ARTICLE

International Journal of Business Governance and Management

DOI: https://doi.org/10.68033/ijbgm.1.1.1-9

Artificial Intelligence in Strategic Human Resource Management: An Integrative Review, Value Alignment Framework, and Systematic Research Agenda

Nandan Limakrisna[1]

[1] *Department of Economic and Business, Universitas Persada Indonesia YAI, Jakarta, Indonesia*

Email: amarta.nandan@gmail.com | ORCID: https://orcid.org/0000-0002-7720-6117

***Corresponding author:** amarta.nandan@gmail.com | ORCID: https://orcid.org/0000-0002-7720-6117

ABSTRACT

Artificial intelligence (AI) is changing strategic human resource management (SHRM) by expanding the capacity of organizations to recruit, allocate, evaluate, develop, and retain employees through data-intensive and algorithm-supported processes. Yet the organizational value of AI-enabled HRM cannot be assessed solely through speed, cost reduction, or predictive accuracy. Algorithmic opacity, biased data, intrusive monitoring, weakened employee autonomy, and declining trust may undermine the very human capabilities that organizations seek to develop. This article provides an integrative review of research on AI-enabled and algorithmic HRM, connecting technology capability, strategic human resource processes, employee experience, and governance. Drawing on recent review studies and foundational work on algorithmic management, the article synthesizes the literature into a Human-Centered AI-HRM Value Alignment Framework. The framework proposes that sustainable outcomes depend on the alignment of five mutually reinforcing dimensions: AI capability, strategic HR architecture, human agency, responsible governance, and organizational outcomes. It explains how AI can create value through augmentation and decision support, while governance mechanisms—transparency, accountability, data protection, fairness auditing, employee participation, and meaningful human oversight—condition the relationship between AI deployment and outcomes. The review identifies research opportunities concerning longitudinal effects, contextual differences, employee voice, managerial accountability, and the distribution of AI-generated value. The article contributes an integrative framework and a research agenda for organizations seeking to deploy AI in ways that are strategically effective, ethically defensible, and supportive of sustainable employee and organizational performance.

Keywords: artificial intelligence, strategic human resource management, algorithmic management, employee well-being, responsible AI, human-centered management.

ARTICLE HISTORY: Received: 1/10/2026 | Revised: 24/10/2026 | Accepted: 2/11/2026

1. INTRODUCTION

Artificial intelligence has moved from a specialist information-technology application to an increasingly consequential element of organizational decision-making. In human resource management (HRM), AI-enabled systems are used or proposed for résumé screening, candidate matching, workforce planning, employee-service chatbots, learning recommendations, performance analytics, talent identification, and retention prediction. These applications promise faster processing, improved pattern recognition, more consistent decisions, and the capacity to connect workforce information with organizational strategy. However, the same systems can reshape managerial authority, the experience of work, and the distribution of opportunities inside organizations.

The central management question is therefore not whether AI should be adopted, but under what organizational and governance conditions AI contributes to sustainable value. A system may improve recruitment throughput while excluding qualified applicants through proxy variables. It may increase visibility of performance while encouraging excessive surveillance. It may personalize learning while narrowing employee development to what an algorithm can measure. Consequently, the evaluation of AI-HRM requires a broader perspective than technological efficiency.

Recent scholarship has begun to consolidate this complex field. A systematic review of AI and workplace outcomes organizes effects across HR processes and emphasizes that AI can generate both opportunities and risks (Tambe et al., 2023). (Gong et al. (2025) examine the integration of AI and HRM and identify implications for HR theory and practice. Research on algorithmic HRM also highlights the need to understand how algorithmic functions create affordances for HR decision-making and how these functions are

© [2026] the Author(s). Published by Shivi Scientific Press. This article is distributed under the terms of the Creative Commons Attribution 4.0 International License

embedded in organizational settings (Gong et al., 2025). Cameron et al. (2024) map the multidisciplinary development of algorithmic HRM and note conceptual fragmentation across terms such as digital HRM, AI in HR, algorithms, and HR analytics. More recent work emphasizes strategic tensions involving fairness, transparency, data management, and employee experience (Úbeda-García et al., 2025).

Although these studies provide important foundations, managers still need an integrative explanation of how technological capability is translated into human and organizational outcomes. The literature often discusses AI applications, employee consequences, and ethical safeguards in partially separate conversations. This article addresses that fragmentation by connecting the strategic, human, and governance dimensions of AI-enabled HRM.

The article addresses three questions: (1) How is AI reshaping the architecture and strategic role of HRM? (2) Through what mechanisms can AI-enabled HRM improve or undermine employee and organizational outcomes? (3) What governance conditions are necessary to align AI deployment with human-centered and sustainable management? The article contributes by proposing a Human-Centered AI-HRM Value Alignment Framework and deriving a structured agenda for future research and managerial practice.

2. Review Approach and Scope

This article adopts an integrative literature review approach. An integrative review is appropriate when a field contains diverse conceptual, empirical, and review-based contributions that need to be connected into a broader explanatory framework. The purpose here is theoretical synthesis rather than a claim of exhaustive systematic coverage or a statistical estimate of effect sizes.

The literature base was scoped around four intersecting domains: (a) AI and algorithmic technologies in HRM; (b) strategic HRM and organizational performance; (c) employee-level outcomes, including autonomy, trust, well-being, and perceived fairness; and (d) responsible AI governance. Priority was given to peer-reviewed review articles and conceptual or empirical contributions published in established management and HRM outlets, with particular attention to work published from 2021 to 2026. Foundational sources were retained where necessary to explain the strategic and governance mechanisms.

Search concepts suitable for replication include combinations of the following terms: “artificial intelligence” OR “machine learning” OR “algorithmic management” OR “algorithmic HRM” AND “human resource management” OR “strategic HRM” AND “employee performance” OR “employee well-being” OR “organizational performance” OR “fairness” OR “transparency” OR “governance”. Relevant databases for a full submission-stage update include Scopus, Web of Science Core Collection, and ABI/INFORM. Reference-list searching should be used to identify influential studies missed by keyword searches.

The synthesis proceeded thematically. First, AI applications were mapped to HR functions. Second, reported benefits and risks were grouped by the level at which they arise: individual, team, organizational, and institutional. Third, governance mechanisms were examined as conditions that shape the relationship between AI deployment and outcomes. Finally, these themes were integrated into the proposed framework. Because a final database export, duplicate-removal log, and independent screening record have not been generated for this draft, no PRISMA flow counts or claims of exhaustive study inclusion are reported. A full systematic review submission should add these records before describing the paper as PRISMA-compliant.

3. AI and the Strategic Transformation of HRM

3.1 From administrative automation to strategic augmentation

The earliest organizational value proposition of HR technology centered on administrative efficiency: digitizing records, standardizing transactions, and reducing processing time. AI extends this logic by enabling prediction, classification, natural-language interaction, and pattern detection across large workforce datasets. In recruitment, for example, AI can support candidate search and matching; in learning and development, it can recommend content based on skills profiles; and in workforce planning, predictive analytics can help identify capability gaps and potential turnover.

The strategic significance of these applications lies not in automation alone but in the possibility of augmenting managerial and professional judgment. AI can process information at a scale that is difficult for individuals, while HR professionals contribute contextual interpretation, ethical reasoning, relationship management, and accountability. The augmentation perspective therefore treats AI as a decision-support capability rather than an autonomous substitute for responsible management.

This distinction matters because HR decisions are consequential and context-sensitive. Hiring, promotion, performance evaluation, and termination affect livelihoods and career trajectories. A technically accurate prediction does not automatically constitute a legitimate or fair decision. Strategic HRM must consequently evaluate whether AI-enabled processes support the organization's intended employment relationship and human-capital strategy.

3.2 AI across the HR value chain

AI applications can be organized across the employee life cycle. In workforce planning, predictive models can estimate future skills demand and identify capability shortages. In recruitment and selection, natural-language processing and matching tools can assist with job descriptions, sourcing, and applicant triage. In learning and development, recommendation systems can personalize training

© [2026] the Author(s). Published by Shivi Scientific Press. This article is distributed under the terms of the Creative Commons Attribution 4.0 International License

pathways and support skills inference. In performance management, analytics can identify patterns in output, collaboration, and goal progress. In retention and employee relations, predictive tools may flag turnover risks or recurring service issues.

These applications are not equivalent in risk. Administrative assistance and learning recommendations may have relatively low consequences when employees can disregard recommendations and correct inaccurate data. Automated candidate rejection, promotion ranking, compensation decisions, or performance sanctions carry higher stakes. The level of human oversight, documentation, validation, and appeal should therefore be proportionate to the consequences of the decision.

A strategic HR architecture must also avoid optimizing each HR function in isolation. For example, a recruitment algorithm designed to maximize short-term productivity may favor candidates whose profiles resemble incumbent employees, reducing diversity and constraining future innovation. Similarly, performance metrics optimized for easily measured output may undervalue mentoring, knowledge sharing, and adaptive problem-solving. AI should be assessed against the broader human-capital strategy rather than a narrow functional KPI.

4. Employee and Organizational Outcomes: A Dual-Pathway Perspective

4.1 Potential value creation

AI-enabled HRM may create value through at least four mechanisms. First, process efficiency can reduce repetitive administrative work and shorten decision cycles. Second, information quality can improve when relevant data are integrated and analyzed systematically. Third, personalization can make learning, career support, and employee services more responsive to individual needs. Fourth, decision augmentation can help managers detect patterns and evaluate alternatives that might otherwise remain unnoticed.

These mechanisms can support organizational outcomes such as workforce agility, better skills allocation, more responsive HR services, and improved strategic alignment. They may also create employee benefits when technology reduces administrative friction, improves access to development opportunities, or makes decisions more consistent. Nevertheless, these benefits depend on data quality, system validity, implementation design, and the willingness of employees and managers to use the technology appropriately.

4.2 Risks and unintended consequences

The risk pathway includes algorithmic bias, opacity, privacy intrusion, surveillance, work intensification, technostress, and diminished autonomy. Bias may enter through historical training data, the selection of target variables, proxy measures, or organizational decisions about how model outputs are used. Opacity makes it difficult for employees and managers to understand why a recommendation was produced or how to challenge it. Excessive monitoring may weaken trust and encourage employees to optimize visible metrics rather than meaningful work.

Algorithmic management can also shift control from direct interpersonal supervision to digitally mediated allocation, evaluation, and discipline. This shift may improve coordination in some settings but can reduce discretion when workers cannot understand or contest automated decisions. A systematic review of algorithmic management and worker well-being emphasizes issues such as fairness, privacy, technostress, and work-life balance in digital labor settings (Sharma et al., 2025).

The relationship between AI and performance is therefore not linear. The same system can improve task efficiency while undermining psychological safety or perceived justice. In the longer term, reduced trust may weaken knowledge sharing, discretionary effort, and organizational commitment. Management should measure both operational benefits and human consequences rather than treating the absence of immediate productivity loss as evidence of successful adoption.

4.3 The mediating role of employee experience

Employee experience provides a mechanism linking AI design to organizational outcomes. When employees perceive AI-supported decisions as understandable, consistent, relevant, and open to review, they may be more willing to use the system and contribute data. When they perceive the system as arbitrary, intrusive, or unchallengeable, they may resist, disengage, or develop defensive work practices.

Trust should not be treated as a communication problem that can be solved through awareness campaigns. It is an outcome of system performance, procedural justice, managerial conduct, and the availability of meaningful recourse. Organizations must demonstrate that data are used for legitimate purposes, that errors can be corrected, and that consequential decisions remain accountable to identifiable human decision-makers.

5. Responsible Governance as a Strategic Capability

5.1 Transparency and explainability

Transparency requires more than disclosing that an algorithm is in use. Employees and applicants should receive meaningful information about the purpose of the system, the categories of data used, the role of algorithmic outputs in decisions, and the routes available to request review. Explainability should be tailored to the audience: technical teams need model documentation, managers

© [2026] the Author(s). Published by Shivi Scientific Press. This article is distributed under the terms of the Creative Commons Attribution 4.0 International License

need decision limitations and operating guidance, and affected individuals need comprehensible explanations of consequential outcomes.

5.2 Fairness, validation, and continuous auditing

Fairness management should begin before deployment. Organizations should examine whether the data represent the relevant population, whether target variables encode historical disadvantage, and whether proxy features produce unjustified differences across groups. Validation should assess accuracy and error distribution across relevant subgroups, not merely aggregate performance. Auditing should continue after implementation because workforce composition, job requirements, and organizational processes change over time.

5.3 Privacy and data stewardship

HR datasets may contain highly sensitive information about identity, compensation, performance, health-related accommodations, and career history. Data governance should define lawful and legitimate purposes, access controls, retention periods, security safeguards, and restrictions on secondary use. Data minimization is particularly important: the fact that a data point can be collected does not establish that it should be collected.

5.4 Human oversight, employee voice, and accountability

Human oversight must be substantive. A manager who routinely accepts a system recommendation without time, information, or authority to challenge it provides only nominal oversight. Meaningful oversight requires trained decision-makers, documented responsibility, escalation procedures, and the power to override an output when contextual evidence warrants it. Employees and their representatives should be involved in system design, pilot evaluation, and periodic review.

Accountability should be allocated across senior leadership, HR, data science, information technology, procurement, legal/compliance, and line management. Vendors may provide technical components, but organizations remain responsible for how systems are selected, configured, and used in employment decisions. Governance is thus not merely a compliance function; it is a strategic capability that protects legitimacy and supports sustainable adoption.

6. The Human-Centered AI-HRM Value Alignment Framework

The synthesis leads to a five-dimensional framework: AI capability, strategic HR architecture, human agency, responsible governance, and sustainable outcomes. The framework treats value creation as an alignment process rather than a direct consequence of technology adoption.

Dimension	Core elements	Management question
1. AI capability	Data quality; model validity; interoperability; usability; security	Is the technology fit for the decision and organizational context?
2. Strategic HR architecture	Workforce strategy; job design; skills; HR process integration; organizational culture	Does the application support long-term human-capital priorities?
3. Human agency	Employee voice; managerial judgment; autonomy; contestability; capability development	Can people understand, influence, and challenge AI-supported decisions?
4. Responsible governance	Transparency; fairness audits; privacy; accountability; human oversight	Are rights, responsibilities, and safeguards clearly established?
5. Sustainable outcomes	Employee well-being; trust; performance; innovation; adaptability; legitimacy	Does the system create durable value for people and the organization?

The five dimensions are interdependent. AI capability without strategic alignment can produce technically sophisticated solutions to low-value problems. Strategic alignment without human agency can generate resistance and weaken the employment relationship. Human agency without governance may leave employees exposed to inconsistent decisions. Governance without operational capability may become a formal checklist that does not change practice. Sustainable outcomes emerge when the five dimensions reinforce one another.

The framework also distinguishes two pathways. The value-creation pathway runs from fit-for-purpose AI capability through strategic HR integration and human augmentation to improved organizational and employee outcomes. The value-erosion pathway emerges when weak data, poor alignment, opaque decisions, or intrusive monitoring reduce fairness and trust, producing resistance, technostress, and potentially lower sustainable performance. Responsible governance moderates both pathways by shaping how systems are designed, interpreted, and contested.

© [2026] the Author(s). Published by Shivi Scientific Press. This article is distributed under the terms of the Creative Commons Attribution 4.0 International License

6.1 Propositions for future empirical testing

P1. The positive relationship between AI-enabled HRM capability and organizational performance is stronger when AI applications are aligned with the organization's human-capital strategy.

P2. The relationship between AI-enabled HRM and employee performance is mediated by employee perceptions of procedural fairness, trust, and perceived usefulness.

P3. Meaningful human oversight weakens the negative relationship between algorithmic opacity and employee trust.

P4. Employee participation in AI-HRM design and evaluation positively influences perceived legitimacy and responsible system use.

P5. The positive effects of AI-enabled HRM on workforce agility are stronger when AI augments rather than replaces managerial and employee judgment in high-consequence decisions.

P6. The relationship between AI-enabled monitoring and employee well-being is contingent on perceived proportionality, transparency, and employee control over data use.

7. Research Agenda

The framework suggests several directions for future research. First, longitudinal studies are needed to establish whether efficiency gains persist and whether employee outcomes change as AI becomes embedded in everyday work. Cross-sectional surveys may capture initial attitudes but cannot adequately explain adaptation, learning, resistance, or cumulative effects.

Second, research should move beyond recruitment and selection. Compensation, promotion, learning, performance management, workforce planning, employee relations, and internal mobility deserve greater attention. Different HR functions involve different levels of decision consequence and therefore require distinct governance arrangements.

Third, future studies should examine employee voice and power. Research can investigate whether employees can correct inaccurate data, appeal algorithm-supported decisions, and influence system design. Comparative studies across employment arrangements—permanent work, temporary work, platform work, and professional work—may reveal important differences in autonomy and exposure to algorithmic control.

Fourth, contextual research is required. Institutional regulation, labor relations, organizational size, sector, national culture, and digital infrastructure may influence both adoption and outcomes. Evidence from emerging economies and small and medium-sized enterprises is particularly important because their data capabilities, bargaining structures, and access to specialist expertise may differ from those of large multinational organizations.

Fifth, research should evaluate governance mechanisms rather than merely recommend them. Field experiments, quasi-experimental designs, longitudinal case studies, and comparative implementation studies can test whether fairness audits, explainability interventions, employee participation, and human review procedures improve outcomes.

Finally, future research should examine the distribution of value. AI may raise productivity, but the resulting benefits may accrue unevenly to shareholders, managers, employees, customers, or technology vendors. A strategic HRM perspective should ask not only whether AI creates value, but also who captures it, who bears its risks, and whether productivity gains are reinvested in skills, job quality, and organizational resilience.

8. Managerial Implications

For senior leaders, AI-HRM should be governed as an enterprise transformation rather than an isolated technology purchase. Each proposed application should have a defined business and human objective, a named accountable owner, a risk classification, and measurable success criteria. Performance indicators should combine process measures—such as time-to-hire or service response—with human measures such as perceived fairness, trust, employee well-being, and access to development.

For HR leaders, implementation should begin with process diagnosis. Organizations should identify the problem to be solved, determine whether AI is necessary, and assess whether existing data are suitable. Pilots should include affected employees and line managers, with clear mechanisms for feedback and correction. High-consequence decisions should retain meaningful human review and documented appeal routes.

For technology and data teams, model documentation, data lineage, access control, testing, monitoring, and incident response should be built into the system life cycle. Procurement should assess vendor claims, explainability, data use, security, audit rights, and the ability to suspend or modify a system. Vendor assurances should not replace the organization's own due diligence.

© [2026] the Author(s). Published by Shivi Scientific Press. This article is distributed under the terms of the Creative Commons Attribution 4.0 International License

For employees and their representatives, participation should occur before systems are fully embedded. Communication should explain what data are collected, what the system can and cannot infer, how outputs are used, and how concerns can be raised. Training should develop both digital literacy and the ability to exercise judgment when system recommendations conflict with contextual knowledge.

9. Limitations

This article is an integrative review and conceptual synthesis, not a completed exhaustive systematic review. Its conclusions are constrained by the selected literature and by the rapid evolution of AI technologies and regulatory environments. The proposed framework is conceptual and requires empirical validation across sectors, countries, organizational sizes, and HR functions. In addition, studies may use inconsistent definitions of AI, algorithmic HRM, digital HRM, and HR analytics, limiting direct comparison. A subsequent systematic review should preregister or document its protocol, search multiple databases, report the full screening process, assess study quality, and provide a transparent evidence table.

10. Conclusion

AI is reshaping strategic HRM by expanding the ability to process workforce information, support decisions, and personalize organizational services. However, technological adoption does not automatically produce better management. The effects of AI depend on strategic fit, employee experience, data quality, decision consequence, and governance. The Human-Centered AI-HRM Value Alignment Framework proposed in this article integrates five dimensions—AI capability, strategic HR architecture, human agency, responsible governance, and sustainable outcomes—to explain how organizations can create value while protecting fairness, trust, and employee well-being.

The central implication is that effective AI-enabled HRM should augment human capability, not remove human responsibility. Organizations that combine analytical power with transparent processes, meaningful employee participation, accountable decision-making, and continuous evaluation are better positioned to achieve sustainable performance. Future research should test the framework, examine long-term effects, and investigate how the benefits and risks of AI are distributed across different groups of workers and organizations.

11. Evidence Mapping of Selected Review Studies

To strengthen the literature positioning, Table 2 summarizes a small set of directly relevant review studies whose bibliographic records and central scope were verified against publisher or journal records during manuscript preparation. This is a purposive evidence map for conceptual positioning, not the final included-study set of an exhaustive systematic review. The number of studies in this table must therefore not be interpreted as the total number of eligible studies.

Study	Outlet	Review scope	Relevance to this manuscript
Cameron, Herrmann, & Nankervis (2024)	Humanities and Social Sciences Communications	Multidisciplinary science mapping of algorithmic HRM from 2000–2022; clarifies algorithmic HRM concepts and distinguishes augmented from automated decisions.	Conceptual clarification; integration of specialized HR applications with strategic HRM.
Tambe, Cappelli, & Yakubovich (2023)	Human Resource Management Review	Systematic review of AI and workplace outcomes using a multi-process perspective across HR functions.	AI creates both opportunities and challenges; effects need to be examined by HR process and workplace outcome.
Gong, Fan, & Bartram (2025)	The International Journal of Human Resource Management	Review of AI-HRM research trends and implications for HR theory and practice.	Supports an integrative agenda connecting AI capability with HRM processes and organizational context.
Sharma, Mittal, & Seema (2025/2026 issue)	Leadership & Organization Development Journal	Systematic review of algorithmic management and worker well-being; publisher record reports synthesis of 29 studies.	Highlights fairness, privacy, technostress, and work-life balance as worker well-being concerns.
Úbeda-García et al. (2025)	Journal of Innovation & Knowledge	Bibliometric analysis of 203 Web of Science articles (2002–2024) on AI, knowledge, and HRM.	Identifies strategic themes and emphasizes transparency, fairness, personal data management, and employee experience.
Anshima, Bhardwaj, & Sharma (2026)	Management Review Quarterly	Systematic review of 53 studies using TCCM and a technological-frame perspective on AI-augmented HRM.	Identifies implementation paradoxes and the need to reconcile technology, organizational and stakeholder perspectives.

© [2026] the Author(s). Published by Shivi Scientific Press. This article is distributed under the terms of the Creative Commons Attribution 4.0 International License

Synthesis. Across these reviews, the field has moved from identifying isolated AI applications toward examining organizational integration, stakeholder tensions, and employee consequences. The remaining opportunity addressed by this manuscript is to connect strategic HR architecture, human agency, responsible governance, and sustainable outcomes in one value-alignment explanation. The proposed framework is intended as a complementary synthesis, not a claim that previous reviews have ignored ethics or employee outcomes.

12. Systematic Search Strategy for the Final Review

The following strategy is provided as a reproducible search protocol for completing a full systematic review. The search must be executed in the institution's subscribed databases and the exact execution date, database interface, result counts, and exported records must be retained. No search counts are reported here because a database export and screening exercise have not been completed within this manuscript preparation.

12.1 Databases and search coverage

Recommended primary databases: Scopus and Web of Science Core Collection. Recommended supplementary sources: ABI/INFORM or Business Source Complete, where access is available. Google Scholar may be used for supplementary citation chasing, but should not replace the primary database search because its coverage and exportability are less controlled. Search coverage should begin in 2000 and extend to the actual final search date.

12.2 Draft Scopus search string

TITLE-ABS-KEY(("artificial intelligence" OR "generative AI" OR "machine learning" OR "algorithmic management" OR "algorithmic HRM" OR "AI-enabled HRM" OR "HR analytics") AND ("human resource management" OR "strategic human resource management" OR recruitment OR selection OR "performance management" OR "learning and development" OR "workforce planning" OR retention) AND (employee OR worker OR workforce OR organization OR organisation))

12.3 Draft Web of Science search string

TS=(("artificial intelligence" OR "generative AI" OR "machine learning" OR "algorithmic management" OR "algorithmic HRM" OR "AI-enabled HRM" OR "HR analytics") AND ("human resource management" OR "strategic human resource management" OR recruitment OR selection OR "performance management" OR "learning and development" OR "workforce planning" OR retention) AND (employee OR worker OR workforce OR organization OR organisation))

The search strings are starting points and should be pilot-tested. Terms that generate irrelevant records should be refined without excluding established synonyms. The final manuscript should reproduce the exact search syntax used in each database, including filters and search dates.

12.4 Eligibility criteria

Criterion	Include	Exclude
Publication type	Peer-reviewed journal articles; review articles and empirical studies relevant to AI-enabled HRM.	Editorials, news, trade articles, non-scholarly web pages, abstracts without sufficient information.
Language	English-language publications for a consistent review corpus.	Non-English records unless translation and screening resources are available and declared.
Time period	2000 to the final search date, with foundational sources retained where conceptually necessary.	Records outside the declared period, except seminal theoretical works explicitly justified.
Topic relevance	AI, machine learning, algorithmic management, or HR analytics applied to HR strategy or HR functions and linked to employee or organizational outcomes/governance.	AI studies with no meaningful HRM or workforce-management application.
Evidence	Sufficient abstract/full text to identify context, method, AI application, and reported implications.	Duplicate records, retracted works, or records with insufficient information after retrieval.

12.5 Screening and data extraction

Export all database records with title, authors, year, source, abstract, keywords, DOI, and database identifier. Deduplicate records using DOI and bibliographic matching. Two reviewers should independently screen titles and abstracts where feasible, then assess full texts against the eligibility criteria. Disagreements should be resolved through discussion or a third reviewer. Record full-text exclusion reasons. Extract at minimum: author/year, country or institutional context, sector, theoretical lens, research design,

© [2026] the Author(s). Published by Shivi Scientific Press. This article is distributed under the terms of the Creative Commons Attribution 4.0 International License

sample/data, HR function, AI type, governance mechanism, employee outcomes, organizational outcomes, limitations, and future research recommendations.

12.6 Quality appraisal and synthesis

Because the expected corpus may include qualitative, quantitative, mixed-method, and review studies, use a design-sensitive appraisal approach rather than a single numerical score that treats all designs as equivalent. Assess clarity of research aims, appropriateness of design, transparency of sampling/data, validity or credibility of analysis, support for conclusions, and acknowledgement of limitations. Synthesize the evidence thematically and organize it through the TCCM lens (Theory, Context, Characteristics, and Methodology), supplemented by the five dimensions of the proposed value-alignment framework.

13. PRISMA 2020 Flow-Reporting Template

PRISMA 2020 is a reporting guideline for transparent systematic-review reporting; it does not itself conduct the review or determine methodological quality. Complete the flow counts only after running the searches and screening records. The boxes below intentionally contain fields rather than invented numbers.

Stage	Field 1	Field 2	Field 3
Identification	Records identified from Scopus: [n]	Records identified from Web of Science: [n]	Records from supplementary sources: [n]
Deduplication	Duplicate records removed: [n]	Records after duplicates removed: [n]	
Title/abstract screening	Records screened: [n]	Records excluded: [n]	
Full-text assessment	Reports sought for retrieval: [n]	Reports not retrieved: [n]	Full-text reports assessed: [n]
Eligibility	Full-text reports excluded, with reasons: [n by reason]	Reasons may include wrong topic, wrong publication type, no HRM application, or insufficient evidence.	
Included	Studies included in qualitative synthesis: [n]	Studies included in quantitative synthesis, if applicable: [n]	

Before submission, convert the completed counts into a PRISMA 2020 flow diagram and ensure that the counts reconcile arithmetically at every stage. Report the full search strings for every database and the number of reviewers involved in each screening stage.

13. Refined Conceptual Framework: Human-Centered AI-HRM Value Alignment

The framework can be represented as an alignment system in which AI capability and strategic HR architecture shape the design and deployment of AI-enabled HRM; human agency and responsible governance condition the translation of these inputs into outcomes. The model distinguishes value creation from value erosion and treats employee experience as a central mechanism.

Framework dimension	Constructs	Expected role
AI capability	Data quality; model validity; explainability; interoperability; security	Technical and informational readiness
Strategic HR architecture	Human-capital strategy; job design; HR process integration; organizational culture	Strategic fit and implementation coherence
Human agency	Employee voice; autonomy; managerial discretion; appeal rights; skill development	Meaningful participation and human judgment
Responsible governance	Fairness testing; privacy; transparency; accountability; human oversight	Legitimacy and risk control
Sustainable outcomes	Employee well-being; trust; performance; innovation; adaptability; organizational legitimacy	Long-term value for people and organization

Proposed mechanism: AI capability + strategic HR architecture → AI-enabled HRM practices → (employee experience: perceived usefulness, procedural fairness, trust, autonomy) → sustainable employee and organizational outcomes. Responsible governance and meaningful human oversight are proposed as boundary conditions that strengthen positive effects and reduce adverse effects. The relationships should be tested empirically rather than treated as established causal effects.

14.1 Proposed hypotheses for empirical validation

H1. Strategic alignment positively moderates the relationship between AI-HRM capability and organizational performance.

H2. Perceived procedural fairness and trust mediate the relationship between AI-enabled HRM practices and employee outcomes.

H3. Meaningful human oversight weakens the negative relationship between algorithmic opacity and employee trust.

H4. Employee participation in AI-HRM design positively influences perceived legitimacy and responsible system use.

© [2026] the Author(s). Published by Shivi Scientific Press. This article is distributed under the terms of the Creative Commons Attribution 4.0 International License

H5. AI augmentation, compared with full automation, is positively associated with employee autonomy in high-consequence HR decisions.

H6. The relationship between AI-enabled monitoring and employee well-being is contingent on transparency, proportionality, and employee control over personal data.

DECLARATIONS

Funding Statement
This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors. The research was conducted independently by the author.

Conflict of Interest Statement
The authors declare no conflict of interest

Acknowledgments
The author would like to express sincere appreciation to Universitas Persada Indonesia YAI, Jakarta, Indonesia, for providing an academic environment that supports research, scholarly development, and the advancement of management knowledge.

REFERENCES

1. Anshima, Bhardwaj, B., & Sharma, D. (2026). Paradoxes of implementing AI-augmented HRM in the workplace: A systematic literature review and future research agenda. Management Review Quarterly. https://doi.org/10.1007/s11301-025-00581-x
2. Cameron, R., Herrmann, H., & Nankervis, A. (2024). Mapping the evolution of algorithmic HRM (AHRM): A multidisciplinary synthesis. Humanities and Social Sciences Communications, 11, Article 303. https://doi.org/10.1057/s41599-024-02786-z
3. Gong, Q., Fan, D., & Bartram, T. (2025). Integrating artificial intelligence and human resource management: A review and future research agenda. The International Journal of Human Resource Management, 36(1), 103–141. https://doi.org/10.1080/09585192.2024.2440065
4. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372, Article n71. https://doi.org/10.1136/bmj.n71
5. Sharma, S., Mittal, A., & Seema, S. (2026). Does leading through algorithmic management impact the workers' well-being: A systematic literature review and research agenda. Leadership & Organization Development Journal, 47(2), 218–242. https://doi.org/10.1108/LODJ-06-2025-0424
6. Pereira, V., Hadjielias, E., Christofi, M., & Vrontis, D. (2023). A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective. Human Resource Management Review, 33(1), Article 100857. https://doi.org/10.1016/j.hrmr.2021.100857
7. Úbeda-García, M., Marco-Lajara, B., Zaragoza-Sáez, P. C., & Poveda-Pareja, E. (2025). Artificial intelligence, knowledge and human resource management: A systematic literature review of theoretical tensions and strategic implications. Journal of Innovation & Knowledge, 10(6), Article 100809. https://doi.org/10.1016/j.jik.2025.100809

HOW TO CITE THIS ARTICLE

Limakrishna, N. (2026). Artificial intelligence in strategic human resource management: An integrative review, value alignment framework, and systematic research agenda. *International Journal of Business Governance and Management, 1(1), 1–9.* https://doi.org/10.68033/ijbgm.1.1.1-9

© [2026] the Author(s). Published by Shivi Scientific Press. This article is distributed under the terms of the Creative Commons Attribution 4.0 International License