The Strategic Challenges of Artificial Intelligence on Human Resource Management Practices

Sandeep Kumar Gupta[1], Billekanti Punitha Sai[2], Patan Ushma[3], Chithanoor Meghana[4], Kakarla Uday Kiran Reddy[5]

[1]*Dr., Professor, School of Commerce and Management, Mohan Babu University, Tirupati, India, ORCID: https://orcid.org/0000-0002-2670-2858*
[2]*School of Commerce and Management, Mohan Babu University, Tirupati, India*
[3]*School of Commerce and Management, Mohan Babu University, Tirupati, India*
[4]*School of Commerce and Management, Mohan Babu University, Tirupati, India*
[5]*School of Commerce and Management, Mohan Babu University, Tirupati, India*

Citation:
Gupta, S. K., Sai, B. P., Ushma, P., Meghana, C., & Reddy, K. U. K. (2025). The Strategic Challenges of Artificial Intelligence on Human Resource Management Practices. *Economics, Finance and Management Review*, (4(24), 72–90. https://doi.org/10.36690/2674-5208-2025-4-72-90

Received: October 22, 2025
Approved: December 29, 2025
Published: December 30, 2025

Abstract. *Artificial intelligence is increasingly embedded in human resource management, shifting HR work from transaction-heavy administration toward data-driven decision support and workforce analytics. This transition creates measurable efficiency gains, but it also raises governance and legitimacy challenges in domains where decisions are high-stakes and socially sensitive. This paper examines the strategic challenges that shape responsible AI adoption in HRM and clarifies how these challenges influence decision quality, fairness, compliance, and trust. The study applies a qualitative approach based on secondary sources published between 2018 and 2024, including peer-reviewed articles, industry reports, and white papers. The evidence is synthesized through thematic analysis and complemented with comparative insights from organizational cases of AI use in recruitment, engagement, performance management, and training. Findings indicate uneven diffusion of AI across HR functions, with earlier uptake in recruitment and learning processes and comparatively lower automation in compensation and succession planning, reflecting higher governance sensitivity. Employee perception evidence shows strong support for efficiency benefits alongside contested views on fairness, with a pronounced preference for human review in consequential decisions. Organizational scale conditions adoption: larger firms exhibit higher budgets, stronger skills, and richer data environments, translating into higher functional uptake than small and medium enterprises. The risk assessment highlights hiring bias, data misuse, legal non-compliance, and employee distrust as priority risks that require proactive mitigation through auditing, privacy safeguards, and transparency measures. Future studies should test causal effects of AI on fairness and workforce outcomes using longitudinal and multi-method designs, including audit studies of recruitment systems. Additional work is needed on practical human-AI workflow design, explainability mechanisms, and scalable governance models suited to resource-constrained organizations.*

Keywords: *artificial intelligence; human resource management; ethics, workforce transformation; automation; strategic challenges; skills gap; ethical HR analytics.*
JEL Classification: M12; M54; O33; J24; K31
Formulas: 0; fig.: 0; table: 7; bibl.: 22

Introduction. Artificial intelligence has developed into a central driver of organizational transformation and is increasingly shaping how firms design processes, allocate resources, and compete in dynamic environments. Within human resource management, AI is no longer positioned merely as a supportive technology but is increasingly treated as a strategic capability that reconfigures how organizations attract, develop, and retain talent. Contemporary HR applications include automated resume screening, chatbot-supported recruitment, predictive analysis for performance and turnover risk, personalized learning recommendations, and advanced workforce planning models. These tools can increase process efficiency and expand analytical capacity, enabling HR units to base decisions on structured evidence rather than solely on subjective judgment. In principle, this shift strengthens organizational performance by improving the speed, consistency, and informational quality of HR interventions across the employee lifecycle.

At the same time, the integration of AI into HRM introduces strategic and ethical challenges that can offset anticipated benefits if they are not addressed through governance and responsible implementation. Data privacy is a foundational concern because AI systems frequently depend on large volumes of employee and applicant data, and weak data handling practices may compromise confidentiality and violate legal requirements. Algorithmic bias is similarly critical, as models trained on historical data may reproduce inequities linked to gender, race, age, or other protected characteristics, even when discrimination is not intentional. In addition, automation can generate employee anxiety about job displacement and intensified monitoring, which may weaken trust, increase resistance to change, and alter organizational culture. These risks are not marginal, because they affect legitimacy, compliance exposure, and the perceived fairness of HR decisions, which are core determinants of workforce engagement and organizational reputation.

The capability dimension is equally important, since effective and ethical AI use in HR requires competencies that extend beyond traditional administrative expertise. HR professionals increasingly need digital literacy, analytical skills to interpret AI outputs, and ethical awareness to recognize when algorithmic recommendations may be inappropriate or harmful. Without these capabilities, organizations may experience over-reliance on automated outputs, inadequate oversight, and weak accountability for consequential decisions. Consequently, AI adoption in HRM should be understood as a socio-technical transformation that demands coordinated change in skills, governance structures, and decision processes, rather than as a simple technology upgrade. A responsible implementation approach therefore involves both technical integration and institutional safeguards that ensure transparency, fairness, and human accountability.

Literature Review. The literature broadly agrees that artificial intelligence is transforming human resource management through automation and data-driven decision support, yet it also shows that the evidence base remains uneven across functions, contexts, and outcomes. Industry-oriented work emphasizes efficiency gains by automating repetitive HR processes, which can reallocate HR capacity toward strategic activities such as talent development and culture building (Deloitte, 2023). At the same time, scholarship and practice reports repeatedly warn that algorithmic systems may reproduce historical biases embedded in training data, particularly in recruitment and screening, where proxies can indirectly encode protected characteristics (Deloitte, 2023). A clear gap is that many publications describe risks conceptually but provide limited longitudinal evidence on whether, and under what conditions, bias actually increases or decreases after AI implementation. Another gap concerns measurement: studies often lack consistent fairness metrics, documentation standards, and comparability across organizations, which constrains the ability to synthesize findings into actionable benchmarks.

Research on employee perceptions highlights that technological adoption is also a socio-psychological process, not merely a technical modernization. Brougham and Haar (2018) find that employees perceive AI as simultaneously improving productivity and threatening job security, which may reduce morale and engagement. Related arguments suggest that AI can intensify labor market polarization by rewarding digital skill holders and marginalizing routine administrative roles (Brynjolfsson & McAfee, 2021). A major gap here is that employee-centered studies often rely on cross-sectional survey designs and self-reported attitudes, leaving uncertainty about causal direction and the durability of these perceptions over time. Another gap is the limited attention to heterogeneity: the literature seldom differentiates effects by age, occupational group, contract type, gender, or prior digital competence, even though these factors are likely to shape exposure to displacement and access to reskilling opportunities. There is also an underdeveloped understanding of how organizational communication and participatory change management can mitigate fear and increase perceived procedural justice during AI-enabled transformation.

People analytics scholarship foregrounds privacy, transparency, and accountability as central to trust in AI-driven HR systems (Tursunbayeva et al., 2019). This stream argues that employees may lose confidence if decision logic is opaque or if data collection practices are unclear, and it emphasizes alignment with legal requirements such as the GDPR and broader ethical frameworks (Tursunbayeva et al., 2019). However, a substantive gap is that many discussions remain normative, prescribing what organizations should do without systematically evaluating what organizations actually do and what outcomes follow. Another gap concerns operationalization: transparency is frequently invoked, yet studies rarely

specify which transparency mechanisms matter most in HR practice, for example model documentation, explanations provided to employees, appeal procedures, or independent audits. In addition, research tends to under-examine data governance capacity in small and medium enterprises, where resource constraints may make compliance and accountability mechanisms more difficult to implement.

The augmented intelligence perspective proposes that AI should complement human judgment rather than replace it, because human reasoning remains essential for contextual interpretation, ethical deliberation, and relational aspects of HR decisions (Jarrahi, 2018). This view supports human-in-the-loop models where AI provides recommendations and humans retain accountable authority. A key gap is that the literature offers limited granular evidence on how to design effective human-AI workflows in HR, including role definitions, escalation protocols, and training for critical interpretation of model outputs. Another gap concerns the risk of automation bias, where decision makers may over-trust algorithmic recommendations, especially under time pressure or where accountability is diffuse. Empirical studies that test how different interface designs, explanation styles, and accountability assignments influence human reliance and decision quality remain relatively scarce in the HR domain.

Strategic management research emphasizes that successful AI adoption depends on alignment with organizational objectives, leadership commitment, supportive culture, and readiness for technological transformation (Strohmeier & Piazza, 2015; Bansal, 2025). This perspective extends evaluation beyond efficiency to include engagement, satisfaction, and sustainability outcomes. A notable gap is that many studies treat “readiness” and “culture” as broad constructs, with limited validated instruments tailored to AI-in-HR contexts. Another gap is that the literature under-specifies the mechanisms through which leadership shapes outcomes, for example governance structures, resource allocation, risk appetite, and communication regimes. Additionally, cross-national comparative work is limited, which weakens understanding of how regulatory environments, labor institutions, and cultural norms moderate the relationship between AI adoption strategies and HR outcomes.

Recent empirical work and reviews report benefits of AI for recruitment precision, engagement analytics, performance monitoring, and retention, while also warning against privacy risks, excessive surveillance, and over-reliance on algorithms (Aksoy, 2023; Ashurbaev & Saidkulov, 2024; Raza et al., 2025; Manwani et al., 2025). Responsible AI studies stress fairness, explainability, and human control as prerequisites for trustworthy systems, and propose governance instruments such as ethical committees and regulatory frameworks (Kumar, 2025; Du, 2025; Belagalla et al., 2025). The gap across this newer wave is fragmentation: many studies are context-specific, methodologically heterogeneous, and difficult to compare, which

hinders accumulation of robust evidence. Another gap is the limited integration of legal, technical, and behavioral dimensions into single explanatory models, even though HR outcomes are shaped by the interaction of compliance regimes, model performance, and employee perceptions. Finally, a critical gap is that outcome evaluation often stops at process indicators, such as speed or accuracy of screening, rather than examining downstream impacts such as diversity outcomes, turnover, grievance rates, psychological safety, and organizational trust over extended periods (Bader et al., 2020; Harchandani, 2025).

Synthesizing across these strands, the literature suggests that AI in HRM is best conceptualized as a socio-technical governance challenge: value creation depends on automation and analytics, but legitimacy depends on fairness, privacy, transparency, and accountable human oversight. The central research gaps cluster around causal evidence, standardized measurement, workflow design, and context sensitivity. Addressing these gaps requires longitudinal and multi-method designs, including field experiments, audit studies of recruitment systems, and comparative case research across industries and regulatory settings. It also requires the development of validated constructs and metrics for fairness, explainability, and trust that can be applied consistently across HR applications. In addition, more attention is needed to practical governance architectures that link ethical principles to enforceable controls, including auditing routines, documentation standards, employee voice mechanisms, and clear accountability assignments.

Aims. The aim of the study is to synthesize evidence on how AI reshapes HRM functions while identifying the strategic, ethical, and capability-related constraints that determine whether adoption improves efficiency without weakening fairness, accountability, and trust.

Methodology. This research adopts a qualitative research approach, focusing on understanding the deeper insights, patterns, and trends related to the use of Artificial Intelligence (AI) in Human Resource Management (HRM). The study primarily relies on secondary data, including peer-reviewed journal articles, conference papers, industry reports, and white papers published between 2018 and 2024. These sources were carefully selected to ensure relevance, credibility, and diversity in perspectives.

To analyze the collected information, thematic analysis was employed. This involved systematically reviewing the literature to identify recurring themes and patterns, particularly concerning ethical challenges, workforce adaptation, and the strategic integration of AI within HR functions. Thematic analysis allowed for a structured synthesis of findings while highlighting emerging trends, best practices, and potential pitfalls.

Additionally, comparative insights were drawn from case studies of organizations that have successfully implemented AI in HR processes, including recruitment, employee engagement, performance management,

and training. These case studies provided practical examples and contextual understanding of how AI-driven solutions are applied in real-world settings. By combining thematic analysis with comparative case study insights, this methodology provides a comprehensive and nuanced understanding of AI's transformative role in HRM while identifying opportunities and challenges for future adoption.

Results. The findings suggest that artificial intelligence can substantially reconfigure human resource management by shifting HR work from transaction-oriented administration toward more strategic, data-driven governance. Automation is consistently presented as a mechanism that reduces time spent on routine processes, such as candidate screening, payroll operations, attendance management, and standardized performance tracking, thereby enabling HR professionals to redirect effort to workforce planning, talent development, and organizational culture. In parallel, predictive analytics expands HR capacity to anticipate staffing needs, identify skill gaps, and support evidence-informed talent decisions, which strengthens the forward-looking role of HR in organizational strategy. At the functional level, the literature associates AI with improved process efficiency and decision support, especially in high-volume tasks where speed and consistency are valued. However, the same evidence indicates that these performance gains do not automatically translate into improved legitimacy or fairness, because algorithmic outputs can embed historical patterns and generate biased or uneven outcomes if not carefully governed.

Across studies, the most persistent challenges cluster around ethics, trust, and organizational capability rather than around technical feasibility alone. Ethical risks include algorithmic discrimination in recruitment and evaluation, misuse or excessive collection of employee data, and limited transparency about how AI systems generate recommendations or decisions. These issues are consequential because they can undermine perceptions of procedural justice and expose organizations to legal and reputational harm, particularly in public sector environments where accountability and compliance expectations are high. In addition, employee apprehension remains a material adoption barrier, often driven by perceived threats to job security and concerns about surveillance or depersonalized decision-making. Capability constraints also recur, as many HR units lack sufficient AI literacy and analytics competence to interpret model outputs critically, detect bias, and implement meaningful oversight. As a result, adoption outcomes depend on whether organizations can align tools with governance standards and workforce readiness rather than on whether AI tools are available in the market.

A coherent response in the literature is the call for responsible AI implementation as an integrated organizational program. This approach emphasizes human-in-the-loop decision processes, transparent communication about data use and decision logic, and the establishment of

formal governance mechanisms that specify accountability, auditing routines, and compliance controls. Continuous upskilling and reskilling are treated as enabling conditions, because HR professionals must be able to manage AI systems, evaluate their limitations, and translate insights into fair and context-sensitive decisions. Employee inclusion is also framed as essential for legitimacy, since participatory approaches can reduce resistance and strengthen trust through clarity about purpose, safeguards, and benefits. Overall, the evidence supports a balanced interpretation: AI can enhance HR efficiency and analytic capacity, but only when implementation is coupled with ethical safeguards, capability development, and trust-preserving governance that ensures AI complements human judgment rather than replacing responsible HR decision-making.

Table 1 reinforces this interpretation by synthesizing survey and evidence-review findings on the perceived benefits and challenges of AI in HRM, with particular relevance for public sector settings characterized by heightened requirements for transparency and institutional trust.

Table 1. Evidence Synthesis of Survey Findings on Perceived Benefits and Challenges of AI in HRM in the Public Sector

Source	Year	Method/Sample	Key finding/stat
McKinsey – "AI in the workplace"	2025	Global company survey & analysis	Leadership readiness is the biggest barrier to successful AI adoption; many orgs lack AI strategy
OECD – 'Using AI in the workplace'	2022	Surveys & literature review	In 2021, only ~8% reported using AI for HR tasks (HR adoption lagged other functions)
PwC – "Global AI Jobs Barometer"	2025	Analysis of ~1 billion job ads	AI changes job content; opportunities for reskilling – AI can complement workers
Nature – "Ethics and discrimination in AI-enabled recruitment"	2023	Literature review	Algorithmic bias in recruitment can reproduce discriminatory outcomes from historical data
AIHR – "Challenges of AI in HR" (industry synthesis)	2025	Practitioner insights	Top practical challenges: bias, data privacy, governance, skill gaps, change management.
My Perfect Resume – HR survey infographic (2024-2025)	2024	HR professional survey	64% of HR managers use some AI; top use-cases include job descriptions, screening, analytic
Springer research – "Potential benefits and challenges of AI in HR"	2025	Cross-sectional survey (n=217)	Perceived benefits (efficiency, decision support) contrasted with privacy & ethics concerns.
Josh Bersin / HR research (industry synthesis)	2024	Industry surveys & reports	Only a small fraction of organizations have a clear AI strategy specifically for HR (strategy gap).

Source: systematized by the authors

By integrating global surveys, large-scale labor market analytics, and ethics-focused reviews, the table demonstrates that organizations simultaneously view AI as a productivity enabler and as a governance-sensitive intervention. The structure of the table makes it possible to compare strategic constraints, such as leadership readiness and the absence of HR-

specific AI strategy, with operational constraints, such as skill gaps, privacy risks, and change-management capacity. It also reveals an adoption gap in which HR frequently lags behind other organizational functions, even as AI use expands in recruitment-adjacent applications and decision-support tools. In analytical terms, Table 1 functions as a compact empirical basis for the claim that HRM benefits are contingent on organizational readiness and robust safeguards, not on technology adoption alone.

Taken together, the findings indicate a stable pattern in how organizations interpret AI in human resource management. AI is primarily associated with efficiency gains and improved decision support, yet the perceived benefits are closely accompanied by governance-sensitive risks, particularly algorithmic bias, privacy violations, and weakened accountability. Importantly, the evidence suggests that obstacles to adoption are rarely technical in isolation. Instead, they concentrate around leadership capability, the presence or absence of a clear HR-focused AI strategy, and the extent to which responsible AI practices are institutionalized through policies, controls, and oversight routines. Where organizations invest in capability development and role redesign, AI is more likely to complement employees by changing job content in ways that support reskilling and higher-value work. In contrast, the prominence of discrimination risks in recruitment underscores that performance improvements are insufficient unless they are coupled with fairness-oriented controls, including transparent decision procedures and audit mechanisms. Consequently, the overall interpretation is integrative: outcomes in AI-enabled HRM depend on the combined maturity of strategy, culture, and governance, rather than on tool deployment alone.

In this context, Table 2 offers a structured synthesis of the challenge landscape by grouping frequently reported barriers into coherent thematic categories. The table separates capability constraints, such as limited AI understanding and skills gaps among HR professionals, from system-level governance risks, including algorithmic bias and data privacy concerns, and from resource limitations, such as budget and cost barriers. This organization clarifies that implementation problems and governance requirements are interdependent, because limited competence and resourcing can weaken oversight and increase the probability of harmful outcomes. By combining illustrative examples with frequency-style comments, the table supports analytical comparison across heterogeneous studies that use different methods and terminology, while maintaining focus on the recurring obstacles that shape adoption across contexts. As a result, Table 2 strengthens the argument that effective AI integration in HRM requires coordinated interventions that develop competencies, secure data governance, and allocate resources for sustainable, accountable practice.

Table 2. Recurring Challenge Categories in AI-Enabled HRM and Their Reported Frequency in the Literature

Challenge Category	Examples	Reported % or Comment
Lack of AI understanding/trust among HR	HR staff lacking AI/analytics capabilities	Identified as a top challenge
Skills gap in HR staff	AI decisions-making may replicate bias	Report mentions "Lack of skills about AI in HR staff"
Inherent algorithmic bias	Concerns over validity of AI decisions, privacy issues	Listed among primary hurdles.
Data privacy & reliability of decisions	Concerns over validity of AI decisions, privacy issues	Included in obstacles.
Budget/ Cost constraints	High cost of adoption and implementation	Listed in challenge set.

Source: systematized by the authors

Table 2 demonstrates that the most enduring barriers to AI adoption in HRM are socio-technical in nature because they merge human capability limitations with concerns about the legitimacy and reliability of AI-mediated decisions. Deficits in skills and trust function as foundational constraints, since insufficient understanding of AI reduces the capacity of HR teams to interpret algorithmic outputs critically, recognize potential bias, and apply effective oversight in practice. Governance-related challenges, particularly algorithmic bias and data privacy risks, emerge as central adoption constraints because they shape perceptions of fairness, determine compliance exposure, and influence employee trust in HR decision processes. These vulnerabilities are further intensified by financial constraints that restrict investment in training, auditing procedures, and secure data infrastructures, thereby increasing the probability of implementation failure or unintended harm. In this sense, the table supports an integrated interpretation in which scalable AI adoption depends on coordinated interventions that build competencies, embed responsible AI controls, and ensure adequate resourcing for sustainable governance.

Table 3 complements this perspective by mapping adoption levels across core HRM functions and associating each function with the AI tools most commonly used in practice. By presenting adoption as a function-specific pattern, the table makes it possible to compare front-end talent processes, such as recruitment and selection, with longer-cycle and higher-stakes domains, such as compensation governance and succession planning. The pairing of adoption percentages with tool typologies clarifies not only where AI is most prevalent, but also which application types dominate within each HR domain, ranging from automation and conversational interfaces to predictive and diagnostic analytics. This framing highlights that maturity is uneven across HRM, reflecting differences in data availability, sensitivity of decisions, regulatory and ethical exposure, and perceived return on investment. As a result, Table 3 supports the conclusion that AI diffusion in HRM proceeds selectively, shaped by both operational feasibility and the governance demands associated with particular HR functions.

Table 3. AI Adoption Levels in HRM Functions

HRM Function	% of Companies Using AI	Most Common AI Tools Used
Recruitment & Selection	55%	Resume screening, chatbots, predictive anaalytics
Learning & Development	40%	Skill-gap analytics, personalized learning
Performance Management	32%	KPI tracking, continuous insights
Employee Engagement	28%	Sentiment analysis, AI surveys
Compensation & Benefits	20%	Benchmarking algorithms, pay-equity tools
Succession Planning	18%	Predictive leadership analytics

Source: systematized by the authors

Table 3 reveals a pronounced adoption gradient across HRM functions. Recruitment and selection occupy the leading position, followed by learning and development, whereas compensation and benefits and succession planning remain less automated. This distribution aligns with the expectation that high-volume and relatively standardized processes are adopted earlier, because they generate immediate efficiency gains and allow organizations to track performance with clearer operational metrics. By contrast, lower adoption in compensation and succession planning is plausibly associated with higher governance sensitivity, since these areas involve equity considerations, legal exposure, and decisions with substantial consequences for employees, which increases the demand for explainability and robust oversight. The pattern of tools reinforces this interpretation: current HR AI use appears concentrated in screening automation, engagement measurement, and dashboard-driven performance insights, while more advanced predictive applications tend to be reserved for leadership pipelines and workforce planning where strategic value is high but typically requires greater data maturity. Overall, the table supports the conclusion that AI diffusion in HRM proceeds incrementally, function by function, and is shaped by the balance between operational benefits, data readiness, and ethical or regulatory risk.

Table 4 extends this analysis by explicitly linking major strategic challenges of AI-enabled HRM to their anticipated impact on HR decision-making outcomes. In this framing, impact is defined not as a technical performance indicator but as the degree to which a challenge can distort decisions, undermine legitimacy, or slow implementation trajectories. The table therefore enables structured prioritization by distinguishing high-impact risks that directly threaten fairness, compliance, and trust from medium-impact constraints that more strongly influence implementation pace and execution stability. This approach is particularly valuable for strategic planning because it translates abstract risk categories into decision-relevant consequences, thereby clarifying where interventions should be concentrated. By connecting governance, capability, and change-management factors to HRM outcomes, Table 4 provides a transparent logic

for sequencing actions and allocating resources toward the most consequential vulnerabilities.

Table 4. Strategic Challenges Vs Impact on HRM Outcomes

Strategic Challenge	Impact on HR Decision-Making	Impact on HR Decision-Making
Algorithmic Bias	Unfair hiring decisions	High
Lack of Explainability	Low trust, disputes	High
Data Privacy Concerns	Legal/non-compliance risk	High
Integration Issues	Implementation delays	Medium
High Cost	Slower transformation	Medium
HR Skill Gaps	Poor AI usage	High
Employee Resistance	Reduced engagement	Medium

Source: systematized by the authors

Table 4 indicates that the most consequential challenges of AI-enabled HRM are concentrated in three interrelated domains: the quality of governance arrangements, the interpretability of AI outputs, and the human capability required to manage AI responsibly. High-impact risks, including algorithmic bias, limited explainability, data privacy concerns, and skills gaps among HR professionals, are positioned as critical because they can directly weaken fairness in decisions, trigger disputes, and increase exposure to legal and reputational consequences. By contrast, medium-impact constraints, such as integration difficulties, high implementation costs, and employee resistance, primarily influence the pace and stability of adoption. Nevertheless, these constraints can indirectly intensify high-impact risks by constraining the time and resources available for auditing, training, and transparent communication. From a strategic perspective, the table supports a sequenced approach in which organizations first establish responsible decision-making through fairness controls, explainability practices, and competence development, and only then expand implementation through integration planning and budgeting. In this way, Table 4 reinforces the argument that sustainable AI adoption in HRM requires alignment between technological change, trustworthy governance, and workforce readiness.

Table 5 complements this strategic view by providing a focused representation of employee perceptions toward AI in HRM through reported levels of agreement and disagreement with four evaluative statements. The items are designed to capture perceived benefits, specifically efficiency and fairness, alongside governance and risk concerns, namely the need for human review and perceived threats to job security. This structure enables interpretation of attitudes as multidimensional rather than binary, because employees may endorse process improvements while simultaneously questioning the legitimacy of AI decisions and the personal implications of automation. The prominence of human review as an evaluative dimension also highlights the social expectation that accountability should remain anchored in human judgment, particularly for consequential HR outcomes. As a result, Table 5 supports analysis of institutionalization conditions by

showing that adoption depends not only on technical performance but also on social acceptance, perceived justice, and confidence that AI use will not erode trust within the workplace.

Table 5. Employee Perception Toward AI in HRM

Survey Statement	% Agree	%Disagree
AI improves fairness	42%	58%
AI decisions need human review	87%	13%
AI improves efficiency	76%	24%
AI threatens job security	61%	39%

Source: systematized by the authors

The results show that employees most strongly endorse AI for its contribution to efficiency, whereas perceptions of fairness remain divided, which indicates that respondents distinguish between faster procedures and equitable outcomes. High levels of support for human review point to a clear expectation that accountability for consequential HR decisions should remain anchored in human judgment, implying that fully automated decision-making may face legitimacy constraints within organizations. At the same time, the predominance of job security concerns suggests a persistent anxiety mechanism that can shape employee engagement, willingness to cooperate with data-driven initiatives, and overall openness to HR digitalization. Taken together, the pattern reflects conditional acceptance: employees tend to value productivity gains, but they also demand oversight and remain sensitive to distributive effects that may arise from automation. This implies that implementation strategies should combine transparent decision procedures with human-in-the-loop governance and credible workforce development pathways that reduce perceived threat while preserving operational benefits.

Table 6 extends the analysis by comparing AI adoption in HRM across large firms and small or medium enterprises through both enabling conditions and functional uptake. The parameters capture differences in resource capacity, including AI budget allocation and skill availability, alongside contextual conditions such as data availability and resistance to change. By linking these structural inputs to adoption rates in recruitment and training, the table clarifies how organizational scale shapes the feasibility, speed, and scope of AI-enabled HR transformation. The comparison suggests that adoption is best understood as a capability-dependent process rather than a uniform trajectory, because firm size influences readiness, governance capacity, and the practical ability to institutionalize AI responsibly. In analytical terms, Table 6 supports the conclusion that unequal resource endowments and differing change dynamics can produce uneven diffusion patterns, with implications for the emerging divide between large organizations and SMEs in HR digital modernization.

Table 6. AI Adoption in Large VS Small Firms

Parameter	Large Companies	Small/Medium Companies
AI Budget Allocation	High	Low
AI in Recruitment	68%	32%
AI in Training	51%	18%
Skill Availability	High	Low
Resistance to Change	Low	High
Data Availability	High	Medium/Low

Source: systematized by the authors

Table 6 demonstrates a clear scale effect in AI adoption for HRM. Large organizations tend to allocate larger budgets to AI initiatives, possess stronger internal skill capacity, and operate with richer and more structured data environments, which together correspond to markedly higher uptake of AI in recruitment and training. By contrast, small and medium enterprises typically face tighter financial constraints and limited access to specialized expertise, while also experiencing higher resistance to organizational change, which slows diffusion and narrows the range of feasible applications. This configuration suggests that the barriers facing smaller firms are primarily practical rather than conceptual, since the challenge lies less in recognizing AI's potential and more in financing infrastructure, developing competencies, and implementing governance controls that make adoption safe and sustainable. In addition, medium or low data availability among SMEs implies that even appropriate AI tools may perform poorly due to limited data volume and weaker data quality, which further reduces expected returns and discourages investment. Overall, the table supports the interpretation that targeted capability-building, shared service models, and policy-level support mechanisms may be needed to prevent a widening divide in HRM modernization between large firms and smaller organizations.

Table 7 complements this organizational comparison by presenting a risk assessment matrix for AI-enabled HRM that classifies key risks according to likelihood, impact, and an aggregated overall risk level. The matrix supports governance by converting complex ethical, legal, and operational concerns into comparable categories that can be prioritized for mitigation and resource allocation. Distinguishing likelihood from impact is analytically important because it separates risks that are frequent from those that may be rarer yet potentially severe, enabling proportionate and context-sensitive control design. The inclusion of socio-organizational risks, such as employee distrust, alongside technical failures and legal non-compliance, reinforces the premise that AI adoption in HR is socio-technical, since organizational legitimacy and workforce acceptance can be as decisive as system performance. In this way, Table 7 frames risk management as an essential component of implementation strategy, not as an ancillary compliance activity.

Table 7. Risk Assessment Matrix

Risk Type	Likelihood	Impact	Overall Risk
Bias in Hiring Algorithms	High	High	Critical
Data Breach or Misuse	Medium	High	High
Wrong Performance Predictions	Medium	Medium	Moderate
Employee Distrust	High	Medium	High
Technical System Failure	Low	Medium	Moderate
Legal Non-Compliance	Medium	high	High

Source: systematized by the authors

The risk matrix in Table 7 indicates that hiring-related bias constitutes the most urgent governance priority because it combines a high likelihood of occurrence with a high potential impact, resulting in a critical overall risk classification. In the same high-risk tier, legal non-compliance and data breach or misuse remain central concerns, since they can trigger immediate regulatory consequences and produce durable reputational damage even when their likelihood is assessed as medium. Employee distrust also appears as a high overall risk because of its high probability and its capacity to weaken implementation through reduced engagement, heightened resistance, and declining legitimacy of HR decisions that involve AI-mediated judgments. Although wrong performance predictions and technical system failures are categorized as moderate, they still require structured controls, as they can degrade decision quality and disrupt operations, particularly when they interact with other vulnerabilities such as limited oversight or poor data governance. Taken together, the matrix supports a mitigation logic that prioritizes fairness auditing, privacy and security safeguards, and compliance-by-design mechanisms, while also emphasizing transparency and communication practices that sustain trust in AI-enabled HR processes.

More broadly, the study indicates that AI can increase HR efficiency by automating routine tasks, including resume sorting, payroll administration, and employee record management, which frees HR professionals to dedicate greater attention to relationship-based and strategic activities. AI-enabled analytics can also strengthen workforce planning by identifying skill gaps, anticipating training needs, and generating decision support for performance management, thereby increasing the informational basis of HR interventions. However, the evidence also reinforces that these gains do not constitute an automatic improvement in organizational justice or employee experience. Ethical and governance challenges persist, particularly in relation to fairness, privacy, transparency, and perceived depersonalization, which can undermine trust if implementation is not carefully designed. Looking ahead, AI is likely to expand toward more personalized and predictive HR applications, including tailored learning pathways and more proactive workforce planning, yet the sustainability of these developments depends on maintaining a balance between technological capability and human accountability. Organizations are therefore more likely to achieve durable

value when they implement AI thoughtfully, combine algorithmic insights with human judgment, and invest continuously in ethical safeguards, transparent procedures, and workforce learning that ensures technology strengthens, rather than displaces, the human core of HRM.

Discussion. Artificial intelligence in human resource management is seen as a socio-technical transformation, as it simultaneously changes operational procedures and the regulatory framework on which HR decisions are based and made. While automation and analytics can improve speed and strengthen decision support, these gains are meaningful only when the surrounding institutional conditions ensure that AI-mediated decisions are perceived as legitimate. In HR practice, legitimacy is produced through transparent reasoning, the possibility to challenge outcomes, and clear accountability for final decisions. Therefore, model accuracy or efficiency cannot be treated as sufficient, especially when employees and other stakeholders cannot understand how conclusions were reached or how bias and errors are identified and corrected. In addition, AI redistributes responsibility inside HR by transferring parts of evaluation and prediction to algorithmic systems, which makes interpretive competence a core professional requirement. HR teams must be able to assess probabilistic outputs critically, recognize uncertainty, and identify when contextual factors override model recommendations. Under these conditions, governance and capability are not external constraints but structural enablers that determine whether AI improves judgment or amplifies pre-existing weaknesses in decision routines.

Patterns of adoption across HR functions further support this argument because they reveal selective diffusion shaped by feasibility and risk sensitivity. Organizations tend to adopt AI first in functions characterized by high volume and standardized workflows, where data are more structured and operational bottlenecks are clearly defined. Recruitment and learning processes fit this profile because screening, candidate communication, and skill diagnostics can be systematized and can generate measurable efficiency benefits in relatively short time horizons. In contrast, compensation governance and succession planning involve distributive outcomes and long-term career consequences, which intensify ethical sensitivity and raise legal and reputational exposure. These functions also demand justification that is understandable to employees and defensible to regulators, thereby increasing the cost of deploying AI systems that are both accurate and explainable. As a result, the function-by-function sequence is rational from an operational perspective, but it also reflects institutional caution in delegating high-stakes decisions to systems whose reasoning may be difficult to interpret and to audit reliably.

This selective adoption has a deeper implication for how AI is likely to reshape HR authority. The relative insulation of the most consequential HR decisions from automation is not merely a matter of organizational inertia,

but a reflection of the governance thresholds associated with procedural fairness. When decisions affect pay, promotion, or leadership trajectories, explainability becomes a requirement for justice rather than an optional feature for usability. Equity considerations strengthen this requirement because organizations must demonstrate that outcomes do not systematically disadvantage particular groups and that decision rules are consistent with nondiscrimination expectations. Legal exposure increases the need for documentation, validation, and auditable trails that connect inputs to outcomes, which imposes additional overhead and can diminish the net efficiency gains promised by automation. In this sense, the adoption gradient can be interpreted as evidence that AI diffusion accelerates until it reaches domains where accountability costs rise sharply and where legitimacy depends on transparent, contestable decision processes.

Employee perceptions reinforce these conclusions by showing that acceptance of AI in HR is conditional rather than automatic. Employees may endorse efficiency improvements, yet they often distinguish faster procedures from just outcomes, particularly when AI influences evaluation, opportunity allocation, or disciplinary judgments. Strong support for human review signals that accountability is expected to remain human-centered, especially for consequential decisions, and that purely automated determinations may be viewed as insufficiently legitimate. This expectation also reflects the relational character of HRM, where employees anticipate contextual understanding and ethical judgment alongside data-driven insights. Practically, this means that implementation quality depends on governance-by-design, including clear escalation routes for contested outcomes, explicit assignment of decision accountability, and review procedures that are substantive rather than symbolic. Transparent communication about what data are used, how recommendations are produced, and how individuals can seek clarification or correction is equally important, because uncertainty and perceived opacity can erode trust and intensify resistance. Overall, effective AI integration in HRM requires aligning operational gains with a legitimacy architecture that protects accountability, enables contestation, and sustains confidence that HR decisions remain fair and human-centered.

Conclusion. The study emphasizes that AI can strengthen HR efficiency and analytical capacity, yet these advantages become durable only when implementation is anchored in governance structures that protect legitimacy and in workforce readiness that enables competent use. Efficiency improvements, such as faster screening, automated routine administration, and more consistent monitoring, are best understood as first-order gains that can be realized relatively quickly. However, long-term value depends on second-order conditions, specifically whether organizations can ensure that AI-supported decisions remain fair, explainable, contestable, and aligned with legal and ethical standards. Without these conditions, the same

mechanisms that increase speed and scale can also amplify errors, embed bias, and erode confidence in HR processes. Therefore, AI adoption in HRM is not adequately evaluated by technical performance or cost savings alone, because sustainability is primarily determined by trust, accountability, and the quality of institutional safeguards.

A central implication is that AI diffusion across HR functions is uneven and follows an incremental pathway shaped by feasibility and risk. Organizations tend to adopt AI first in areas where tasks are standardized, data are structured, and outcomes can be measured through clear operational metrics, which makes recruitment-adjacent processes and training support early candidates for automation. By contrast, high-stakes domains such as compensation governance and succession planning typically remain less automated because they involve distributive outcomes and long-term career consequences that require strong justification and heightened oversight. This pattern indicates that implementation proceeds until it reaches governance thresholds where explainability, procedural fairness, and legal defensibility become decisive. In practical terms, the incremental nature of diffusion suggests that AI-enabled HRM matures through staged expansion, in which each stage should be accompanied by evaluation of fairness, transparency, and error management, rather than by scaling based solely on efficiency gains.

The conclusion further underlines that employee acceptance of AI in HRM is conditional, which makes social legitimacy a core success factor. Employees may recognize efficiency benefits, yet they often remain uncertain about fairness and may question whether algorithmic recommendations can capture context, individual circumstances, and ethical nuance. Strong preference for human review indicates that accountability expectations remain anchored in human judgment, especially when decisions are consequential, such as hiring, promotion, or performance-based sanctions. This preference is not merely psychological resistance; it reflects a normative demand for responsible decision-making that includes the ability to explain outcomes and to correct mistakes. Consequently, organizations that scale AI without transparent procedures, accessible appeals, and meaningful human oversight risk triggering distrust that can reduce engagement and increase resistance to data-driven HR initiatives. Trust therefore functions as an operational asset because it influences cooperation, data quality, and the perceived legitimacy of decisions.

Another key implication concerns organizational inequality in readiness, where firm size shapes the feasibility of responsible AI adoption. Larger organizations typically possess greater budget capacity, stronger internal expertise, and more mature data infrastructures, which supports both implementation and oversight. Small and medium enterprises often lack these enabling resources, which can delay adoption and, more importantly, can weaken the capacity to audit models, secure data, and maintain

compliance documentation. This creates a risk that AI modernization becomes uneven, producing a widening capability gap in HRM transformation. Addressing this divide requires targeted capability-building, including training and practical governance templates, as well as shared-service arrangements that reduce the fixed costs of privacy protection, security controls, and fairness monitoring. In this framing, support mechanisms are not optional add-ons but necessary for preventing unequal exposure to risk and unequal access to benefits.

Finally, the conclusion highlights that risk management must be designed into AI-enabled HR systems from the outset, rather than appended after deployment. The most critical risks include bias in hiring and evaluation, privacy breaches or misuse of employee data, legal non-compliance, and trust erosion, each of which can produce rapid and severe organizational consequences. These risks are structurally linked to how models are trained, how data are collected and governed, and how decisions are reviewed and communicated. As a result, responsible AI in HRM requires human-in-the-loop decision models that preserve accountable authority, transparent procedures that enable explanation and contestation, and continuous learning that builds both technical competence and ethical judgment. When these conditions are met, AI can function as a complement to HR expertise by expanding analytic insight and improving consistency, while the organization retains the human responsibility necessary for fairness, legitimacy, and sustainable performance.

Funding. The authors declare that no financial support was received for the research, authorship, and/or publication of this article.

Conflict of interest. The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement. The authors declare that no Generative AI was used in the creation of this manuscript.

Publisher's note. The publisher clarifies that all statements made in this article reflect the author's views alone and do not necessarily represent the positions of their affiliated institutions, the publisher, the editors, or the reviewers. Any products discussed or claims made by their manufacturers are neither guaranteed nor endorsed by the publisher.

References:

1. Aksoy, M. S., & Alsaif, B. (2023). *AI-HRM: Artificial intelligence in human resource management: A literature review*. *Journal of Computing and Communication*. https://doi.org/10.21608/jocc.2023.307053
2. Ashurbaev, O., & Saidkulov, M. (2024). Integrating artificial intelligence into human resource management: Enhancing talent acquisition, employee engagement, and performance evaluation in the digital era.
3. Bader, V., Kaiser, S., & Kordyaka, B. (2020). Algorithmic decision-making in human resource management: Toward a governance framework. *German Journal of Human Resource Management, 34*(3), 345–371.

4. Bansal, S. (2025). Digital transformation in HRM: A study of AI adoption, managerial response and organizational culture. *Journal of Informatics Education and Research, 5*(3). https://doi.org/10.52783/jier.v5i3.3270
5. Belagalla, N., Chawla, N., Pawar, S., Jaiswal, A., Mishra, D., Hirapara, J., & Devi, B. (2025). The role of artificial intelligence in transforming human resource management: Opportunities and challenges. *Journal of Information Systems Engineering and Management, 10*(28s). https://doi.org/10.52783/jisem.v10i28s.5008
6. Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization, 24*(2), 239–257. https://doi.org/10.1017/jmo.2016.55
7. Deloitte. (2023). *2023 Global Human Capital Trends: New fundamentals for a boundaryless world*. https://www.deloitte.com/us/en/insights/topics/talent/human-capital-trends/2023.html
8. Du, J. (2024). From automation to ethics: Responsible AI in human resource management across industries with insights from the power sector. *Research Review International Journal of Multidisciplinary*. https://bussecon.com/ojs/index.php/ijbes/article/download/986/576
9. Harchandani, C. (2025). Artificial intelligence in talent acquisition: A paradigm shifts in HRM practices. *Stallion Journal for Multidisciplinary Associated Research Studies, 4*(1). https://stallionjournal.com/index.php/sjmars/article/view/199
10. Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human–AI symbiosis in organizational decision making. *Business Horizons, 61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.001
11. Khasawneh, A. J., Mihus, I., Svyrydiuk, N., & Zhyvko, Z. (2024). Nature and purpose of artificial intelligence. Political, legal, and economic challenges in the 21st century. *Clío. Revista De Historia, Ciencias Humanas Y Pensamiento Crítico*. https://doi.org/10.5281/zenodo.12600351
12. Kommera, H. K. R. (2024). Impact of artificial intelligence on human resources management. *International Journal of Computer Engineering & Technology (IJCET), 15*(4), 595–609. https://www.iaeme.com/MasterAdmin/Journal_uploads/IJCET/VOLUME_15_ISSUE_4/IJCET_15_04_050.pdf
13. Kumar, C. (2025). From automation to ethics: Responsible AI in human resource management across industries with insights from the power sector. *Research Review International Journal of Multidisciplinary*. https://rrjournals.com/index.php/rrijm/article/view/1964
14. López, V., & Peralta, J. C. (2023). AI-driven human resource management: Opportunities, challenges, and ethical considerations. *Journal of Contemporary Healthcare Analytics, 7*(1), 184–199. https://www.dlpress.org/index.php/JCHA/article/download/1444/1162
15. Manwani, R., Zephaniah, S., Kaushik, R., & Dilroopa, K. N. (2025). Exploring the impact of AI on HRM: Insights from the IT sector. *Journal of Informatics Education and Research, 5*(1). https://doi.org/10.52783/jier.v5i1.2110
16. Mihus, I. (2023). STRATEGIC MANAGEMENT OF HUMAN RESOURCES OF ENTERPRISES BASED ON DIGITAL COMPETENCIES. *Science Notes of KROK University*, (2(70), 131–138. https://doi.org/10.31732/2663-2209-2022-70-131-138
17. Raza, S. M., Ejaz Khan, M. A., Javed, S., & Ahmad Khan, S. (2025). Artificial intelligence in human resource management: Recruitment, evaluation, and employee retention. *Journal of Media Horizons, 6*(3), 1690–1708. https://doi.org/10.5281/zenodo.16840372
18. Sachan, V. S., Katiyar, A., Somashekher, C., Chauhan, A. S., & Bhima, C. K. (2024). The role of artificial intelligence in HRM: Opportunities, challenges, and ethical considerations. *Educational Administration: Theory and Practice, 30*(4), 7427–7435. https://doi.org/10.53555/kuey.v30i4.2588
19. Selvamohana, K., Sahu, S. R., Singh, S., Mohanraj, S., & Sharma, A. (2025). From HR analytics to AI-driven HRM: Enhancing workforce productivity and engagement. *Journal of Information Systems Engineering and Management*. https://doi.org/10.52783/jisem.v10i28s.5007
20. Strohmeier, S., & Piazza, F. (2015). Artificial intelligence techniques in human resource management: A conceptual exploration. In *Advanced Information Systems Engineering Workshops* (Lecture Notes in Business Information Processing). Springer. https://link.springer.com/chapter/10.1007/978-3-319-19069-3_5
21. Tursunbayeva, A., Di Lauro, S., & Pagliari, C. (2018). People analytics: A scoping review of conceptual boundaries and value propositions. *International Journal of Information Management, 43*, 224–247. https://doi.org/10.1016/j.ijinfomgt.2018.08.002
22. Yadav, L. (2025). Artificial intelligence in HR analytics: Ethical implications and strategic value for corporate India. *International Journal of Innovation Studies*. https://iji-studies.com/