AI decision making for organizations. Huang and Rust (2018) explore AI in services and the evolution of human/artificial competence. Shrestha et al. (2019) Artificial intelligence-based decision-making architectures: a review of... Decision Augmentation as a term for human decision-making with the support of AI, in organizations.

Glikson, Y., & Woolley, A. (2020). Human trust in artificial intelligence: Review of empirical literature. Advances in Human-Computer Interaction, 2020. Trust is not simply about the blind acceptance of algorithmic outputs. Appropriate trust is when a user understands what a system "does and does not do," knows where the uncertainty is, and has a plan for how they can challenge recommendations. This is especially pertinent in HRM, where there are decision points where users may want to challenge nonusers from the system data or questions of logic within them.

But the learning algorithm is also someone to work with and organize around (Faraj, Pachidi, & Sayegh, 2018). Davenport and Ronanki (2018) emphasize the best ways to adopt AI in organizations. All those works advocate for an approach when humans and artificial intelligence are able to provide enough context and knowledge for decision-making as well as ethical/moral judgment, empathy, sense of responsibility, etc.

2.5 Algorithmic management, employee autonomy, and well-being

Algorithmic management replaces the workplace with (algorithmic) management and disconnects workers from the new (algorithmic)'management" (Kellogg et al., 2020); Algorithmic management … measures, monitors 'work'" (Kellogg et al., 2020); "Algorithmic management … reconnects the technologically mediated workplace with (workers or workers' representations) as a [third party]" (Kellogg et al., 2020). "The labor process of '[algorithmic] management'... Subverts the agency and autonomy of workers, working conditions, and resistance" (Kellogg et al., 2021). Brougham, D., & Haar, J. (2018). Smart Idea: Talent, Automation, and Results: Innovation and Machines at Work. Zhang, T. & Zhu, L. (2021). The Disappearing Face of the Car: A Dialog between AI and Occupational Medicine. Ghosh, P., & Basu, A. (2022). Artificial Intelligence and Employee Participation: Privacy Protection in Indian Context. These papers are against the use of AI for employee response and workplace performance. Then task th AI and thus covert neutralized surveillance questions lead to mistrust and loss of autonomy. Transparency also involves proportionality of data-usage limits, employee inputs, and evaluation expectations. The productivity j-curve (Brynjolfsson et al 2018) also indicates that productivity effects of general-purpose technologies are lagged and require presence and further investments. Technology is not the silver bullet of better organizational performance.

2.6 Strategic capabilities and responsible adoption

Responsible AI adoption involves the alignment of standard artificial intelligence (AI) technology, organizational strategy, and human capabilities." Langer, König & Kraft (2019) The human resources digital transformation – The strategic role of HR. Minbaeva (2021) highlights the new roles and competencies in HR necessitated by the emergence of AI (e.g., data literacy, ethical governance). Van den Broek & Zierahn (2019) research AI & future work and policy and managerial implication: The role of skills and skills formation accounting for the future workforce.

According to the literature, HR professionals will need skills to interpret the output of algorithms, understand limitations of algorithms, ask questions about the data of algorithms and model design, communicate with the employees, and have the power and ability to ask these questions. Managers also need to be clear on their role when the AI tools are informing decisions. Responsible adoption is thus an ongoing governance process of system evaluation, human capacity building, stakeholder engagement, and organizational learning.

2.7 Synthesis and research gap

In this paper, the literature matrix highlights themes such as algorithmic management, digital HRM, ethics, HR analytics, recruitment automation, workforce competencies, trust, employee well-being, and talent management. There appear to be several themes. First, while prior research has focused on specific HR functions to which artificial intelligence may be applied, an employee-lifecycle view provides useful insights. Second, ethical risks (such as privacy, transparency, accountability, and bias) are well acknowledged, but these need to be operationalized in governance mechanisms. Third, the need for AI-human collaboration is better recognized, but organizations need operational mechanisms to enable meaningful human governance over important decisions. Fourth, AI governance should stem from employee trust, autonomy, engagement, and well-being, not be a side issue.

It thus fills an integration gap by offering a framework adaptable for integrating five governance dimensions and human-centred HRM outcomes and

organizational performance. The gap is extrapolated from the thematic synthesis of the given literature matrix and does not mean that no such framework exists. To argue for complete originality, a systematic search of additional databases would be required.

3. Theoretical Foundations

3.1 Sociotechnical Systems Approach

The sociotechnical view argues that the organizational outcomes rely on the fit of technical setups and social systems. When applied to AI in HRM, this perspective implies that the performance of a system is not measured by the accuracy of the model or the speed of processing. AI design and applications should therefore include employee involvement, management practices, corporate culture, communication, and working environment for effectiveness. Thus, the framework proposes AI governance as a process of organization and society rather than as direct technical control.

3.2. The Issue of Organizational Justice

Organizational justice is a perspective where the employees assess fairness in decisions and processes within the workplace. AI-driven fair HRM is about consistency of criteria, ensuring a fair opportunity for employee groups, accountability, and challenge ability of decisions. This orientation refers to algorithmic fairness and the review and transparency politics promoted by the framework.

3.3 The Human + AI Perspective

Knowing the advantages and disadvantages of human and computerized systems, it is no surprise to see human and AI working together. AI is able to scale data analysis and pattern recognition; humans make sense of context, values, exceptions, and accountability. This notion is taken directly from Jarrahi (2018). Within this framework, the author argues that is the AI should not be an unaccountable decision maker but an augmenting tool to the human decision making.

3.4 Responsible AI Governance Perspectives

Responsible AI governance is institutional arrangements for selecting and designing, deploying, monitoring, and reviewing artificial intelligence systems. In HRM, this would involve role definitions, risk assessment, fairness testing, data protection, oversight by humans, and communication with employees, audits, and avenues for appeal/redress. Such a view should connect ethics to organizational practice and, therefore, form a basis of all the 5 pillars of the proposed framework.

4. Research Methodology

This study adopts a conceptual research design based on a thematic synthesis of literature. It does not report primary survey, interview, experimental, or organizational data. Its purpose is to integrate the themes represented in the supplied literature matrix and develop a governance framework and propositions for future empirical research.

The immediate source base is the literature matrix and reference list supplied by the author in the uploaded document. The matrix basically consists of research studies and publications from 2016-2024 and takes into account AI in HRM, digital HRM, digital recruitment, analytics, algorithmic management, ethics, trust, employee engagement, well-being, and workforce planning. The paper uses the descriptions and bibliographic details as supplied. It does not claim that the list is exhaustive or that every bibliographic entry has been independently verified.

The identified studies were categorized into the following themes: (1) digital transformation and HR analytics; (2) AI applications in HR functions; (3) ethics, bias, transparency, and accountability; (4) human–AI collaboration and trust; (5) algorithmic management and employee outcomes; and (6) strategic capabilities and governance. The themes were then cross-referenced for links, tensions and areas for conceptual integration. These themes have been distilled into five governance pillars.

This is a conceptual paper based on literature and thus no causal relationships are estimated and no statistical tests are performed on the propositions. The underlying literature matrix is a blend of journal articles, books, practitioner publications, working papers and news reporting. Some entries may need to be corrected or further checked bibliographically. Future systematic review should use transparent database search strings, inclusion and exclusion criteria, duplicate removal, quality appraisal, and a documented screening process.

5. Proposed Human-Centred Responsible AI Governance Framework

The framework proposed conceptualizes responsible AI governance as the organizational mechanism that links AI adoption to human-centered HRM outcomes. It has 5 pillars of governance that strengthen each other." The pillars should be applied throughout the entire employee lifecycle and adapted to the risk and context of each HR application.

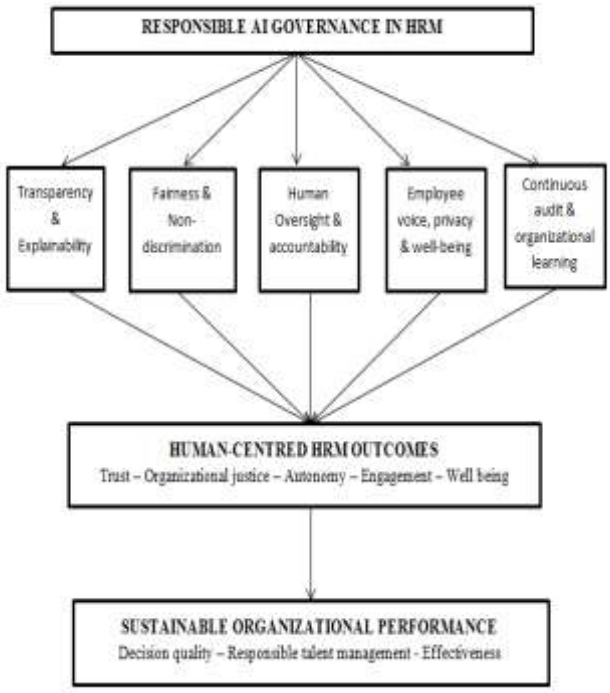


Figure 2: Human-Centered Responsible AI Governance Framework for HRM.

5.1 Pillar one: Algorithm transparency and Explainability.

Organizations should inform about the use of AI in HR processes and explain the purpose of the system, what kind of information will be taken into consideration, and the weight of algorithmic outputs in the final decisions. The explanations should be meaningful (not just technical documentation) to affected employees and HR decision makers. Organizations should document the purpose of the system, data sources, limitations, version changes, and decision pathways. Transparency permits review, trust, and informed use.

5.2 Pillar 2: The algorithms need to be non-discriminative and fair

Organizations should ask if standard artificial intelligence systems create or perpetuate disparities in relevant groups. Governance processes should include data-quality checks, tests for disparate outcomes, examination of proxy variables, periodic audits, and remediation when risks are identified. Fairness should be evaluated before deployment and during use (as data, roles, and other organizational circumstances evolve). There should be a human review where a decision can have a major impact on someone's job/career opportunity.

5.3 Pillar 3: Sufficient human control and responsibility

Human supervision must be meaningful, not perfunctory. Decision makers should be equipped (and empowered, as well as informed and given time) to question AI outputs and to override them when necessary. Organizations need to decide which decisions can be left to an algorithm and which should be human-signed or not manageable to an AI system. Accountability should not be blurred; using an algorithm should not be an excuse for evading managerial or institutional responsibility. Employees must have a clear channel for asking for explanation, correction or review.



Figure 3: Risk-based human oversight pathway for AI-supported HR decisions

5.4 Pillar 4. Participation, privacy and wellbeing of the employee

If artificial intelligence (AI) systems that affect employees' work are introduced or used, this should be done in consultation with the employees concerned and their representatives. The organization should be open about the data it collects, why it is collected,

who has access, for how long, and whether it is used outside of the original context. Collect and follow data in relation to an actual organizational purpose. Think about welfare & productivity/efficiency; system evaluations; employee feedback.

5.5: Pillar 5: Learning and Continuous Evaluation in the organization

The governance should not stop with deploying the systems. Organizations should monitor performance, but also fairness, employee experience, security, and unintended consequences. Reviews should be conducted periodically to ensure the system is fit for purpose and that no changes in the organization or technology landscape would suggest a need to withdraw or adapt. Ongoing training should be provided to HR professionals and managers in data literacy and AI limitations, ethics, decision-making, and appropriate usage. Learning in organizations should be audit, appeals, incident, and employee feedback driven.

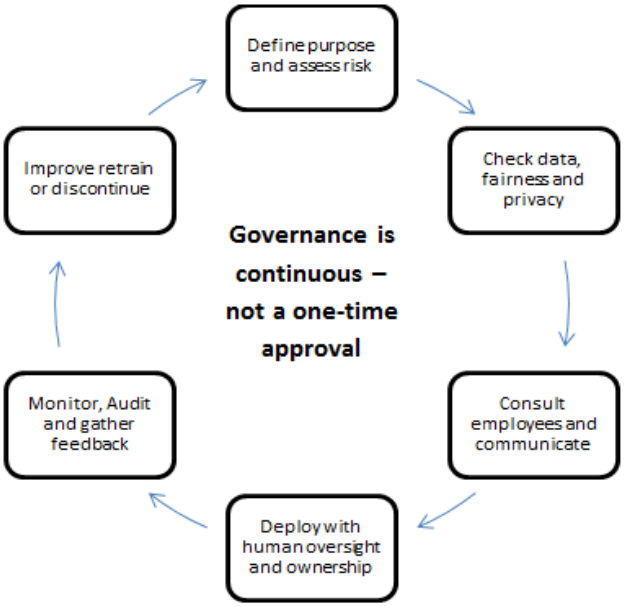


Figure 4: Continuous responsible AI governance cycle

5.6 Framework outcomes

The five pillars of AI-supported HRM enable the realization of certain human-centered outcomes: employee trust in the AI-supported process, perceived organizational justice, employee autonomy, engagement, and well-being at work. These outcomes can enable better HR decisions and sustainable talent management and organizational effectiveness. The framework does not assume an automatic relationship; outcomes will depend on the quality of implementation and organizational contexts, the nature of the AI application, and the effectiveness of governance enforcement.

6. Research Propositions

The following propositions operationalize the conceptual framework in terms of testable relationships in future empirical work:

P1. Transparency and trust of employees: Explainable AI in HR decisions leads to higher trust of the systems of the organisation from the employees.

P2: The fair and equitable organisation: As far as fairness and non-discrimination are concerned, the mechanisms of organizational justice tend to enhance the two from the employee perspective.

P3: Human control and agency: Trust to Organization: Meaningful human monitoring of AI-enabled HR decision-making is positively related with the autonomy and trust of employee to organization.

P4: Well-being, participation, and privacy: AI-based HR practices with employee participation and proper privacy protection are positively associated with the well-being and employee engagement.

P5: Maintaining governance and effectiveness: Positive links of HR and development of AI capabilities, organisational learning, and auditing AI for responsibility and effectiveness of AI.

P6: Human-centred workplaces and governance: Transparency, fairness, oversight by humans, employee participation and ongoing monitoring are positively associated with human-centred workplaces.

P7: Human-centred results and sustainable performance: Human-centred outcomes of HRM (trust, justice, autonomy, engagement and well-being) and sustainable organizational performance.

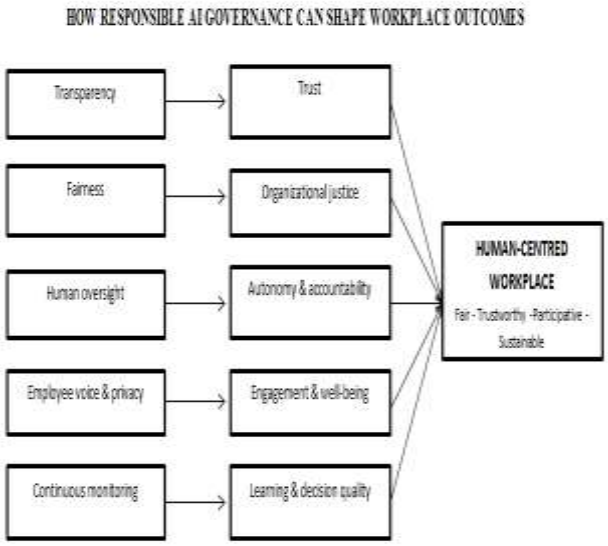


Figure 5: Conceptual pathways linking governance practices with human-centred workplace outcomes

7. Discussion

The proposed framework responds to the central tension in AI-enabled HRM: organizations seek the speed, scale, and analytical capabilities of algorithms, while employment decisions require fairness, contextual understanding, accountability, and respect for individuals. The reviewed literature indicates that AI can support recruitment, candidate communication, workforce planning, learning, and HR service delivery. Yet these benefits do not remove the need to evaluate the consequences of algorithmic systems for employees and organizational relationships.

First, the framework moves the discussion beyond isolated AI applications. Recruitment automation, talent analytics, performance appraisal, and employee monitoring are often examined as separate functions. A governance approach should instead follow the employee lifecycle because data and decisions at one stage may influence later opportunities. For example, historical recruitment data may shape future screening, performance records may influence promotion recommendations, and monitoring data may affect managerial assessments. Lifecycle governance makes it possible to consider cumulative effects.

Second, the framework treats human oversight as an organizational design requirement. Human involvement should not be reduced to approving a recommendation without scrutiny. Meaningful oversight requires competence, access to relevant information, authority to challenge outputs, and clear accountability. This interpretation is consistent with the human–AI collaboration perspective discussed by Jarrahi (2018) and the organizational decision-making structures considered by Shrestha et al. (2019).

Third, the framework positions employees as stakeholders in AI governance. Employee trust and acceptance cannot be assumed from the availability of a technically capable system. Employees need understandable information, proportionate data practices, channels for feedback, and opportunities to challenge consequential outcomes. This emphasis connects the literature on trust and employee perceptions with research on algorithmic control and workplace resistance.

Fourth, the framework broadens the criteria for evaluating AI adoption. Efficiency, cost reduction, and predictive performance remain relevant, but they should be assessed alongside fairness, autonomy, privacy, well-being, and the quality of employment relationships. The productivity J-curve perspective suggests that realizing the benefits of new technologies may require complementary organizational changes. Responsible AI governance is one such complementary capability.

Finally, the framework recognizes that governance is dynamic. Systems can change through model updates, new data, altered organizational objectives, or changes in the workforce. Periodic audits and feedback are therefore necessary. Organizations should be prepared not only to improve a system but also to restrict or discontinue it when risks cannot be adequately controlled.

8. Managerial Implications

- Develop an HR AI Governance Policy that states what is acceptable and what is not, what approvals should look like, and what the roles are.
- Prioritize HR applications by risk and effect. Administrative (low impact) systems such as discipline, firing, promotion, and hiring and compensation (non-highly administrative ones) should be more-inclusive attended then administrative systems with no high impact.

- Verify data and data with data bias, data validity, data security, and data privacy before launch.
- Foster human supervision on major personnel decisions and the right to question and supersede AI recommendations on major personnel decisions.
- Be open and transparent with your employees about your AI use, including how you use data, how you report decisions, and how you correct/appeal decisions.
- Form a governance team that crosses organizational lines and which includes representation from senior leadership, HR, legal, IT, data protection, risk management, and employees (as appropriate).
- Emphasize AI literacy and ethics training for line and human resource (HR) managers.
- Humans score better on Trust, Autonomy, Decision Quality, Fairness, Engaging, and Efficiency. Well-being scorecard.

9. Policy Implications

At the policy level, organizations should operationalize high-level ethical tenets into operational standards. Internal policies could set out requirements regarding documentation, impact assessments to undertake, frequency of audits, data minimization, human review, incident reporting, and employee redress. Policymakers and professional bodies can help organizations by establishing benchmarks for high-impact employment applications, encouraging independent assessment where appropriate, and promoting access to skills. Governance arrangements should be commensurate to scheme impact and remember that employment decisions may be life changing for individuals.

This is not a legal analysis for a particular jurisdiction. Organizations in India or in multiple jurisdictions should separately analyse their particular data protection, employment, equality, and other sectoral requirements before introducing AI in HRM. We believe that compliance cannot be an alternative to a wider ethical obligation, and compliance must be the minimum.

10. Conclusion

Artificial Intelligence is changing the structure and practice of Human Resource Management. It is an area for improvement around effectiveness, analytics, recruiting, workforce planning, employee services, and learning. However, AI-augmented decision algorithms suffer from bias, lack of transparency, privacy, and employees' autonomy and wellbeing issues. This paper contends that from algorithm-oriented practices, responsible AI is the route to human-centric governance.

Based on the literature matrix provided to the study, the paper suggests a framework consisting of five pillars, including transparency and Explainability, fairness and non-discrimination, meaningful human supervision and accountability, employee participation, privacy and well-being, and ongoing surveillance and organisational learning. These pillars are expected to enhance a culture of trust, fairness, autonomy, engagement, and well-being of employees that bear on sustainable organisational performance. Hence, the paper proposes seven research propositions for future empirical research.

The main contribution in the framework is to bring the two sides, governance of technology and employee-oriented outcome, into one HRM window. It does not reject automation, but argues that the level of automation should be appropriate to the importance of the decision and the nature of sensitive decisions. Artificial intelligence can serve as an aid to analysis; however, institutions need to ensure clear accountability in critical hiring decisions. After all, a human-centred workplace is one in which technology can be used participative and with accountability to provide dignity and fairness towards both organisational and human needs.

11. Limitations and Future Research

A matrix of researcher' paper are literature by theory. No database data, secondary data, test data, database searches or appraisal quality. They are mixed in terms of publication types, and some bibliographic records might need to be verified independently. It should be considered a model of reasoning to the current paradigm rather than a validated instrument.

Future research may test the propositions with employee surveys, HR interviews, comparative case studies, or mixed-method designs. Measures can be developed and validated for those governance pillars, and their relations with trust, perceived justice, autonomy, engagement, well-being and organisational performance can be explored. Comparative research across sectors, public and private organisations, and international contexts may reveal contextual

distinctions. Longitudinal studies can be deployed to ascertain changes in governance and perceptions from employees with larger systems of AI over time. Future work could also tease apart low-stakes administrative automation (e.g., recordkeeping) from more consequential systems that determine worker employ, pay, promotion, or firing.

References

1. Ajunwa, I. (2020). The paradox of automation in HR. Harvard Law Review Forum, 133, 1–12.
2. Agarwal, R., Gautham, L., & Sinha, P. (2022). AI for skill gap analysis and personalized learning. Journal of Workplace Learning, 34(5), 1–14.
3. Basu, S., & Ghosh, R. (2022). AI and employee engagement: Evidence from India. Asian Journal of Management, 11(2), 45–60.
4. Bondarouk, T., & Brewster, C. (2016). Conceptualising e-HRM and the digital future of HRM. The International Journal of Human Resource Management, 27(21), 1–18.
5. Brougham, D., & Haar, J. (2018). Smart technology and HRM: Employee perceptions. Journal of Management & Organization.
6. Brynjolfsson, E., Rock, D., & Syverson, C. (2018). The productivity J-curve: How intangibles complement general purpose technologies. NBER Working Paper No. 24554.
7. Cappelli, P. (2019). Talent on demand: Managing talent in an age of uncertainty. Harvard Business Review Press.
8. Dastin, J. (2018, October 10). Amazon scraps secret AI recruiting tool that showed bias against women. Reuters.
9. Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108–116.
10. Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. Information and Organization, 28(1), 1–12.
11. Fernandez, A., & Gallardo-Gallardo, E. (2021). AI in talent management: A systematic mapping. European Journal of International Management, 15(5), 1–22.
12. Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical literature. The Leadership Quarterly, 31(1), 101–121.
13. Ghosh, R. (2020). AI in performance appraisal: Evidence from field studies. International Journal of Human Resource Management, 31(10), 1–20.
14. Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service. Journal of Service Research, 21(2), 155–172.
15. Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Journal of the Association for Information Science and Technology, 69(1), 22–31.
16. Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contests of control. American Sociological Review, 85(5), 1–30.
17. Kellogg, K. C., Valentine, M. A., & Christin, A. (2021). Algorithmic management and worker resistance. Annual Review of Sociology, 47, 1–22.
18. Kshetri, N. (2018). Big data's role in HRM and analytics. Business Horizons, 61(2), 233–241.
19. Langer, J., König, C., & Kraft, K. (2019). Digital transformation in HR: Implications for strategy. European Journal of Information Systems, 28(5), 1–15.
20. Leicht-Deobald, U., Busch, T., Schank, C., Weibel, A., Schafheitle, S., & Rump, K. (2019). The challenges of algorithm-based HR decision-making for personal integrity. Journal of Business Ethics, 160(2), 377–392.
21. Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR analytics. Human Resource Management Review, 28(2), 149–162.
22. Meijerink, J., Bondarouk, T., & Lepak, D. P. (2021). Algorithmic HRM: Frameworks and consequences. The International Journal of Human Resource Management, 32(12), 1–25.
23. Minbaeva, D. (2021). HRM in the age of artificial intelligence: New competencies and roles. Human Resource Management Journal, 31(4), 1–18.

24. Rodgers, M. (2023). Ethical frameworks for AI in HRM. Journal of Business Ethics, 170(3), 1–18.
25. Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures and AI. California Management Review, 61(4), 38–56.
26. Sivathanu, B., & Pillai, R. (2018). Smart HR 4.0: Opportunities and challenges. International Journal of Human Resources Development and Management, 18(3/4), 250–270.
27. Strohmeier, S. (2020). Digital HRM: A critical review and research agenda. Human Resource Management Review, 30(1), 1–14.
28. Suen, H. Y., Ching, A. K., & Ma, M. (2019). Chatbots for HR: Candidate experience and efficiency. International Journal of Information Management, 45, 1–10.
29. Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. Academy of Management Annals, 13(1), 1–35.
30. Upadhyay, A. K., & Khandelwal, K. (2018). Applying artificial intelligence in recruitment and selection. Strategic HR Review, 17(3), 1–8.
31. Van Esch, P., Black, J. S., & Ferolie, J. (2019). Recruiting automation: A classification and framework. Journal of Business and Psychology, 34(1), 1–15.
32. Van den Broek, A., & Zierahn, U. (2019). AI and the future of work: Policy and managerial implications. OECD Working Papers.
33. Yadav, P. (2024). AI for talent analytics and workforce planning. Journal of Business Research, 152, 100–112.
34. Zhang, X., & Zhu, J. (2021). AI and employee well-being: Monitoring and interventions. Journal of Occupational Health Psychology, 26(3), 210–225.