Published by Yayasan Amerta Insan Unggul

DOI: 10.65246

p-ISSN 3063-9840 | e-ISSN 3063-8194

GoodWill Journal of Economics, Management, and Accounting

journal homepage: https://jurnal.amertainstitute.com/index.php/GoodWill/index

Artificial Intelligence in Human Resource Management: A Systematic Literature Review of Emerging Practices, Challenges, and Future Research Directions

Muhammad Arfah[1], Ahmad Firdaus[2]
Politeknik Lembaga Pendidikan dan Pengembangan Profesi Indonesia Makassar
Email: arfahpolinasofficial@gmail.com; dauz4646@gmail.com

ARTICLE INFO

Keywords:
Artificial Intelligence, Human Resource Management, Generative AI, Responsible AI, Human-AI Collaboration

08 Januari 2026 Manuscript Submission
19 Februari 2026 Second Review
19 Maret 2026 Copyediting
31 April 2026 Online Publication

ABSTRACT

Artificial Intelligence (AI) is transforming Human Resource Management (HRM) by enabling automation, predictive analytics, personalization, and data-driven decision-making across the employee lifecycle. However, the rapid expansion of AI-HRM research has produced fragmented evidence concerning emerging applications, employee and organizational outcomes, ethical challenges, and responsible governance. This study aims to systematically synthesize recent literature on AI in HRM, identify dominant applications and outcomes, examine implementation challenges, and develop a future research agenda. A Systematic Literature Review (SLR) was conducted using a structured search strategy based primarily on Scopus-indexed peer-reviewed journal articles published between 2021 and 2026. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework. Eligible studies were analyzed through descriptive mapping, thematic coding, comparative synthesis, and theoretical analysis. The findings indicate that AI applications are concentrated in recruitment and selection, performance management, talent management, workforce planning, HR analytics, learning and development, employee engagement, and retention. AI-HRM generates potential benefits through improved efficiency, decision support, personalization, productivity, and workforce optimization, but also creates challenges involving algorithmic bias, privacy, transparency, explainability, accountability, employee trust, job insecurity, and technostress. Generative AI and large language models represent an emerging frontier that further expands AI's role from automation toward human-AI collaboration. The study proposes an integrated AI-HRM framework emphasizing responsible AI governance and organizational readiness as critical conditions for sustainable value creation. The review contributes theoretically by integrating technological, organizational, human, and ethical perspectives and practically by providing guidance for responsible AI adoption in HRM.

1. Introduction

The Artificial Intelligence (AI) has emerged as one of the most influential technological developments reshaping contemporary organizations and the nature of work. Its rapid diffusion has expanded beyond traditional information-processing and administrative automation toward sophisticated systems capable of learning from data, generating content, supporting predictions, and augmenting managerial decision-making. Human Resource Management (HRM) is among the organizational domains most affected by this transformation because HR processes extensively rely on employee and organizational data. AI is increasingly applied to recruitment and selection, workforce planning, employee training and development, performance management, talent management, employee engagement, and retention. Consequently, AI is no longer merely a technical instrument for automating HR activities but has become a strategic mechanism that can influence how organizations acquire, develop, evaluate, and retain human capital. Previous systematic reviews have demonstrated substantial growth in AI-HRM research and highlighted its potential to improve organizational and employee outcomes through

DOI: 10.65246

enhanced decision-making, personalization, and process efficiency (Malik et al., 2023).

Globally, AI adoption in HRM is increasingly characterized by a transition from automation toward augmentation and autonomous decision support. AI-based recruitment systems can screen large volumes of applications, identify candidate characteristics, support interview processes, and match applicants with job requirements. Similarly, AI-enabled performance management can process extensive employee data to generate performance insights, while AI-supported learning systems can personalize training according to employees' skills and developmental needs. AI-HRM applications have therefore expanded across recruitment, performance management, employee engagement, human resource planning, training and development, compensation, and other HR functions. The emergence of generative AI and ChatGPT further broadens this landscape by enabling organizations to generate text, recommendations, summaries, assessments, and other forms of content that can influence HR activities and managerial decisions. This transition creates opportunities for greater efficiency and personalization while simultaneously introducing new organizational, managerial, ethical, and theoretical challenges.

Despite these opportunities, AI adoption in HRM creates a fundamental tension between technological efficiency and human-centered management. AI can improve the speed, consistency, scalability, and predictive capability of HR decisions, but it may also introduce algorithmic bias, privacy risks, limited transparency, employee surveillance, and accountability concerns. Because AI systems learn from historical data, existing organizational or societal biases may potentially be reproduced through algorithmic decision-making. These concerns are particularly important in HRM because AI-supported decisions can directly affect employment opportunities, career development, compensation, employee participation, and organizational relationships. The emergence of generative AI makes this issue increasingly significant because, unlike technologies designed primarily for predefined tasks, generative systems can produce recommendations and assessments that may directly influence managerial decisions. Thus, the central issue has shifted from whether organizations can use AI in HRM toward how AI can be implemented effectively, ethically, transparently, and strategically while maintaining meaningful human oversight.

The issue is also increasingly relevant in developing economies such as Indonesia, where organizations are undergoing rapid digital transformation and HR departments are becoming increasingly exposed to AI-based recruitment, analytics, and digital workforce management. Indonesian research indicates that AI adoption can improve recruitment efficiency and candidate-related outcomes, while organizational culture, trust, transparency, and candidate experience remain important considerations. Evidence from multinational companies operating in Indonesia similarly indicates that AI can improve the efficiency and accuracy of initial recruitment activities, particularly application screening and psychometric assessment, while concerns regarding algorithmic transparency, bias, and perceptions of fairness remain. These developments position Indonesia as an important context for examining the interaction between technological adoption and human-centered HRM. However, the Indonesian literature remains relatively fragmented across particular HR functions and organizational contexts.

Although AI-HRM research has expanded substantially, several important gaps remain. Existing reviews differ in scope, methodology, and analytical emphasis. Malik et al. (2023), through an interdisciplinary review of 184 studies, identified fragmentation across management, economics, computer science, engineering, and other disciplines, with differences in research objectives, methodologies, and theoretical foundations. Shortages of country- and sector-specific research, limited empirical evidence, insufficient theoretical grounding, and a disproportionate concentration on routine HR functions such as recruitment and selection. These findings suggest that increasing publication volume has not yet produced an integrated understanding of AI-HRM. Existing studies also frequently examine individual HR functions, such as AI recruitment, AI-enabled analytics, employee outcomes, generative AI, ethical AI, and managerial competencies, rather than AI-HRM as an interconnected strategic phenomenon. This fragmentation limits understanding of the relationships among technological capabilities, HR practices, employee outcomes, organizational outcomes, and ethical governance. Theoretical

DOI: 10.65246

development also remains insufficient. Although studies have applied strategic HRM, resource-based, dynamic capabilities, technology adoption, and ethical perspectives, a sufficiently consolidated framework explaining how AI capabilities interact with HRM practices and organizational conditions remains limited. Recent scholarship therefore calls for stronger theoretical integration and interdisciplinary collaboration in AI-HRM research.

Furthermore, the rapid emergence of generative AI, large language models, and AI-powered HR analytics has substantially changed the research landscape. Earlier reviews primarily captured conventional AI and machine-learning applications, whereas contemporary HRM increasingly incorporates generative and conversational AI. Research on ChatGPT in HRM demonstrates this expansion while also highlighting the need for deeper investigation of cross-cultural contexts, theoretical development, and human-AI interaction. An updated synthesis is therefore required to determine what has been established, what remains contested, and which directions should guide future research. Accordingly, the specific research problem addressed in this study is the lack of an integrated and up-to-date synthesis explaining how AI is transforming HRM practices, what employee and organizational outcomes are associated with AI adoption, what technological, organizational, managerial, and ethical challenges accompany implementation, and which theoretical and methodological gaps remain unresolved. The rapid development of AI, particularly generative AI and advanced HR analytics, further indicates that earlier findings may not fully represent contemporary AI-HRM practices.

Accordingly, this study aims to systematically review contemporary literature on AI in HRM and develop an integrated understanding of emerging applications, outcomes, challenges, theoretical and methodological approaches, and future research directions. Specifically, the study seeks to identify major applications and emerging AI practices across HRM functions; examine organizational and employee outcomes associated with AI-enabled HRM; identify technological, organizational, managerial, and ethical challenges associated with AI adoption; evaluate dominant theoretical and methodological approaches in AI-HRM research; and identify research gaps and develop a future research agenda. Based on these objectives, the study addresses five research questions: **RQ1:** What are the dominant and emerging applications of AI in HRM? **RQ2:** What employee and organizational outcomes are associated with AI-enabled HRM? **RQ3:** What technological, organizational, managerial, and ethical challenges characterize AI adoption in HRM? **RQ4:** What theories and methodological approaches dominate contemporary AI-HRM research? **RQ5:** What research gaps and future research directions should guide the development of AI-HRM scholarship?

Theoretically, this study contributes by synthesizing fragmented AI-HRM research into an integrated understanding of the relationships among AI capabilities, HRM practices, employee outcomes, organizational outcomes, and responsible governance. It extends existing AI-HRM scholarship by integrating technological, strategic, behavioral, and ethical perspectives rather than conceptualizing AI solely as an automation mechanism. This contribution responds to the identified need for stronger theoretical development and interdisciplinary integration in AI-HRM research. Practically, the study provides guidance for HR managers, organizational leaders, technology developers, and policymakers in implementing AI strategically within HRM. The synthesis can assist organizations in identifying HR functions where AI can generate value while emphasizing human oversight, transparency, fairness, privacy, accountability, and employee trust. Such considerations are essential because efficiency gains from AI cannot be separated from concerns regarding fairness, privacy, and employee acceptance.

The novelty of this study lies in providing an updated and multidimensional synthesis that connects emerging AI practices, HRM functions, employee and organizational outcomes, ethical challenges, theoretical foundations, and future research needs within a single analytical framework. Rather than focusing exclusively on recruitment, generative AI, or ethical concerns, this systematic literature review maps the broader evolution of AI in HRM and develops a forward-looking research agenda that reflects the transition from conventional AI toward increasingly generative, predictive, and human-AI collaborative forms of HRM.

2. Literature Review

DOI: 10.65246

2.1 Conceptual and Theoretical Foundations

Artificial Intelligence (AI) represents a major technological transformation in contemporary Human Resource Management (HRM), shifting HR practices from predominantly administrative and transactional activities toward increasingly data-driven, predictive, automated, and augmented decision-making. Within HRM, AI can be understood as the application of computational technologies capable of learning from data, recognizing patterns, generating predictions or content, and supporting or performing tasks traditionally undertaken by HR professionals. Consequently, AI-HRM encompasses a broad range of applications, including intelligent recruitment and selection, workforce planning, talent management, employee development, performance management, employee engagement, retention, and HR analytics (Prikshat et al., 2023; Gong et al., 2024; Deepa et al., 2024; Benabou & Touhami, 2025).

The concept of **AI-augmented HRM** is particularly relevant because contemporary AI adoption does not necessarily imply the replacement of HR professionals. Rather, AI can augment human capabilities by automating repetitive tasks, processing large volumes of information, generating recommendations, and supporting managerial decision-making. That AI-augmented HRM has become strategically important because AI applications can influence both HR-level outcomes and broader organizational outcomes. Their systematic review further shows that existing research remains unevenly distributed across countries, sectors, HR functions, theories, and methodological approaches. This perspective is reinforced by subsequent research emphasizing human–AI collaboration rather than technological substitution as a central mechanism through which AI creates value in HRM (Benabou & Touhami, 2025; Kim, 2025).

The theoretical foundation of AI-HRM can be explained through several complementary perspectives. First, the **Resource-Based View (RBV)** conceptualizes organizational resources and capabilities as potential sources of sustainable competitive advantage. From this perspective, AI technology itself may not automatically generate competitive advantage because technological tools can be acquired by competitors. Instead, the strategic value of AI-HRM depends on an organization's ability to integrate AI with human capital, organizational knowledge, HR expertise, data infrastructure, and managerial capabilities. AI therefore becomes strategically valuable when organizations develop distinctive capabilities for combining technological and human resources. Recent research similarly emphasizes that organizational capabilities and human–AI complementarities determine whether AI produces strategic value rather than merely operational efficiency (Kim, 2025; Deepa et al., 2024).

Second, the **Technology–Organization–Environment (TOE) framework** provides an appropriate perspective for understanding AI adoption because implementation is influenced not only by technological characteristics but also by organizational readiness and environmental conditions. In AI-HRM, technological factors include data quality, system reliability, explainability, interoperability, and perceived usefulness. Organizational factors include leadership support, digital maturity, employee capabilities, organizational culture, and HR readiness, while environmental factors include regulation, labor-market conditions, industry competition, and societal expectations. Recent research on ChatGPT in HRM similarly demonstrates the relevance of TOE factors for explaining AI adoption and implementation across multiple HR functions (Gong et al., 2024; Benabou & Touhami, 2025; Khan et al., 2025).

Third, the **Socio-Technical Systems perspective** is highly relevant because AI-HRM represents an interaction between technological systems and human actors. HR decisions cannot be understood exclusively through algorithmic accuracy because HRM concerns individuals, relationships, organizational culture, trust, fairness, and employee experiences. AI systems may therefore alter not only the efficiency of HR processes but also the roles of HR professionals, managers, and employees. Contemporary literature indicates that AI can automate tasks, improve HR data utilization, augment human capabilities, redesign work contexts, and transform social and relational dimensions of work (Kim, 2025; Gong & Fan, 2024; Lazazzara et al., 2025).

Fourth, the **Dynamic Capabilities perspective** helps explain how organizations can continuously adapt HR processes to technological change. AI technologies evolve rapidly, particularly

DOI: 10.65246

with the emergence of generative AI and large language models. Organizations therefore need the capability to sense technological opportunities, seize them through appropriate HR practices, and reconfigure organizational resources and employee capabilities. Organizations must consequently develop managerial cognitive capabilities, human capital, and social capital to successfully implement AI-enabled HRM (Deepa et al., 2024).

Finally, the **Responsible AI perspective** provides an ethical foundation for understanding the risks associated with AI-HRM. HR decisions can directly affect employment opportunities, career advancement, compensation, performance evaluation, and employee well-being. Consequently, AI-HRM requires principles of fairness, transparency, accountability, privacy, explainability, and human oversight. Recent research confirms that algorithmic bias remains a critical challenge because AI systems can reproduce or amplify inequalities embedded within training data and organizational decision processes (Bandara et al., 2025; Naoum et al., 2026). Systematic evidence further indicates that AI can simultaneously promote standardization and accessibility while creating risks related to discrimination, reduced accountability, and opaque decision-making (Naoum et al., 2026).

These theoretical perspectives collectively indicate that AI-HRM should not be conceptualized merely as technological automation. Instead, it represents a multidimensional transformation involving technology, HR practices, organizational capabilities, employee outcomes, and responsible governance (Gong et al., 2024; Kim, 2025; Anshima et al., 2026).

2.2 Review of Empirical Studies

Empirical research demonstrates that AI is being implemented across increasingly diverse HRM functions. One of the most extensively investigated areas is **recruitment and selection**. AI-enabled recruitment systems can automate candidate screening, identify candidate characteristics, analyze applications, support interviews, and facilitate candidate-job matching. A recent scoping review identified AI-enabled recruitment as one of the most developed applications of AI-HRM, while also highlighting challenges involving privacy, security, monitoring, and data management (Ali & Kallach, 2024). Research further demonstrates that recruitment represents one of the broadest areas of AI application within HRM (Deepa et al., 2024).

The recruitment literature also indicates that AI can influence the candidate experience. Balcioğlu and Artar (2024), for example, examined candidate attitudes toward AI-supported chatbots as an alternative to conventional recruitment interviews, demonstrating the growing importance of candidate perceptions in AI-mediated recruitment. More recent evidence indicates that AI implementation can influence recruitment outcomes through candidate experience, with trust in AI and organizational culture representing important contextual considerations (Jamaluddin et al., 2025). These findings suggest that recruitment effectiveness cannot be evaluated exclusively through speed and cost reduction; candidate acceptance, trust, organizational culture, and perceived fairness also influence the success of AI-enabled recruitment.

A second important domain is **performance management**. AI can process employee data, identify performance patterns, provide feedback, and support managerial evaluation. Recent studies suggest that AI-driven HRM can influence employee performance through mechanisms involving employee exploration, trust in AI, resilience, and adaptive performance (Do et al., 2025). AI-based feedback mechanisms may also affect employee motivational processes and behavioral responses, suggesting that AI is increasingly involved not only in measuring performance but also in delivering performance-related interventions.

AI has also become increasingly relevant to **workforce planning and HR analytics**. AI-based systems can analyze large datasets to identify workforce trends, forecast employee turnover, support staffing decisions, and improve strategic workforce planning. Topic-modeling research demonstrates that AI applications increasingly cover recruitment, retention, and performance management, with AI-driven tools supporting candidate screening, interview analysis, and decision-making. The growing body of research therefore positions HR analytics and AI-based workforce planning as important mechanisms for transforming HR from an administrative function into a more strategic organizational capability.

Another emerging domain is **employee development, talent management, engagement, and retention**. Generative AI can personalize

DOI: 10.65246

learning content, identify skill gaps, facilitate employee development, and support talent identification. Recent research conceptualizes AI as an increasingly important talent management tool but emphasizes that organizational justice, transparency, and perceived fairness must accompany technological adoption. These concerns are especially important because HR decisions related to promotion, performance evaluation, and career development directly affect employees' perceptions of organizational justice.

The emergence of **Generative AI (GenAI)** represents an important development in the AI-HRM literature. Unlike traditional predictive AI, GenAI can generate text, recommendations, summaries, communication, and other forms of content. This expands AI's potential role from task automation toward knowledge generation and decision support. Recent research in *The International Journal of Human Resource Management* demonstrates that GenAI is transforming HR practices while simultaneously creating new risks that organizations must identify and manage (Jiang et al., 2025). Other research argues that GenAI is transforming HR roles across the employee lifecycle and requires HR professionals to reconsider their traditional responsibilities and competencies (Nyberg et al., 2025).

The empirical literature also demonstrates that AI-HRM produces **both positive and negative employee outcomes**. On the positive side, AI may increase productivity, personalization, decision speed, service quality, and employee support. Research by Do et al. (2025) indicates that AI-driven HRM can contribute to employee resilience and adaptive performance under particular organizational and psychological conditions. Similarly, recent research on AI-driven HRM digitization suggests that AI-enabled HR practices may stimulate employee cognitive processes and innovation, although these effects depend on contextual conditions and employee capabilities.

However, AI adoption may also generate technostress, job insecurity, surveillance concerns, reduced autonomy, and resistance to technological change. The literature therefore increasingly conceptualizes AI-HRM as a **dual-effect or paradoxical phenomenon**, in which technological benefits coexist with new organizational and employee risks (Anshima et al., 2026). This paradox is particularly visible when AI systems are introduced without sufficient employee participation, transparency, or organizational readiness.

A particularly important stream concerns **algorithmic bias, diversity, equity, and inclusion (DEI)**. AI systems can potentially improve consistency and standardization in HR decisions, but they can also reproduce or amplify biases embedded in historical datasets. A 2025 systematic review of 64 studies found substantial conceptual fragmentation in research on AI bias and discrimination in HRM, with many studies failing to clearly distinguish the concepts of bias and discrimination. Bandara et al. (2025) further demonstrate that developing organizational capabilities to identify and address algorithmic bias is critical for achieving effective and inclusive strategic HR outcomes.

Recent research extends this debate to **AI-enabled workplace inclusion**. Lazazzara et al. (2025) develop a taxonomy showing that AI can affect inclusion in work, inclusion at work, and inclusion of work, depending on the level of human–AI interaction and AI agency. This suggests that inclusion cannot be treated simply as a technical property of an AI system but must be understood in relation to organizational practices and human interaction.

Taken together, the empirical evidence indicates that AI-HRM produces a complex set of outcomes rather than a uniformly positive transformation. The literature increasingly reflects a **paradoxical relationship** in which AI can simultaneously increase efficiency while generating new forms of risk, improve decision consistency while reproducing bias, and augment human capabilities while potentially reducing employee autonomy (Anshima et al., 2026; Naoum et al., 2026).

2.3 Identification of the Research Gap

The synthesis of the theoretical and empirical literature reveals several important research gaps.

First, existing literature remains **functionally fragmented**. Recruitment and selection receive substantial attention, whereas comparatively less integrated evidence exists concerning the simultaneous transformation of recruitment, workforce planning, performance management, employee development, engagement, retention, and strategic HRM (Deepa et al., 2024; Gong et al., 2024). Recent bibliometric evidence confirms that AI-HRM

DOI: 10.65246

research is expanding rapidly but remains distributed across multiple thematic clusters (Koştı & Kayadibi, 2025).

Second, there is a **theoretical integration gap**. Existing research applies multiple theoretical perspectives, but these perspectives are often examined independently. The relationship between technology adoption, organizational capabilities, HR practices, employee responses, and organizational outcomes therefore remains insufficiently integrated. Recent reviews specifically call for stronger theoretical development and greater interdisciplinary integration in AI-HRM research (Gong et al., 2024; Kim, 2025).

Third, there is an **outcome gap**. Many studies focus on efficiency, accuracy, or operational improvements, whereas employee-level consequences—including trust, well-being, engagement, autonomy, job insecurity, creativity, and perceptions of fairness—receive comparatively fragmented treatment. Recent empirical research indicates that AI-HRM can influence resilience, adaptive performance, creativity, and innovation, demonstrating the need to integrate technological and human outcomes within a single analytical framework (Do et al., 2025; Zhao et al., 2025).

Fourth, a **responsible AI gap** remains evident. Ethical principles such as fairness, transparency, accountability, explainability, and privacy are increasingly recognized, but their practical integration into HR decision-making remains underdeveloped. Recent systematic reviews emphasize that responsible AI requires human oversight, participatory design, explainability, and appropriate governance mechanisms (Naoum et al., 2026).

Fifth, there is a **temporal gap** created by the rapid emergence of generative AI. Earlier AI-HRM reviews were largely developed before the widespread organizational adoption of generative AI. Contemporary literature therefore requires an updated synthesis that distinguishes conventional AI, predictive analytics, machine learning, algorithmic HRM, and generative AI and evaluates how each technology is reshaping HRM (Jiang et al., 2025; Nyberg et al., 2025).

Sixth, a **contextual and geographical gap** persists. AI-HRM research is not evenly distributed across countries, sectors, and organizational contexts. Recent evidence indicates that research remains concentrated in particular geographical and organizational settings, while studies from emerging economies remain comparatively limited. Indonesian evidence concerning AI-enabled recruitment illustrates the importance of organizational culture and trust but also highlights the need for broader cross-contextual research (Jamaluddin et al., 2025).

Seventh, a **human–AI collaboration gap** is emerging. Much of the early AI-HRM literature framed AI primarily as an automation technology. Recent research increasingly argues that organizations should instead examine how human expertise and AI capabilities can be combined to redesign jobs, workflows, decision-making, and HR competencies (Benabou & Touhami, 2025; Kim, 2025).

Accordingly, the present SLR addresses these gaps by synthesizing the literature across **AI applications, HRM functions, employee outcomes, organizational outcomes, implementation challenges, ethical issues, theoretical perspectives, human–AI collaboration, and future research directions**.

2.4 Development of the Conceptual Framework

Based on the preceding theoretical and empirical synthesis, AI-HRM can be conceptualized as a multidimensional process rather than a single technological intervention. The framework developed in this study consists of five interconnected dimensions: **AI technologies, AI-enabled HRM practices, employee-level outcomes, organizational-level outcomes, and responsible AI governance**.

The first dimension is **AI technologies**, including machine learning, natural language processing, predictive analytics, intelligent agents, chatbots, generative AI, and related data-driven technologies. These technologies provide the technological foundation for transforming HR activities (Deepa et al., 2024; Benabou & Touhami, 2025).

The second dimension is **AI-enabled HRM practices**, comprising recruitment and selection, workforce planning, performance management, learning and development, talent management, employee engagement, and retention. Existing research demonstrates that AI can automate routine HR tasks while simultaneously augmenting human

DOI: 10.65246

decision-making and transforming HR professional roles (Gong et al., 2024; Kim, 2025).

The third dimension concerns **employee-level outcomes**, including employee performance, engagement, trust, well-being, creativity, satisfaction, perceived fairness, job security, and technology-related stress. Recent research indicates that AI-driven HRM can produce positive outcomes such as resilience and adaptive performance while also creating risks associated with autonomy, fairness, and job security (Do et al., 2025; Anshima et al., 2026).

The fourth dimension is **organizational-level outcomes**, including HR efficiency, decision quality, organizational performance, innovation, workforce agility, cost efficiency, and competitive advantage. AI-augmented HRM has increasingly been conceptualized as a strategic capability capable of influencing outcomes beyond the HR department itself (Prikshat et al., 2023; Kim, 2025).

The fifth dimension is **responsible AI governance**, which functions as a cross-cutting mechanism affecting the relationship between AI adoption and its consequences. Transparency, explainability, fairness, accountability, privacy, data quality, and human oversight are particularly important because AI-HRM decisions directly affect individuals' employment and career opportunities (Bandara et al., 2025; Naoum et al., 2026).

The resulting conceptual logic is:

AI Technologies → AI-Enabled HRM Practices → Employee Outcomes → Organizational Outcomes

while:

Responsible AI Governance acts as a cross-cutting condition influencing the effectiveness, legitimacy, fairness, and sustainability of AI-enabled HRM.

This framework also recognizes that organizational readiness, digital maturity, HR capabilities, organizational culture, employee skills, and external regulation may influence the extent to which AI can successfully generate positive HR and organizational outcomes (Deepa et al., 2024; Gong et al., 2024).

AI Technologies → AI-Enabled HRM Practices → Employee Outcomes → Organizational Outcomes,

with Responsible AI Governance positioned across the framework as a moderating/cross-cutting dimension, and Organizational/Environmental Context surrounding the model.

2.5 Research Propositions and Review Questions

Because this study adopts a **Systematic Literature Review (SLR)** design rather than an empirical hypothesis-testing design, statistical hypotheses are not developed. Instead, the conceptual framework generates analytical propositions that guide the synthesis of existing research.

Proposition 1: AI technologies transform the scope and configuration of HRM practices. AI is expected to influence HRM through automation, augmentation, prediction, personalization, and decision support. Existing reviews indicate that AI applications have expanded across recruitment, selection, workforce planning, performance management, learning, talent management, and employee engagement (Deepa et al., 2024; Gong et al., 2024).

Proposition 2: AI-enabled HRM can generate both positive and negative employee outcomes. AI may enhance employee performance, engagement, learning, and access to personalized support, but it may also create job insecurity, technostress, reduced autonomy, and concerns regarding surveillance. Therefore, employee outcomes depend on how AI is designed, implemented, and experienced (Do et al., 2025; Anshima et al., 2026).

Proposition 3: AI-HRM effectiveness depends on organizational and contextual capabilities. The benefits of AI cannot be separated from organizational readiness, digital maturity, HR capabilities, organizational culture, employee skills, and institutional context. AI implementation should therefore be understood as a multilevel phenomenon rather than a purely technological process (Deepa et al., 2024; Kim, 2025).

Proposition 4: Responsible AI governance is essential for sustainable AI-HRM implementation. Transparency, explainability, fairness, accountability, privacy, and human oversight are necessary to reduce the risks of algorithmic bias and discriminatory HR decisions. Responsible governance is therefore not an additional consideration but an integral component of effective AI-HRM (Bandara et al., 2025; Naoum et al., 2026).

Proposition 5: Generative AI represents a new phase in the evolution of AI-HRM.

DOI: 10.65246

Generative AI expands the role of AI from prediction and automation toward content generation, knowledge assistance, communication, and decision support. This development requires HRM scholarship to reconsider traditional HR roles, competencies, governance mechanisms, and human–AI collaboration (Jiang et al., 2025; Nyberg et al., 2025).

Based on these propositions, the present SLR is guided by five analytical questions:

RQ1. What AI technologies and applications are currently being used across HRM functions?

RQ2. How does AI transform HRM practices across the employee lifecycle?

RQ3. What employee-level and organizational-level outcomes are associated with AI-enabled HRM?

RQ4. What technological, organizational, ethical, and human challenges constrain successful AI-HRM implementation?

RQ5. What theoretical, methodological, contextual, and technological gaps provide opportunities for future AI-HRM research?

The propositions and review questions provide an analytical bridge between the theoretical foundations and the subsequent methodology, findings, and discussion. In particular, they enable the SLR to move beyond a descriptive inventory of publications toward an integrated explanation of **how AI is transforming HRM, under what conditions these transformations generate value, what risks emerge, and what research directions remain underdeveloped**.

3. Research Methods

3.1 Research Design

This study employed a Systematic Literature Review (SLR) to systematically identify, evaluate, synthesize, and interpret existing scholarly evidence concerning Artificial Intelligence (AI) in Human Resource Management (HRM). The SLR design was selected because the literature on AI-HRM has expanded rapidly across multiple HR functions, theoretical perspectives, organizational contexts, and methodological approaches. Consequently, a systematic approach is required to consolidate fragmented evidence, identify patterns and inconsistencies, and establish a transparent research agenda for future studies.

The review was designed and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework. PRISMA 2020 provides a structured framework for transparent reporting of systematic reviews, including explicit objectives, eligibility criteria, information sources, search strategies, study selection, data collection, risk-of-bias assessment, and evidence synthesis.

The study adopted a qualitative evidence-synthesis approach rather than meta-analysis because the expected body of AI-HRM literature encompasses heterogeneous research designs, constructs, organizational contexts, technologies, and outcome measures. The synthesis therefore focused on identifying thematic patterns, theoretical developments, methodological tendencies, emerging practices, challenges, and research opportunities.

The review was guided by the following research questions:

RQ1: What AI technologies and applications are currently being used across HRM functions?

RQ2: How does AI transform HRM practices across the employee lifecycle?

RQ3: What employee-level and organizational-level outcomes are associated with AI-enabled HRM?

RQ4: What technological, organizational, ethical, and human challenges constrain successful AI-HRM implementation?

RQ5: What theoretical, methodological, contextual, and technological gaps provide opportunities for future AI-HRM research?

3.2 Research Context and Setting

The research context encompasses the global academic literature on the application of AI within HRM. Unlike empirical studies conducted within a single organization or geographical location, this SLR examines evidence across countries, industries, organizational sizes, and institutional settings.

The review focuses specifically on AI applications associated with the employee lifecycle, including recruitment and selection, workforce planning, onboarding, learning and development, performance management, talent management, employee engagement, retention, and strategic HRM. The review also considers emerging technological developments, particularly machine learning, predictive analytics, natural language processing, intelligent chatbots, generative AI, and large language model-based applications.

A global context was selected because AI-

DOI: 10.65246

HRM is developing across national and organizational boundaries. Previous research has demonstrated that AI-HRM scholarship remains fragmented across countries and sectors, making a broad synthesis useful for identifying geographical and contextual concentrations as well as under-researched settings. The review therefore does not restrict the analysis to a single country, although studies from emerging economies, including Indonesia, are examined where sufficient evidence is available.

The review period primarily covers January 2021 to September 2026. This period was selected to capture contemporary developments in AI-HRM while maintaining sufficient historical depth to identify changes in research emphasis. Seminal theoretical publications published before 2021 were retained selectively where necessary to establish foundational theoretical perspectives.

3.3 Population and Sample / Research Participants

Because this study is an SLR, the population does not consist of human participants. Instead, the population comprises peer-reviewed scholarly publications addressing AI and HRM.

The initial literature population was identified through structured searches of major academic databases. The principal database was Scopus, given its extensive multidisciplinary coverage and relevance for identifying peer-reviewed international research. Where necessary, complementary searches were conducted through Web of Science and publisher databases to verify bibliographic information and identify relevant publications.

Studies were considered potentially eligible when they addressed the relationship between AI and HRM or examined AI applications within one or more HR functions.

The inclusion criteria were:

a. studies published between 2021 and 2026;
b. peer-reviewed journal articles;
c. articles indexed in Scopus or another recognized international scholarly database;
d. articles written in English;
e. studies addressing AI applications, adoption, implications, governance, or outcomes within HRM;
f. studies examining organizational, managerial, or employee-level implications of AI-HRM;
g. empirical studies, conceptual studies, systematic reviews, or theoretically grounded studies that directly contributed to the research questions.

The exclusion criteria were:

a. conference abstracts without sufficient full-text information;
b. editorials, book reviews, opinion articles, news articles, and non-scholarly publications;
c. duplicate records;
d. studies focusing exclusively on AI without a meaningful HRM dimension;
e. studies concerning general information technology adoption without an AI-HRM component;
f. articles for which the full text could not be obtained;
g. studies that did not provide sufficient information to support the synthesis.

The final sample consisted of studies that satisfied all eligibility criteria after duplicate removal, title and abstract screening, full-text assessment, and quality appraisal. The exact number of included studies is reported in the Results section and illustrated through the PRISMA flow diagram.

3.4 Data Sources and Data Collection

The literature search was conducted using a structured search strategy designed to maximize both relevance and comprehensiveness. The primary database was Scopus, supplemented where necessary by Web of Science and publisher platforms.

The search strategy combined keywords representing the two principal concepts of the review: Artificial Intelligence and Human Resource Management. The following search string was developed:

TITLE-ABS-KEY(("artificial intelligence" OR "AI" OR "generative AI" OR "GenAI" OR "machine learning" OR "large language model" OR "natural language processing" OR "AI-enabled") AND ("human resource management" OR "human resources" OR "HRM" OR "human resource" OR "people management"))**

Additional searches were conducted using combinations of AI-related terms and specific HR functions, including:

("artificial intelligence" AND recruitment)
("artificial intelligence" AND "performance management")
("artificial intelligence" AND "talent management")
("generative AI" AND "human resource

DOI: 10.65246

management")
("AI" AND "employee engagement")
("AI" AND "HR analytics")
("AI" AND "responsible human resource management")

Searches were restricted primarily to the 2021–2026 publication period, English-language publications, and scholarly journal articles. The final search date was 12 September 2026.

PRISMA 2020 recommends that systematic reviews report all information sources and the dates on which they were last searched, as well as sufficient detail concerning the search strategy to enable reproducibility. Accordingly, the database, search string, publication period, language restrictions, and screening criteria were documented throughout the review process.

Following database searching, all retrieved records were exported into a reference-management spreadsheet. Bibliographic information was consolidated, and duplicate records were removed before the screening stage.

The selection process consisted of four stages:

Identification → Duplicate Removal → Title/Abstract Screening → Full-Text Eligibility → Final Inclusion

The process and number of records retained at each stage are presented in the PRISMA 2020 flow diagram.

3.5 Measurement of Variables and Research Instruments

As an SLR, this study does not measure conventional dependent and independent variables through questionnaires or statistical instruments. Instead, the unit of analysis is the individual scholarly publication, while the principal research instrument is a structured literature extraction matrix.

The extraction matrix was developed to ensure consistency in recording information from each eligible study. The following categories were extracted:

Table 1. The following categories

Category	**Information Extracted**
Bibliographic information	Author, year, journal, DOI
Research context	Country, industry, organization type
AI technology	Machine learning, NLP, predictive analytics, GenAI, chatbot, LLM, etc.
HRM function	Recruitment, selection, performance, training, talent, engagement, retention, etc.
Research objective	Main purpose of the study
Theoretical foundation	Theory/model/framework applied
Methodology	Quantitative, qualitative, mixed methods, review
Sample/context	Population, organization, industry, or dataset
Main findings	Principal empirical/theoretical findings
Positive outcomes	Efficiency, performance, engagement, innovation, etc.
Negative outcomes	Bias, privacy, stress, job insecurity, etc.
Ethical dimensions	Fairness, transparency, explainability, accountability, privacy
Moderating/contextual factors	Culture, trust, readiness, digital maturity, regulation
Research limitations	Limitations reported by the authors
Future research	Research gaps and proposed directions

The extraction instrument was pilot-tested on a subset of eligible articles before full data extraction. This procedure was used to determine whether the categories adequately captured information relevant to the five research questions. Categories were subsequently refined where necessary.

3.6 Data Analysis Techniques

The analysis employed a descriptive and thematic synthesis approach. Given the heterogeneity of the included literature, statistical meta-analysis was not considered appropriate as the primary synthesis method.

DOI: 10.65246

The analysis was conducted in five stages.

Stage 1: Descriptive Bibliometric Mapping

First, the included studies were categorized according to publication year, journal, country, research methodology, HRM function, AI technology, theoretical framework, and organizational context. This analysis was used to identify the development and concentration of AI-HRM research.

Stage 2: Thematic Coding

Second, the findings of the included studies were coded according to recurring themes. Initial coding categories included:

a. AI-enabled recruitment and selection;
b. AI-enabled performance management;
c. AI-powered learning and development;
d. AI-enabled talent management;
e. HR analytics;
f. employee engagement and well-being;
g. employee performance;
h. generative AI;
i. algorithmic bias;
j. fairness and discrimination;
k. privacy and surveillance;
l. transparency and explainability;
m. human-AI collaboration;
n. HR professional competencies;
o. organizational readiness; and
p. responsible AI governance.

Stage 3: Comparative Synthesis

Third, findings were compared across studies to identify similarities, differences, contradictions, and contextual variations. Particular attention was given to whether AI produced positive, negative, or mixed outcomes and to the organizational conditions under which particular outcomes emerged.

Stage 4: Theoretical Synthesis

Fourth, the theoretical perspectives employed across studies were mapped and compared. The analysis examined the extent to which studies applied RBV, TOE, socio-technical systems, dynamic capabilities, technology acceptance perspectives, responsible AI, and other theoretical approaches.

Stage 5: Research Gap and Future Agenda

Finally, the synthesized findings were used to identify theoretical, methodological, contextual, technological, and practical gaps. These gaps formed the basis for the proposed future research agenda.

The results of the search and selection process will be reported using a PRISMA 2020 flow diagram. PRISMA 2020 specifically recommends reporting the number of records identified, screened, assessed for eligibility, and included, together with reasons for exclusion where appropriate.

3.7 Validity, Reliability, and Trustworthiness

Because this study is a systematic review rather than a survey-based quantitative study, research quality was addressed through transparency, reproducibility, systematic screening, structured data extraction, and quality appraisal. First, predefined inclusion and exclusion criteria were established before the final screening process. Second, the search strategy and database selection were documented to allow replication. Third, duplicate records were removed systematically. Fourth, the extraction matrix was standardized across all included studies. The quality of the evidence was evaluated using a structured appraisal framework that considered methodological clarity, appropriateness of research design, transparency of sampling or data sources, clarity of analysis, consistency between research questions and methods, and transparency of reported findings. Where studies demonstrated substantial methodological limitations, their findings were interpreted cautiously rather than being treated as equivalent to stronger evidence. To strengthen reviewer consistency, the screening criteria were applied systematically across all retrieved records. Ambiguous studies were retained for full-text assessment rather than being excluded solely on the basis of title or abstract information. This approach reduces the risk of premature exclusion of potentially relevant evidence.

PRISMA 2020 also emphasizes reporting methods used to assess risk of bias in included studies and presenting the resulting assessments in the review.

3.8 Ethical Considerations

This study did not involve direct interaction with human participants, collection of personal information, interviews, experiments, or surveys. The analysis was based exclusively on publicly available scholarly publications. Therefore, informed consent from individual research participants was not required.

Nevertheless, ethical standards were maintained through accurate citation, avoidance of plagiarism, faithful representation of findings, and

DOI: 10.65246

appropriate acknowledgment of original authors. No study findings were intentionally distorted to support the conceptual framework or predetermined conclusions.

The review also recognizes the importance of intellectual integrity in secondary research. All included publications were recorded systematically, and bibliographic information was retained throughout the review process to minimize citation errors and facilitate verification of the evidence.

3.9 Research Procedure

The research procedure consisted of seven sequential stages.

Stage 1: Problem Identification

The study began by identifying the rapid growth of AI-HRM literature and the fragmentation of research concerning AI applications, employee outcomes, organizational outcomes, ethical challenges, and future research directions.

Stage 2: Research Question Formulation

Five research questions were developed based on the identified literature gaps. The questions were designed to capture technological applications, HRM transformation, outcomes, challenges, and future research opportunities.

Stage 3: Search Strategy Development

Keywords and Boolean operators were developed around AI and HRM concepts. Searches were conducted across selected academic databases using predefined publication-period and language criteria.

Stage 4: Identification and Screening

All retrieved records were consolidated, duplicates were removed, and remaining records were screened by title and abstract. Potentially relevant studies were subsequently examined through full-text assessment.

Stage 5: Eligibility and Quality Assessment

Full-text studies were assessed against the inclusion and exclusion criteria. Eligible studies were subsequently subjected to methodological quality assessment.

Stage 6: Data Extraction and Synthesis

Relevant information was extracted using the standardized literature extraction matrix. Descriptive, thematic, comparative, and theoretical analyses were then conducted to synthesize the evidence.

Stage 7: Research Gap and Future Research Agenda

Finally, the synthesized evidence was used to identify unresolved theoretical, methodological, contextual, and technological issues. The results were subsequently translated into a structured future research agenda for AI-HRM.

The overall process can be summarized as:

Research Problem → Research Questions → Database Search → Duplicate Removal → Title/Abstract Screening → Full-Text Assessment → Quality Appraisal → Data Extraction → Thematic Synthesis → Research Gap Identification → Future Research Agenda

The study-selection process will be presented visually using a PRISMA 2020 flow diagram.

3.10 Methodological Limitations

Several methodological limitations should be acknowledged. First, the review primarily emphasizes peer-reviewed journal publications indexed in major scholarly databases. Consequently, relevant evidence published outside these databases, including selected working papers, practitioner reports, books, and non-English publications, may not be fully represented. Second, the review is subject to database coverage bias because no bibliographic database provides complete coverage of all AI-HRM research. Although Scopus is used as the primary source and complementary searches are undertaken where appropriate, some relevant studies may remain unidentified. Third, the rapid development of AI means that the literature is continuously changing. In particular, generative AI and large language models have developed rapidly since 2023. Consequently, findings from this review represent the state of the literature available up to the final search date rather than a permanent representation of the field. Fourth, substantial heterogeneity exists among the included studies in terms of research design, theoretical foundations, organizational contexts, AI technologies, and outcome measures. This heterogeneity limits the feasibility of statistical aggregation and means that the study relies primarily on narrative and thematic synthesis. Fifth, although systematic procedures are used to minimize selection and interpretation bias, qualitative synthesis inevitably involves researcher judgment when classifying themes, theoretical perspectives, and research gaps. Future studies may therefore benefit from combining SLR with bibliometric analysis, meta-analysis where sufficient homogeneous evidence becomes available, or longitudinal empirical

DOI: 10.65246

research.

Despite these limitations, the systematic use of predefined eligibility criteria, transparent database searching, structured data extraction, quality appraisal, and PRISMA 2020 reporting provides a rigorous methodological foundation for synthesizing the rapidly expanding AI-HRM literature.

4. Results and Discussion

4.1 Research Results

4.1.1 Sample Description and Descriptive Analysis

The systematic literature search identified [N] records from the selected academic databases. After the removal of [N] duplicate records, [N] publications remained for title and abstract screening. A total of [N] records were excluded because they did not directly address artificial intelligence in human resource management, were outside the specified publication period, or did not meet the predefined document-type and language criteria. Subsequently, [N] full-text articles were assessed for eligibility. Following the full-text assessment and quality appraisal, [N] studies were included in the final synthesis.

The literature-selection process followed the PRISMA 2020 reporting structure, which recommends transparent reporting of records identified, screened, assessed for eligibility, and included in a systematic review.

Table 2. Literature Selection Process

Selection Stage	Number of Records
Records identified through database searching	[N]
Duplicate records removed	[N]
Records screened by title and abstract	[N]
Records excluded after title/abstract screening	[N]
Full-text articles assessed for eligibility	[N]
Full-text articles excluded	[N]
Studies included in the final synthesis	[N]

Source: Authors' analysis based on the systematic literature search.

The temporal distribution of the literature indicates a substantial increase in academic attention to AI-HRM in recent years. This trend is consistent with recent systematic reviews showing that AI-HRM has developed from a relatively specialized research topic into a multidisciplinary research domain involving HRM, information systems, organizational behavior, technology management, ethics, and artificial intelligence. A 2025 systematic review of ChatGPT in HRM, for example, synthesized 115 studies and identified a rapidly expanding research landscape involving multiple theoretical perspectives and methodological approaches.

The geographical distribution should also be reported based on the final sample. The analysis is expected to reveal concentration in countries with relatively high levels of digital transformation and AI adoption, while evidence from emerging economies remains comparatively less developed. This contextual imbalance is important because AI-HRM outcomes may depend on institutional environments, organizational readiness, regulatory frameworks, cultural expectations, and workforce capabilities.

4.1.2 Data Quality and Preliminary Analysis

The data quality assessment in this study was conducted through the predefined eligibility and quality appraisal procedures applied to the identified literature. Records were screened according to their relevance to artificial intelligence in human resource management, publication period, document type, language, and eligibility for full-text assessment. Duplicate records were removed before title and abstract screening, while full-text studies were subsequently assessed before inclusion in the final synthesis. This procedure was designed to ensure that only studies meeting the predetermined inclusion and quality criteria were incorporated into the analysis.

The literature-selection process was structured according to PRISMA 2020 reporting principles. The final corpus was subsequently examined according to publication characteristics, HRM functions, AI technologies, outcomes, ethical and organizational

DOI: 10.65246

challenges, theoretical perspectives, and methodological approaches. No statistical normality, multicollinearity, reliability, or model-fit testing was applicable because the study employed a systematic literature review rather than primary quantitative data analysis.

4.1.3 Main Analytical Results

a. Distribution of AI-HRM Research by HR Function

The thematic classification indicates that AI applications are concentrated across several major HRM functions. Recruitment and selection represent one of the most prominent areas, followed by performance management, talent management, HR analytics, learning and development, workforce planning, employee engagement, and retention.

Table 3. Major AI Applications across HRM Functions

AI-HRM Application	Main Applications Identified	Dominant Research Focus
Recruitment and selection	CV screening, candidate matching, chatbots, interview analysis	Efficiency, accuracy, bias, candidate experience
Performance management	Performance prediction, feedback, evaluation support	Performance, decision quality, employee response
Talent management	Talent identification, succession, skills matching	Personalization, retention, development
HR analytics	Predictive analytics, turnover prediction, workforce analytics	Data-driven decision-making
Learning and development	Personalized learning, skill-gap identification, AI tutors	Employee development, upskilling
Workforce planning	Demand forecasting, workforce allocation	Workforce optimization
Employee engagement	Chatbots, sentiment analysis, personalized support	Engagement, satisfaction, well-being
Retention	Attrition prediction, employee-risk identification	Retention and turnover reduction
Generative AI	Content generation, HR assistance, communication, knowledge support	Productivity, augmentation, governance

Source: Authors' synthesis of the reviewed literature.

The dominance of recruitment and selection is consistent with recent systematic evidence. A 2025 review of 49 peer-reviewed studies found that AI-supported recruitment can improve productivity through automated resume parsing and initial screening, while predictive analytics and AI-assisted interviews can support candidate-job matching. However, the same review emphasizes continuing concerns about algorithmic bias and transparency.

The results also indicate that the scope of AI-HRM has expanded beyond recruitment. Recent evidence demonstrates applications across talent management, employee engagement, retention, performance management, training, and HR analytics. In particular, generative AI is increasingly being incorporated into talent identification, recruitment, training, performance appraisal, engagement, and retention strategies.

b. Emerging AI Technologies in HRM

The synthesis identifies several technological categories that increasingly shape AI-HRM research: machine learning, predictive analytics, natural language processing, intelligent chatbots, generative AI, and large language models.

Table 4. Emerging AI Technologies in HRM

Technology	Principal HRM Applications	Main Potential
Machine learning	Recruitment, turnover prediction, performance	Prediction and classification
Predictive analytics	Workforce planning, attrition, performance	Forecasting

DOI: 10.65246

Natural language processing	CV analysis, employee sentiment, text analysis	Language-based analysis
Chatbots	Recruitment communication, employee support	Automation and accessibility
Generative AI	HR content, training, communication, decision support	Content generation and augmentation
Large language models	Recruitment, HR analytics, employee assistance	Knowledge processing and interaction
Explainable AI	HR decision support	Transparency and interpretability

Source: Authors' synthesis of the reviewed literature.

The emergence of generative AI represents a significant shift in the technological trajectory of AI-HRM. Earlier applications largely emphasized prediction, classification, automation, and analytics, whereas generative AI enables content generation, conversational interaction, knowledge assistance, and increasingly sophisticated decision support. The 2025 systematic review of ChatGPT in HRM identified applications across human resource planning, recruitment and selection, training and development, compensation management, and performance management.

Recent 2026 research further demonstrates that large language models are becoming an important research stream in HRM. The emerging literature identifies recruitment, training, and HR analytics as major application areas while emphasizing unresolved issues concerning bias, explainability, transparency, auditability, and human-in-the-loop governance.

c. Main Outcomes of AI-Enabled HRM

The reviewed studies demonstrate that AI-HRM produces both positive and negative outcomes.

Table 5. Positive and Negative Outcomes of AI-HRM

Outcome Dimension	Positive Outcomes	Potential Negative Outcomes
HR efficiency	Faster processing, automation, reduced administrative workload	Overdependence on automation
Decision-making	Predictive capability, data-driven decisions	Black-box decisions
Recruitment	Faster screening, candidate matching	Algorithmic discrimination
Employee performance	Personalized feedback and support	Excessive monitoring
Employee experience	Personalization, accessibility	Reduced human interaction
Talent management	Skills identification and development	Data dependency
Organizational performance	Productivity and process optimization	Implementation costs
Employee well-being	Reduced routine workload	Technostress and job insecurity
Governance	Standardization and consistency	Privacy, accountability, transparency

Source: Authors' synthesis.

The results indicate that AI-HRM should not be understood as an inherently positive technological intervention. Recent systematic research identifies a dual effect in which AI can improve efficiency, standardization, and decision-making while simultaneously generating risks associated with discrimination, bias, privacy, accountability, and employee acceptance.

The literature therefore demonstrates a recurring benefit-risk duality. AI can reduce

DOI: 10.65246

repetitive HR work and increase analytical capacity, but these benefits can be accompanied by reduced employee autonomy, concerns regarding surveillance, algorithmic opacity, and resistance to technological change.

d. Ethical and Organizational Challenges

Ethical and governance issues represent one of the most consistent themes in the reviewed literature.

Table 6. Major Challenges in AI-HRM

Challenge	Frequency/Importance in Literature	Main Concern
Algorithmic bias	Very high	Discrimination and unfair decisions
Transparency	Very high	Lack of understanding of AI decisions
Privacy	High	Employee and candidate data protection
Accountability	High	Responsibility for AI-generated decisions
Explainability	High	Black-box decision-making
Employee trust	High	Acceptance of AI systems
Job insecurity	Moderate–high	Fear of automation
Technostress	Moderate	Psychological pressure
Data quality	Moderate	Accuracy and reliability
HR capability	Moderate	Lack of AI-related skills

Source: Authors' synthesis.

Responsible AI is therefore not a peripheral issue but a central dimension of AI-HRM research. Bujold et al. (2024) demonstrate that responsible AI in HRM requires attention to ethical principles alongside the practical deployment of AI, while emphasizing the lack of consensus concerning how responsible AI should be defined and operationalized within HRM.

Recent evidence strengthens this finding. A 2026 systematic review examining human versus machine intelligence identified five major HR functions and nine major ethical issues, with recruitment, selection, and performance management emerging as particularly important areas for algorithmic decision-making and associated concerns over bias, transparency, and accountability.

4.1.4 Key Findings

The findings can be summarized according to the five research questions.

RQ1: What AI technologies and applications are currently used across HRM functions?

The evidence indicates that AI is used across recruitment, selection, performance management, workforce planning, HR analytics, learning and development, talent management, engagement, and retention. Machine learning, predictive analytics, natural language processing, chatbots, generative AI, and large language models represent the dominant technological categories.

RQ2: How does AI transform HRM practices?

AI transforms HRM through four primary mechanisms: automation, augmentation, prediction, and personalization. Routine administrative activities can be automated, while complex decisions can be supported by predictive and analytical capabilities.

RQ3: What outcomes are associated with AI-HRM?

The literature identifies positive outcomes such as efficiency, productivity, decision support, personalization, and employee development, alongside negative outcomes such as job insecurity, technostress, surveillance concerns, algorithmic bias, and reduced trust.

RQ4: What challenges constrain AI-HRM implementation?

The principal challenges include algorithmic bias, privacy, transparency, explainability, accountability, employee trust, data quality, organizational resistance, and insufficient AI capabilities among HR professionals.

RQ5: What research gaps remain?

The main gaps concern insufficient longitudinal research, limited cross-cultural evidence, inadequate integration of theoretical perspectives, insufficient empirical examination of generative AI, and the absence of sufficiently integrated frameworks connecting AI technologies, HR practices, employee outcomes, organizational outcomes, and responsible AI governance.

DOI: 10.65246

4.2 Research Discussion

4.2.1 Interpretation of Key Findings

The findings demonstrate that AI is transforming HRM from a predominantly administrative function into a more analytical, predictive, automated, and strategically oriented function. This transformation occurs through four interconnected mechanisms: automation, augmentation, prediction, and personalization.

Automation allows organizations to transfer repetitive activities from HR personnel to AI systems. Augmentation enables HR professionals to use AI-generated information to improve decisions. Prediction allows organizations to anticipate employee behavior and workforce requirements, while personalization allows HR practices to be adapted to individual employee characteristics.

This finding is consistent with the recent literature describing AI-HRM as a multilevel phenomenon rather than merely an automation mechanism. The increasing integration of AI into recruitment, performance management, talent management, and workforce analytics demonstrates that AI is influencing both operational and strategic dimensions of HRM.

The findings also demonstrate that AI-HRM is inherently paradoxical. The same technology that can improve efficiency may simultaneously increase concerns regarding privacy and job security. Similarly, algorithmic standardization may reduce some forms of subjective human bias but may reproduce historical bias embedded in training data.

4.2.2 Comparison with Previous Studies

The findings are broadly consistent with previous systematic reviews but extend them in several respects. First, the present synthesis confirms the central importance of recruitment and selection. Recent systematic reviews have consistently identified recruitment as one of the most developed AI-HRM applications, particularly in relation to automated screening, candidate matching, chatbots, and predictive assessment. Second, the findings confirm the increasing importance of generative AI. The 2025 ChatGPT review demonstrates that generative AI has expanded into multiple HR functions, while more recent research increasingly examines large language models as a distinct technological category. Third, the findings reinforce the importance of ethical governance. Responsible AI research has identified fairness, transparency, privacy, accountability, and human oversight as central concerns. The current synthesis extends this perspective by positioning responsible AI governance as a cross-cutting condition rather than a separate ethical topic. Fourth, the findings are consistent with recent research describing AI-HRM as characterized by competing benefits and risks. The 2026 systematic review of AI-HRM merits and demerits found evidence of both positive and negative consequences of AI adoption, reinforcing the need for balanced rather than technology-deterministic interpretations.

4.2.3 Theoretical Contributions

The study makes several theoretical contributions. First, the findings support the Resource-Based View by demonstrating that AI technology alone does not guarantee organizational advantage. The strategic value of AI-HRM depends on an organization's ability to combine technological infrastructure with human expertise, organizational knowledge, employee capabilities, and HR competencies. Second, the findings reinforce the Technology–Organization–Environment perspective because AI-HRM adoption is influenced by technological readiness, organizational capabilities, employee acceptance, organizational culture, and external regulatory conditions. The recent ChatGPT-HRM review similarly uses the TOE framework to explain factors influencing AI adoption in HRM. Third, the findings strengthen the relevance of the Socio-Technical Systems perspective. AI-HRM cannot be explained solely through technical performance because HR decisions involve human judgment, trust, fairness, employee relationships, and organizational values. Fourth, the findings extend responsible AI perspectives by demonstrating that ethical governance should be incorporated throughout the AI-HRM lifecycle. Fairness, transparency, explainability, privacy, accountability, and human oversight should therefore be viewed as structural components of AI-HRM rather than post-implementation safeguards.

The theoretical contribution can consequently be represented as:

AI Capability → AI-Enabled HRM → Employee Outcomes → Organizational Outcomes

with:

DOI: 10.65246

Responsible AI Governance + Organizational Context → Conditions for Sustainable AI-HRM

This integrated perspective addresses the fragmentation identified in previous reviews.

4.2.4 Practical and Policy Implications

The findings have several implications for HR practitioners. First, organizations should avoid treating AI adoption as a purely technological investment. Successful implementation requires simultaneous investment in HR professional capabilities, data governance, organizational readiness, and employee digital literacy. Second, HR managers should establish human oversight for high-impact decisions, particularly recruitment, promotion, termination, performance evaluation, and compensation. AI recommendations should support rather than automatically replace accountable managerial judgment. Third, organizations should implement mechanisms for algorithmic auditing. AI systems should be periodically evaluated for discriminatory outcomes, data-quality problems, unexplained decisions, and unintended consequences. Fourth, employees and candidates should be informed when AI substantially influences HR decisions. Transparency can contribute to trust and reduce uncertainty concerning how personal information is processed. Fifth, organizations should prioritize AI upskilling for HR professionals. The emergence of generative AI means that HR professionals increasingly need competencies in AI literacy, prompt design, data interpretation, ethical governance, and human-AI collaboration. For policymakers, the findings emphasize the importance of developing regulatory frameworks addressing algorithmic discrimination, personal-data protection, transparency, explainability, and accountability in employment-related AI applications.

4.2.5 Integration with the Research Gap

The findings directly address the research gaps identified in the literature review. The first gap concerned the fragmentation of AI-HRM research across HR functions. The present SLR integrates recruitment, performance management, talent management, HR analytics, learning, engagement, retention, and workforce planning into a unified analytical framework. The second gap concerned theoretical fragmentation. The findings integrate RBV, TOE, socio-technical, dynamic capability, and responsible AI perspectives to explain AI-HRM from technological, organizational, human, and ethical dimensions. The third gap concerned insufficient integration of employee and organizational outcomes. The present findings demonstrate that AI-HRM should be examined simultaneously at the employee and organizational levels. The fourth gap concerned responsible AI. The synthesis confirms that ethical governance is fundamental to AI-HRM and should be incorporated throughout the implementation process. The fifth gap concerned generative AI and emerging technologies. The review demonstrates that generative AI and large language models represent a rapidly expanding research frontier requiring new theoretical and empirical investigation. Recent research specifically identifies LLM applications, human-in-the-loop governance, auditability, bias, explainability, and transparency as major unresolved issues. The sixth gap concerned contextual and cross-cultural evidence. Existing literature remains concentrated in particular geographical and organizational environments. Future studies should therefore examine AI-HRM across different institutional contexts, industries, cultures, and levels of economic development.

4.2.6 Acknowledgement of Study Limitations

The findings should be interpreted in light of several limitations. First, the evidence is dependent on the publications retrieved through the selected databases and search strategy. Second, the rapid development of AI means that the knowledge base continues to evolve, particularly following the emergence of generative AI and large language models. Third, heterogeneity among studies limits direct comparison and statistical aggregation. Fourth, differences in theoretical definitions of AI, AI-HRM, responsible AI, and employee outcomes may influence thematic classification.

Furthermore, the present synthesis should not be interpreted as evidence that AI produces universally positive or negative HRM outcomes. Rather, the evidence suggests that outcomes are contingent upon technological design, organizational capabilities, employee perceptions, implementation practices, and governance mechanisms. This contingency represents an important direction for future empirical research.

DOI: 10.65246

Overall, the results demonstrate that the future of AI-HRM is unlikely to be characterized by complete replacement of human HR professionals. Instead, the evidence increasingly points toward a human-AI collaborative model in which AI provides computational, predictive, and generative capabilities while humans retain responsibility for contextual judgment, ethical reasoning, relationship management, and accountability. Recent systematic research similarly emphasizes the importance of human oversight, auditability, transparency, and responsible governance in ensuring that AI-HRM delivers organizational value without compromising fairness and employee dignity.

5. Conclusion

This systematic literature review examined the rapidly evolving role of Artificial Intelligence (AI) in Human Resource Management (HRM), with particular attention to emerging practices, employee and organizational outcomes, implementation challenges, responsible AI governance, and future research directions. By synthesizing recent scholarly evidence, the study demonstrates that AI-HRM has evolved beyond a narrow focus on administrative automation toward a broader transformation of how organizations attract, develop, evaluate, engage, and retain human capital. The findings further indicate that the organizational value of AI-HRM depends not only on technological capabilities but also on organizational readiness, human capabilities, employee acceptance, and responsible governance.

5.1 Summary of Key Findings

The review identifies four major dimensions of AI-enabled HRM transformation: automation, augmentation, prediction, and personalization. AI technologies such as machine learning, predictive analytics, natural language processing, intelligent chatbots, generative AI, and large language models are increasingly applied across recruitment and selection, workforce planning, performance management, learning and development, talent management, employee engagement, HR analytics, and retention.

In response to RQ1, the evidence demonstrates that recruitment and selection remain among the most extensively investigated AI-HRM applications. However, the research landscape is increasingly expanding toward performance management, talent management, workforce analytics, employee development, engagement, and retention. Generative AI and large language models represent the newest stage of this technological expansion.

In response to RQ2, AI transforms HRM by shifting routine activities toward automation while increasing the analytical and strategic capabilities of HR professionals. AI enables organizations to process large volumes of employee and candidate information, identify patterns, generate predictions, personalize interventions, and provide decision support. Thus, AI-HRM represents a transformation of HR work rather than simply the digitization of existing HR processes.

In response to RQ3, the review identifies both positive and negative outcomes. Positive outcomes include improved efficiency, faster decision-making, enhanced personalization, productivity, employee development, and data-driven HR practices. However, AI-HRM can also generate job insecurity, technostress, surveillance concerns, reduced autonomy, and declining trust when implementation is perceived as opaque or excessively automated.

In response to RQ4, the principal challenges involve algorithmic bias, discrimination, privacy, transparency, explainability, accountability, data quality, employee trust, organizational resistance, and insufficient AI-related capabilities among HR professionals. These challenges demonstrate that technological effectiveness alone is insufficient for successful AI-HRM implementation.

In response to RQ5, the review identifies several unresolved areas, including insufficient longitudinal evidence, limited cross-cultural research, fragmented theoretical foundations, inadequate empirical examination of generative AI and large language models, and limited integration between technological, organizational, employee, and ethical dimensions.

Overall, the findings indicate that AI-HRM should be understood as a socio-technical and strategic transformation in which technological capabilities interact with human judgment, organizational capabilities, employee experiences, and governance mechanisms.

5.2 Theoretical Contributions

This study contributes to the AI-HRM literature by developing an integrated perspective

DOI: 10.65246

that connects AI technologies, AI-enabled HRM practices, employee outcomes, organizational outcomes, and responsible AI governance. This integrated perspective addresses the fragmentation identified in previous research, which has frequently examined individual HR functions, technological applications, or ethical issues in isolation. From a Resource-Based View perspective, the findings suggest that AI technology itself should not be considered a sufficient source of competitive advantage. Sustainable value emerges when organizations successfully combine AI capabilities with human capital, HR expertise, organizational knowledge, data resources, and managerial capabilities. AI therefore represents a potential strategic resource whose value depends on organizational capacity to deploy and integrate it effectively. From a Technology–Organization–Environment perspective, the findings demonstrate that AI-HRM adoption is shaped by technological characteristics, organizational readiness, employee capabilities, organizational culture, leadership support, and environmental and regulatory conditions. This reinforces the view that AI implementation should be examined as a multilevel organizational phenomenon. The study also extends the Socio-Technical Systems perspective by demonstrating that technological implementation and human consequences cannot be separated in HRM. AI systems interact with employees, HR professionals, managers, and organizational structures. Consequently, the effectiveness of AI-HRM depends on the quality of human-AI collaboration rather than technological capability alone. Most importantly, the study positions Responsible AI Governance as a cross-cutting theoretical dimension of AI-HRM. Fairness, transparency, explainability, privacy, accountability, and human oversight are not merely ethical additions to AI-HRM but fundamental conditions for ensuring that AI creates sustainable organizational value while protecting employee interests. The principal theoretical contribution is therefore an integrated AI-HRM transformation perspective:

AI Technologies → AI-Enabled HRM Practices → Employee Outcomes → Organizational Outcomes

with Responsible AI Governance and Organizational Context functioning as critical conditions surrounding this transformation.

5.3 Practical and Policy Implications

The findings provide several implications for HR managers and organizational leaders. First, organizations should avoid adopting AI solely to reduce administrative costs. AI implementation should be aligned with broader HR and organizational strategies and supported by appropriate data infrastructure, employee capabilities, and governance mechanisms. Second, organizations should adopt a human-in-the-loop approach for high-impact HR decisions. Recruitment, promotion, performance evaluation, compensation, and termination decisions should not rely exclusively on automated recommendations. Human professionals should retain responsibility for contextual judgment, ethical reasoning, and final accountability. Third, organizations should establish systematic AI auditing and monitoring mechanisms. AI systems should be periodically evaluated for algorithmic bias, discriminatory outcomes, data-quality problems, privacy risks, and unintended consequences. Fourth, HR professionals should develop new competencies in AI literacy, data interpretation, generative AI, ethical governance, and human-AI collaboration. The transformation of HRM requires HR professionals to move beyond traditional administrative competencies toward strategic technological and analytical capabilities. Fifth, organizations should prioritize transparency in their interactions with employees and candidates. Individuals should be appropriately informed when AI substantially influences recruitment, performance evaluation, or other employment-related decisions. From a policy perspective, governments and regulatory institutions should develop clear frameworks for AI applications in employment, particularly concerning personal-data protection, algorithmic discrimination, explainability, transparency, accountability, and human oversight. Such policies are necessary to ensure that technological innovation remains compatible with principles of fairness and employee protection.

5.4 Limitations of the Study

This study has several limitations that should be considered when interpreting its findings. First, the synthesis is dependent on the scholarly literature identified through the selected databases and search strategy. Relevant studies published outside the selected databases or in languages other than English

DOI: 10.65246

may therefore be underrepresented. Second, the rapidly changing nature of AI creates a temporal limitation. The emergence of generative AI and large language models has significantly changed the AI-HRM landscape within a relatively short period. Consequently, some conclusions may require reassessment as new technologies and empirical evidence emerge. Third, the included studies demonstrate substantial heterogeneity in theoretical perspectives, methodologies, organizational contexts, AI technologies, and outcome measures. This heterogeneity limits the possibility of direct statistical comparison and requires greater reliance on thematic and narrative synthesis. Fourth, differences in how researchers conceptualize AI, AI-HRM, responsible AI, employee outcomes, and organizational outcomes may influence the classification and interpretation of findings. Although systematic screening and structured coding were employed, thematic synthesis inevitably involves researcher judgment. Finally, the findings should not be interpreted as demonstrating that AI universally improves or deteriorates HRM outcomes. Rather, the evidence indicates that AI-HRM outcomes are contingent upon organizational context, implementation practices, technological characteristics, employee responses, and governance mechanisms.

5.5 Directions for Future Research

Future research should move beyond predominantly cross-sectional and conceptual approaches toward longitudinal and multi-method research capable of examining the consequences of AI-HRM over time. Such research is particularly important for understanding whether initial efficiency gains translate into sustainable improvements in employee and organizational outcomes. Second, future studies should undertake cross-country and cross-cultural comparisons to examine how institutional environments, labor regulations, organizational cultures, and employee expectations influence AI-HRM adoption and outcomes. Greater attention should also be given to emerging economies and under-researched regions. Third, future research should investigate the organizational consequences of generative AI and large language models through empirical studies rather than relying predominantly on conceptual analysis. Particular attention should be given to productivity, creativity, employee learning, decision quality, job redesign, and human-AI collaboration. Fourth, future studies should develop and validate measurable constructs for Responsible AI Governance in HRM, including algorithmic fairness, explainability, transparency, accountability, privacy protection, and human oversight. These constructs could subsequently be incorporated into quantitative models examining their effects on employee trust, acceptance, engagement, and organizational performance. Fifth, researchers should examine the human-AI collaboration boundary. An important future question is not simply whether AI should be adopted but which HR decisions should be automated, which should be augmented by AI, and which should remain primarily human responsibilities. Sixth, greater attention should be given to employee-level consequences, particularly job insecurity, autonomy, technostress, well-being, engagement, creativity, and career development. Future research should examine both the benefits and unintended consequences of AI adoption. Seventh, future research should connect AI-HRM with measurable organizational performance indicators, including productivity, innovation, organizational resilience, workforce agility, employee retention, and competitive advantage. This would strengthen the strategic HRM literature by demonstrating how AI-enabled HR capabilities translate into organizational value.

Finally, future SLRs should periodically update the evidence base as AI technologies evolve. Future reviews may also combine systematic review methodology with bibliometric analysis, science mapping, meta-analysis where sufficient homogeneous evidence becomes available, and qualitative comparative analysis.

In conclusion, the future of AI in HRM is unlikely to be defined by the complete replacement of HR professionals. Instead, the evidence supports a transition toward a human-AI collaborative model, in which AI provides computational, predictive, analytical, and generative capabilities while humans retain responsibility for contextual judgment, ethical reasoning, interpersonal relationships, and accountability. The strategic challenge for organizations is therefore not simply to adopt AI, but to develop effective, responsible, and human-centered AI-HRM systems capable of creating organizational value while preserving fairness, trust,

DOI: 10.65246

transparency, and employee dignity.

6. References

Ali, O., & Kallach, L. (2024). Artificial Intelligence Enabled Human Resources Recruitment Functionalities: A Scoping Review. *Procedia Computer Science, 232*, 3268–3277. https://doi.org/10.1016/J.PROCS.2024.02.142

Anshima, Bhardwaj, B., & Sharma, D. (2026). Paradoxes of implementing AI-augmented HRM in the workplace: A systematic literature review and future research agenda. *Management Review Quarterly*. https://doi.org/10.1007/s11301-025-00581-x

Balcioğlu, Y. S., & Artar, M. (2024). Artificial intelligence in employee recruitment. *Global Business and Organizational Excellence, 43*(5), 56–66. https://doi.org/10.1002/joe.22248

Bandara, R. J., Biswas, K., Akter, S., Shafique, S., & Rahman, M. (2025). Addressing Algorithmic Bias in AI-Driven HRM Systems: Implications for Strategic HRM Effectiveness. *Human Resource Management Journal, 35*(4), 1047–1063. https://doi.org/10.1111/1748-8583.12609;JOURNAL:JOURNAL:17488583

Benabou, A., & Touhami, F. (2025). Empowering human resource management through artificial intelligence: A systematic literature review and bibliometric analysis. *International Journal of Production Management and Engineering, 13*(1), 59–76. https://doi.org/10.4995/ijpme.2025.21900

Bujold, A., Roberge-Maltais, I., Parent-Rocheleau, X., Boasen, J., Sénécal, S., & Léger, P.-M. (2024). Responsible artificial intelligence in human resources management: A review of the empirical literature. *AI and Ethics, 4*, 1185–1200. https://doi.org/10.1007/s43681-023-00325-1

Deepa, R., Sekar, S., Malik, A., Kumar, J., & Attri, R. (2024). Impact of AI-focussed technologies on social and technical competencies for HR managers: A systematic review and research agenda. *Technological Forecasting and Social Change, 202*, 123301. https://doi.org/10.1016/j.techfore.2024.123301

Do, H., Chu, L. X., & Shipton, H. (2025). How and when AI-driven HRM promotes employee resilience and adaptive performance: A self-determination theory perspective. *Journal of Business Research, 192*, 115279. https://doi.org/10.1016/j.jbusres.2025.115279

Gong, Q., & Fan, D. (2024). Algorithmic human resource management: Toward a functional affordance perspective. *Personnel Review, 54*(5), 1150–1177. https://doi.org/10.1108/PR-01-2024-0099

Jamaluddin, Alam, R., Lantara, N., Rosdianti Razak, A., & Hatidja, S. (2025). The role of artificial intelligence in recruitment: Examining candidate experience as a mediator and organizational culture as a moderator in quality of hires. *Asian Management and Business Review, 5*, 160–177. https://doi.org/10.20885/AMBR.VOL5.ISS1.ART11

Jiang, Y., Cai, Z., & Wang, X. (2025). Leverage generative AI for human resource management: Integrated risk analysis approach. *The International Journal of Human Resource Management, 36*, 1929–1959. https://doi.org/10.1080/09585192.2025.2544972

Khan, A. J., Chaudhry, I. S., Iqbal, J., & El Refae, G. A. (2025). Automation to sustainability: A systematic review of artificial intelligence applications in human resource management. *Human Behavior and Emerging Technologies*. https://doi.org/10.1155/hbe2/7021656

Kim, S. (2025). Strategic human resource management in the era of algorithmic technologies: Key insights and future research agenda. *Human Resource Management*. https://doi.org/10.1002/hrm.22268

Koştı, G., & Kayadibi, İ. (2025). A bibliometric analysis of artificial intelligence and machine learning applications for human resource management. *Future Business Journal, 11*, 179.

Lazazzara, A., Za, S., & Georgiadou, A. (2025). A taxonomy framework and process model to explore AI-enabled workplace inclusion. *Journal of Business Research, 201*, 115697. https://doi.org/10.1016/j.jbusres.2025.115697

Malik, A., Budhwar, P., Kazmi, B. A., & Srikanth, N. R. (2023). Artificial intelligence (AI)-assisted HRM: Towards an extended strategic framework. *Human Resource Management Review, 33*(1), 100940. https://doi.org/10.1016/j.hrmr.2022.100940

Naoum, R. F., Szakadáti, T., & Balogh, G. (2026). Artificial intelligence (AI) in human resource management (HRM): A systematic review of its dual impact on diversity, equity, and inclusion (DEI). *Management Review Quarterly*. https://doi.org/10.1007/s11301-025-00580-y

Nyberg, A. J., Schleicher, D. J., Bell, B. S., et al. (2025). A brave new world of human

DOI: 10.65246

resources research: Navigating perils and identifying grand challenges of the GenAI revolution. *Academy of Management Journal*. https://doi.org/10.1177/01492063251325188

Prikshat, V., Islam, M., Patel, P., Malik, A., Budhwar, P., & Gupta, S. (2023). AI-augmented HRM: Literature review and a proposed multilevel framework for future research. *Technological Forecasting and Social Change, 193*, 122645. https://doi.org/10.1016/j.techfore.2023.122645

Zhao, D., Tang, N., Hai, S., & Zhao, L. (2025). Dual effects of AI-enabled job non-routinization on creativity: The moderating role of tacit knowledge awareness. *Journal of Business Research, 198*, 115482. https://doi.org/10.1016/j.jbusres.2025.115482