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ARTIFICIAL INTELLIGENCE IN HUMAN RESOURCE MANAGEMENT: OPPORTUNITIES, CHALLENGES, AND A HUMAN-CENTERED FRAMEWORK FOR EMPLOYEE DEVELOPMENT IN INDONESIA

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Abstract
Artificial intelligence (AI) is reshaping human resource management (HRM) by extending the use of analytics, automation, algorithmic decision support, and personalized employee services across the employment lifecycle. This article critically examines the opportunities and challenges of AI-enabled HRM for employee development, with particular attention to the Indonesian organizational context. The study uses a critical integrative literature review of 30 peer-reviewed journal articles covering AI-assisted HRM, algorithmic HRM, people analytics, recruitment, employee experience, learning and development, responsible AI, and human–AI collaboration. The synthesis shows that AI can strengthen recruitment efficiency, workforce analytics, personalized learning, talent development, employee experience, and evidence-informed decision making. At the same time, the literature consistently identifies risks involving algorithmic bias, opacity, privacy, accountability, perceived injustice, employee resistance, and organizational capability gaps. The review further indicates that AI value is not generated by technology alone; it depends on complementary human capabilities, organizational readiness, governance, and meaningful employee participation. Based on this synthesis, the article proposes a human-centered AI-HRM framework consisting of five mutually reinforcing dimensions: strategic alignment, data and AI capability, employee development, responsible governance, and human oversight and collaboration. For Indonesia, the framework highlights the need to move beyond technology adoption toward context-sensitive implementation that protects employee rights while developing digital and AI-related competencies. The article contributes by integrating employee development with responsible AI governance and by translating fragmented international evidence into a context-sensitive framework for Indonesian HRM.
Keywords: artificial intelligence, human resource management, employee development, algorithmic HRM, people analytics, responsible AI, Indonesia

Abstrak
Kecerdasan buatan (AI) sedang mengubah wajah manajemen sumber daya manusia (MSDM) dengan memperluas penerapan analitik, otomatisasi, dukungan pengambilan keputusan berbasis algoritma, serta layanan karyawan yang dipersonalisasi di seluruh siklus kerja. Artikel ini mengkaji secara kritis peluang dan tantangan MSDM yang didukung AI bagi pengembangan karyawan, dengan fokus khusus pada konteks organisasi di Indonesia. Studi ini menggunakan tinjauan pustaka integratif kritis terhadap 30 artikel jurnal yang telah ditelaah sejawat yang mencakup HRM yang dibantu AI, HRM algoritmik, analitik sumber daya manusia, rekrutmen, pengalaman karyawan, pembelajaran dan pengembangan, AI yang bertanggung jawab, serta kolaborasi manusia–AI. Sintesis tersebut menunjukkan bahwa AI dapat memperkuat efisiensi rekrutmen, analitik tenaga kerja, pembelajaran yang dipersonalisasi, pengembangan bakat, pengalaman karyawan, dan pengambilan keputusan berdasarkan bukti. Pada saat yang sama, literatur secara konsisten mengidentifikasi risiko yang melibatkan bias algoritmik, ketidakjelasan, privasi, akuntabilitas, persepsi ketidakadilan, resistensi

karyawan, dan kesenjangan kapabilitas organisasi. Tinjauan ini lebih lanjut menunjukkan bahwa nilai AI tidak dihasilkan oleh teknologi semata; hal ini bergantung pada kemampuan manusia yang saling melengkapi, kesiapan organisasi, tata kelola, dan partisipasi karyawan yang bermakna. Berdasarkan sintesis ini, artikel ini mengusulkan kerangka kerja HRM berbasis AI yang berpusat pada manusia, yang terdiri dari lima dimensi yang saling memperkuat: keselarasan strategis, kemampuan data dan AI, pengembangan karyawan, tata kelola yang bertanggung jawab, serta pengawasan dan kolaborasi manusia. Bagi Indonesia, kerangka kerja ini menyoroti perlunya melampaui sekadar adopsi teknologi menuju implementasi yang peka terhadap konteks, yang melindungi hak-hak karyawan sekaligus mengembangkan kompetensi digital dan terkait AI. Artikel ini memberikan kontribusi dengan mengintegrasikan pengembangan karyawan dengan tata kelola AI yang bertanggung jawab, serta menerjemahkan bukti-bukti internasional yang terfragmentasi menjadi kerangka kerja yang peka terhadap konteks untuk manajemen sumber daya manusia di Indonesia.
Kata kunci: *kecerdasan buatan, manajemen sumber daya manusia, pengembangan karyawan, manajemen sumber daya manusia berbasis algoritma, analitik SDM, AI yang bertanggung jawab, Indonesia*

Introduction

Artificial intelligence has moved from an experimental digital technology to an organizational capability that can influence how firms recruit, allocate, evaluate, develop, and retain employees. In HRM, this shift is visible in algorithmic recruitment, people analytics, automated employee services, predictive workforce analysis, personalized learning, and AI-supported managerial decision making. The literature no longer treats AI-HRM as a narrow automation issue; instead, it increasingly frames AI as a socio-technical transformation that changes HR practices, managerial roles, employee experiences, and organizational capabilities (Jarrahi, 2018; Qamar et al., 2021; Vrontis et al., 2021).

The evidence base nevertheless remains fragmented. Systematic reviews have identified rapid growth in AI-HRM research but also uneven theoretical development, concentration on recruitment and selection, limited country-specific evidence, and insufficient empirical attention to organizational and employee-level outcomes (Jatobá et al., 2023; Verma et al., 2023). Other reviews show that research is distributed across HRM, information systems, organizational behavior, ethics, and technology studies, making it difficult to translate findings into an integrated HR implementation logic (Basu et al., 2023; Qamar et al., 2021).

This fragmentation is especially consequential for employee development. Much of the early AI-HRM literature emphasized automation and recruitment, while employee development requires a broader understanding of skills, learning pathways, career agency, employee experience, and human capability. AI-enabled systems can personalize learning and identify development needs, but they can also intensify surveillance, standardize judgments, or reproduce historical patterns if data and governance are weak. Research on AI-mediated talent management and employee experience illustrates both sides: AI can improve personalization and HR service delivery, while the quality of employee experience remains dependent on how the technology is embedded within organizational relationships (Malik et al., 2021, 2022, 2023).

The Indonesian context adds a further layer of complexity. The source manuscript originally presented examples of AI use by Indonesian firms and reported an adoption estimate, but it did not provide a reproducible primary-data collection procedure or a traceable empirical dataset. Those claims therefore cannot be treated as original empirical findings. In this revision, the Indonesian cases are reframed as contextual illustrations rather than as evidence generated by the authors. This methodological correction is necessary because international journal reviewers are likely to challenge unsupported adoption statistics or claims of empirical analysis when the research protocol is not documented.

The central problem addressed by this article is therefore not whether AI is simply beneficial or harmful to HRM. The more useful question is under what organizational and governance conditions AI can create employee-development value without weakening fairness, privacy, human agency, or trust. The objectives are to: (1) synthesize evidence on the principal AI applications in HRM; (2) identify opportunities for employee development; (3) examine ethical, organizational, and employee-related risks; (4) interpret the implications for Indonesia; and (5) develop a human-centered framework that connects AI capability with employee development and responsible governance.

The article makes three contributions. First, it integrates literature on AI-HRM applications with the employee-development perspective rather than treating automation as the primary outcome. Second, it connects technological capability with responsible governance, employee experience, and human oversight. Third, it translates international evidence into a context-sensitive implementation framework for Indonesian organizations while explicitly distinguishing evidence from illustrative contextual claims.

Digital HRM refers broadly to the use of digital technologies to support HR processes, whereas algorithmic HRM adds a stronger decision component in which software algorithms use digital data to augment or automate HR activities. This distinction matters because algorithmic systems can influence not only administrative efficiency but also consequential judgments about recruitment, performance, development, and retention (Meijerink et al., 2021). People analytics provides an important precursor to AI-HRM by enabling organizations to use workforce data for descriptive, predictive, and increasingly prescriptive purposes (Marler & Boudreau, 2017; Tursunbayeva et al., 2018; Margherita, 2022).

AI-enabled HRM can therefore be understood as a socio-technical configuration in which AI systems, HR professionals, managers, employees, data infrastructures, and organizational rules interact. The socio-technical perspective is important because AI implementation does not create value merely by installing software. Employees need to understand the system, managers need to interpret outputs, and organizations need processes for accountability and adaptation (Makarius et al., 2020). Jarrahi (2018) similarly emphasizes human–AI complementarity: AI can extend computational and analytical capacity, while humans retain contextual, relational, and judgment-based capabilities.

The literature identifies several interconnected HRM functions in which AI is being applied. Recruitment and selection remain the most visible domain, including resume screening, candidate matching, automated communication, assessment support, and decision assistance. Algorithmic decision support can change managerial work by shifting some evaluative tasks from human judgment toward system-mediated recommendations (Langer et al., 2021). However, digital selection also creates applicant-reaction issues, including concerns about fairness, emotional discomfort, and opportunities to demonstrate capability (Köchling et al., 2023; Woods et al., 2020).

Training, development, and talent management represent a second domain. AI can identify skill gaps, recommend learning resources, personalize development pathways, support knowledge sharing, and assist career-related decisions. Evidence from AI-enabled talent practices suggests that personalization can improve employee experience, job satisfaction, and commitment when employees perceive the technology as supportive rather than controlling (Malik et al., 2021, 2022, 2023).

A third domain is performance and workforce analytics. HR analytics can integrate employee data to identify patterns related to performance, absence, retention, engagement, and workforce planning (Marler & Boudreau, 2017; Margherita, 2022). The strategic value of these capabilities depends on data quality, analytical maturity, managerial competence, and the extent to which analytics is connected to meaningful organizational decisions rather than used merely as a reporting technology.

Finally, generative AI expands the scope of AI-HRM by supporting communication, policy drafting, employee assistance, knowledge retrieval, learning content, and other cognitive tasks. Budhwar et al. (2023) emphasize that generative AI creates opportunities across HRM while simultaneously introducing uncertainty around accuracy, privacy, bias, misinformation, and the future configuration of work. Thus, generative AI should be treated as an extension of the AI-HRM transformation rather than as a separate phenomenon.

Research Method

This article adopts a critical integrative literature review design. The purpose is to synthesize heterogeneous evidence across AI-HRM, algorithmic HRM, people analytics, employee experience, responsible AI, recruitment, and employee development rather than to estimate a single pooled effect. The source manuscript described its approach as a conceptual literature review combined with empirical analysis, but it did not report a reproducible empirical sampling procedure, interview protocol, company-level dataset, or statistical analysis. The present revision therefore removes the unsupported empirical framing and treats the Indonesian organizational examples as contextual illustrations.

Evidence corpus and selection logic

The revised evidence corpus contains 30 peer-reviewed journal articles. Priority was given to systematic literature reviews, integrative reviews, empirical studies, and theoretically developed articles published in established international journals. Selection emphasized five criteria: (1) direct relevance to AI and HRM; (2) explicit treatment of recruitment, development, employee experience, analytics, governance, or human–AI collaboration; (3) methodological or conceptual clarity; (4) relevance to organizational and employee outcomes; and (5) bibliographic verifiability through publisher or institutional records.

The corpus is intentionally multidisciplinary because AI-HRM is not adequately explained by HRM literature alone. The selected studies span Human Resource Management Review, The International Journal of Human Resource Management, Human Resource Management Journal, Technological Forecasting and Social Change, Business Research, Information Systems Frontiers, Journal of Business Research, Journal of International Management, and related outlets. Several selected reviews explicitly use systematic review methods, including studies of AI-HRM interactions, AI-assisted HRM, algorithmic HRM, responsible AI, and the broader technological transformation of HRM (Basu et al., 2023; Bujold et al., 2024; Jatobá et al., 2023; Malik et al., 2023; Verma et al., 2023).

Analytical procedure

The literature was synthesized using four analytical categories: AI applications, employee-development opportunities, implementation risks, and organizational conditions. Within each category, findings were compared across studies and then interpreted for the Indonesian context. The analysis followed an evidence-to-implication logic: a documented finding was first summarized, its boundary conditions were considered, and only then was an implication for HR practice or Indonesia formulated. This procedure prevents vendor claims or isolated company examples from being treated as equivalent to peer-reviewed evidence.

Scope and limitation of the review

The review is integrative rather than a formal PRISMA systematic review conducted from a registered protocol. Therefore, it should not be interpreted as an exhaustive census of all AI-HRM research. Its purpose is analytical synthesis and framework development. The final article should not claim a specific number of records retrieved, screened, or excluded unless the authors conduct and document that search independently.

Results and Discussion

AI creates value when it augments rather than simply automates HR work

Across the literature, the most consistent opportunity is augmentation: AI can process large volumes of data, identify patterns, automate repetitive tasks, and generate decision support while allowing HR professionals to focus on interpretation, communication, and intervention. Jarrahi (2018) conceptualizes this relationship as human–AI symbiosis, while Makarius et al. (2020) demonstrate why AI adoption must be accompanied by socialization and employee integration. In HRM, this means that the relevant unit of analysis is not the algorithm alone but the human–technology configuration.

Systematic reviews support this interpretation. Vrontis et al. (2021) document the expansion of AI, robotics, and advanced technologies across HRM, while Qamar et al. (2021) show that AI applications span multiple HR functions and raise an ethical research agenda. Basu et al. (2023) further demonstrate that AI-HRM outcomes depend on configurations of technology, organizational adoption, and human responses rather than on technology in isolation. These findings challenge a simple automation narrative.

The strategic implication is that organizations should define AI-enabled HRM in terms of tasks and decisions rather than technology labels. Administrative tasks that are repetitive, high-volume, and rule-based may be suitable for automation. Tasks involving contextual judgment, employee well-being, conflict, career counseling, or sensitive performance decisions require stronger human oversight. This distinction is consistent with the extended strategic framework proposed by Malik et al. (2023) and the multilevel perspective developed by Verma et al. (2023).

Recruitment and selection: efficiency gains with fairness risks

Recruitment is among the most mature AI-HRM applications. AI can support resume screening, candidate matching, scheduling, communication, and decision support. These applications may reduce administrative workload and increase processing speed. However, algorithmic efficiency should not be equated with validity or fairness. Tambe et al. (2019) emphasize that HR phenomena are complex and that accountability and employee reactions constrain the value of data-driven decision systems.

The fairness problem is particularly important because recruitment models can learn from historical organizational data. Köchling and Wehner (2020) identify discrimination and perceived unfairness as recurring concerns in algorithmic HR recruitment and development. Rigotti and Fosch-Villaronga (2024) further show that fairness is multidimensional and cannot be reduced to a single technical metric; applicant and HR perspectives may differ regarding what counts as fair treatment. Naoum et al. (2026) similarly synthesize evidence showing that AI can standardize HR decisions while also reproducing historical inequities when data, design, or implementation are deficient.

Applicant experience also matters. Köchling et al. (2023) found that AI support at later recruitment stages can reduce perceived opportunities to perform and increase emotional discomfort, while Woods et al. (2020) emphasize the continuing importance of applicant reactions and validity in digital selection. Thus, recruitment systems should be evaluated not only by speed or cost but also by validity, fairness, transparency, applicant experience, and opportunities for human review.

Employee development: personalization without excessive surveillance

Employee development is the area in which AI has particular potential to contribute beyond administrative efficiency. People analytics can identify skill patterns and workforce needs, while AI-enabled systems can support personalized learning, knowledge sharing, career information, and employee services. Malik et al. (2021) found that AI-mediated knowledge sharing in an IT multinational enterprise was associated with personalization and positive talent experiences. Malik et al. (2022) similarly examined AI-enabled HR practices in an MNE and highlighted cost-effectiveness alongside individualized employee experiences. Malik et al. (2023) further connected an AI-based HR ecosystem with employee experience and engagement.

However, personalization is not automatically beneficial. The same data infrastructure used to recommend learning or career opportunities may also enable extensive monitoring. Responsible HR analytics therefore requires attention to purpose limitation, proportionality, transparency, and employee understanding (Meijerink et al., 2021; Tursunbayeva et al., 2020). If employees perceive AI as a surveillance mechanism, the developmental value of personalization may be undermined by distrust or defensive behavior.

For this reason, AI-supported employee development should be designed around an explicit developmental contract: employees should know what data are collected, why they are collected, how recommendations are produced, and how human decision makers will use them. Developmental AI should support employee agency rather than create an opaque ranking system.

People analytics and the development of AI capability

AI-HRM depends on a broader analytics capability. Marler and Boudreau (2017) established the importance of evidence-based HR analytics, while Tursunbayeva et al. (2018) showed that people analytics has developed across multiple disciplines and that ethical issues were historically underdeveloped. Margherita (2022) subsequently systematized the field and demonstrated the expanding role of HR analytics in organizational decision making.

The capability question is therefore broader than acquiring an AI platform. HR professionals require data literacy, algorithmic literacy, critical interpretation skills, and the ability to communicate analytical findings to managers and employees. Deepa et al. (2024) specifically emphasize the social and technical competencies required by HR managers in AI-intensive environments. Jatobá et al. (2023) similarly show that organizational HR capability is central to successful AI adoption.

This finding is particularly relevant to Indonesia, where organizational readiness can vary substantially across sectors and firm sizes. Rather than assuming that AI adoption is primarily an infrastructure problem, organizations should assess four forms of readiness: data readiness, human capability, governance readiness, and change readiness. The absence of any one of these can reduce the value of the others.

Table 1. AI applications, employee-development opportunities, and principal risks

HRM FUNCTION	AI-ENABLED APPLICATION	DEVELOPMENT OPPORTUNITY	KEY RISK REQUIRING GOVERNANCE
RECRUITMENT & SELECTION	CV screening, matching, scheduling, decision support	Faster access to talent and potentially more consistent screening	Historical bias, opacity, applicant distrust
LEARNING & DEVELOPMENT	Skill-gap analysis, personalized learning, recommendation systems	Individualized learning pathways and reskilling	Surveillance, inaccurate recommendations, over-standardization
PERFORMANCE MANAGEMENT	Analytics, feedback support, pattern detection	Timely developmental feedback and targeted support	Opaque evaluation, unfair inference, employee resistance
TALENT MANAGEMENT	Talent identification, career recommendations, knowledge sharing	Personalized career and talent development	Profiling, privacy, managerial over-reliance
EMPLOYEE SERVICES	Chatbots, self-service HR information, generative AI	Faster access to HR information and support	Misinformation, privacy, dehumanization
WORKFORCE ANALYTICS	Turnover, absence, engagement, workforce planning analytics	Evidence-informed workforce development	Data quality, spurious prediction, accountability gaps

Algorithmic bias, opacity, and accountability

The risk literature converges on three interconnected governance problems: biased data, opaque decision processes, and unclear accountability. Algorithmic HRM may appear objective because it produces numerical outputs, but numerical outputs do not guarantee neutral decision making. Köchling and Wehner (2020) demonstrate how algorithmic decision making can reproduce discrimination, while Langer and König (2023) explain that opacity can emerge from technical complexity, organizational choices, intellectual-property constraints, and the division of responsibilities among stakeholders.

Meijerink et al. (2021) argue that responsible HR analytics requires explicit attention to ethical implications, while Bujold et al. (2024) show from empirical literature that responsible AI in HRM involves more than a list of principles: the principles must be translated into actual design, deployment, and evaluation practices. The governance problem is therefore operational. Organizations need documented responsibility for data quality, model validation, bias testing, human review, explanation, incident response, and employee complaints.

This is especially important for consequential decisions. Bankins et al. (2022) found that workers' perceptions of justice and respectful treatment can differ depending on whether decisions are made by humans or AI. An organization can therefore achieve technical accuracy while still producing poor perceptions of procedural or interactional justice. HR governance should consequently include employee experience as a quality criterion.

Human touch is not an optional component of AI-HRM

The original article correctly identified the risk of losing the human touch, but the argument requires stronger theoretical grounding. AI can automate transactions; it cannot automatically reproduce the relational legitimacy of HR work. Employees often need explanation, empathy, negotiation, and contextual judgment, especially when decisions affect career progression, performance, compensation, or employment continuity.

Jarrahi (2018) and Makarius et al. (2020) support a complementary rather than substitutional view of human–AI relations. Malik et al. (2023) demonstrate that AI-assisted HR ecosystems can improve employee experience when integrated with broader organizational practices. Conversely, Bankins et al. (2022) show that the decision maker itself can shape perceptions of dignity and justice. The practical implication is that human involvement should be deliberately designed into high-impact HR processes.

A human-in-the-loop principle should therefore be mandatory for high-stakes decisions. AI may recommend, prioritize, detect patterns, or provide information, but a trained human should retain responsibility for interpreting the recommendation, considering contextual evidence, explaining the decision, and providing an avenue for review or appeal.

Organizational readiness and the Indonesian context

The source manuscript positioned Indonesia as a developing AI-HRM environment and identified infrastructure, digital literacy, organizational readiness, and ethical governance as important challenges. These themes remain relevant, but the revised article avoids unsupported national adoption percentages and company-level claims. The available evidence supports a more defensible conclusion: the international literature itself identifies country-specific research and implementation capability as underdeveloped areas, making contextual adaptation important (Jatobá et al., 2023; Verma et al., 2023).

For Indonesian organizations, implementation should be aligned with the national data-protection environment, including Law No. 27 of 2022 on Personal Data Protection, as well as organizational policies on information security, employee rights, and responsible technology use. The legal context should not be treated as a substitute for ethical governance; rather, legal compliance represents a minimum requirement within a broader responsible-AI framework.

Indonesia also requires attention to organizational heterogeneity. Large technology-oriented firms may possess stronger data infrastructures and specialist capabilities than smaller firms, while public organizations, manufacturing firms, services, and MSMEs may face different constraints. Therefore, an AI-HRM strategy should begin with a capability diagnosis rather than a technology purchase. The relevant question is not whether an organization can acquire AI, but whether it can govern, interpret, and use AI responsibly.

Proposed human-centered AI-HRM framework

Based on the synthesis, this article proposes a five-dimensional human-centered AI-HRM framework. The framework is a conceptual synthesis rather than an empirically validated model and should therefore be tested in future research.

FRAMEWORK DIMENSION	CORE PRINCIPLE	EVIDENCE BASE
STRATEGIC ALIGNMENT	AI use is linked to explicit HR and organizational objectives rather than technology adoption for its own sake.	Strategic HRM; AI-assisted HRM
DATA AND AI CAPABILITY	Data quality, analytics maturity, AI literacy, and HR professional competence support meaningful interpretation.	People analytics; capability development
EMPLOYEE DEVELOPMENT	AI is used to identify skills, personalize learning, support career development, and strengthen knowledge sharing.	Employee development; talent management

RESPONSIBLE GOVERNANCE	Fairness, privacy, transparency, explainability, accountability, and risk monitoring are embedded in the AI lifecycle.	Responsible AI; algorithmic HRM
HUMAN OVERSIGHT AND COLLABORATION	High-impact decisions retain human responsibility, employee voice, contextual judgment, and avenues for review.	Human–AI symbiosis; socio-technical systems

The framework can be represented as a sequence of mutually reinforcing conditions: strategic alignment establishes why AI is adopted; data and AI capability establishes whether the organization can use it; employee development defines the value proposition for people; responsible governance establishes the boundaries of acceptable use; and human oversight protects judgment, dignity, and accountability. Weakness in one dimension can undermine the others. For example, a technically sophisticated recruitment system without governance may increase efficiency while amplifying discrimination; a personalized learning platform without employee trust may increase data collection without producing meaningful development.

The framework also clarifies the article's theoretical contribution. Existing literature often separates efficiency-oriented AI-HRM research from ethics-oriented research. The proposed framework integrates these perspectives by treating employee development as the mechanism through which AI capability should generate human value, while responsible governance and human oversight function as boundary conditions. In this formulation, AI is neither inherently beneficial nor inherently harmful; its organizational consequences depend on the configuration of technology, people, data, governance, and context.

Table 3. Implementation priorities for Indonesian organizations

PRIORITY	RECOMMENDED ORGANIZATIONAL ACTION	INDICATIVE SUCCESS MEASURE
CAPABILITY DIAGNOSIS	Assess data quality, AI literacy, HR analytical capability, infrastructure, and change readiness before deployment.	Documented readiness assessment and competency gap analysis

RESPONSIBLE DATA GOVERNANCE	Define purpose, access, retention, security, and employee communication for HR data.	Data-governance policy and auditable access controls
HUMAN-IN-THE-LOOP DESIGN	Identify decisions that require human review and create review/appeal procedures.	Percentage of high-impact decisions with documented human review
EMPLOYEE DEVELOPMENT	Use AI to map skills, recommend learning, and support reskilling/upskilling rather than only monitor performance.	Learning participation, skill-gap closure, employee-perceived usefulness
ALGORITHMIC ASSURANCE	Test models for bias, validity, drift, explainability, and unintended consequences.	Regular model audits and documented remediation
EMPLOYEE PARTICIPATION	Involve HR professionals and employees in system design, implementation, and evaluation.	Feedback cycles, acceptance indicators, and documented changes

Implications

Implications for HR practice

Treat AI adoption as an HR transformation project, not merely an IT procurement project.

Match automation intensity to task characteristics: automate routine processes more readily, while retaining human judgment for high-impact and relational decisions.

Develop AI literacy among HR professionals, including data interpretation, model limitations, bias detection, and responsible-use principles.

Design employee development applications around skills, learning, career agency, and knowledge sharing rather than surveillance.

Establish governance responsibilities before deployment, including data stewardship, model validation, human review, explanation, and appeal mechanisms.

Evaluate AI-HRM systems using a balanced scorecard that includes efficiency, validity, employee experience, fairness, privacy, and development outcomes.

Implications for theory

The review suggests that AI-HRM research should move from a technology-centric model toward a capability-and-governance model. The proposed framework integrates strategic alignment, AI capability, employee development, responsible governance, and human oversight. It also responds to the recurring finding that AI-HRM research has been fragmented across functions and disciplines (Qamar et al., 2021; Verma et al., 2023). Future empirical research can operationalize the five dimensions as organizational capabilities and test their relationships with employee development, trust, engagement, performance, and organizational outcomes.

Implications for research in Indonesia

Research in Indonesia should expand beyond descriptive reports of technology use. Suitable future designs include multi-organization comparative case studies, mixed-method studies of AI adoption, quasi-experimental evaluations of AI-supported learning, longitudinal studies of employee outcomes, and survey models testing the relationships among AI readiness, responsible governance, employee trust, and development outcomes. Cross-cultural comparison is also important because evidence from North America, Europe, India, and multinational firms cannot automatically be generalized to Indonesian organizations.

Limitations

The review has several limitations. First, it is an integrative review rather than a fully registered systematic review; therefore, the 30-article corpus should not be interpreted as exhaustive. Second, the international evidence base is heterogeneous in theory, method, sector, and country. Third, the Indonesian implications are contextual interpretations rather than findings from a nationally representative dataset. Fourth, several AI-HRM technologies are evolving rapidly, particularly generative AI, meaning that recommendations may require periodic updating. Finally, the proposed five-dimensional framework is conceptual and requires empirical validation before it can be used as a measurement model or causal explanation.

Conclusion

Artificial intelligence is changing HRM from a predominantly administrative function toward a more data-intensive and technologically mediated organizational capability. The literature reviewed in this article shows substantial opportunities in recruitment, workforce analytics, employee services, talent management, and employee development. However, these opportunities are accompanied by recurring risks involving algorithmic bias, opacity, privacy, accountability, employee reactions, and organizational capability.

The central conclusion is that AI-HRM value should be evaluated through a human-centered lens. Technology can improve processing capacity and personalization, but sustainable value depends on the interaction among AI capability, organizational readiness, employee development, responsible governance, and human judgment. For Indonesia, this means that successful AI-HRM implementation should not be measured primarily by the number of automated processes. It should be assessed by whether AI improves organizational decision quality and employee development while maintaining fairness, privacy, transparency, dignity, and meaningful human oversight.

The proposed five-dimensional framework—strategic alignment, data and AI capability, employee development, responsible governance, and human oversight and collaboration—offers a basis for future empirical testing. It provides a more defensible conceptual foundation than an efficiency-only model and positions employee development as a central human outcome of AI-enabled HRM.

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