JEMSI:
Jurnal Ekonomi Manajemen Sistem Informasi
E-ISSN: 2686-5238
P-ISSN: 2686-4916
DINASTI REVIEW
https://dinastirev.org/JEMSI dinasti.info@gmail.com +62 811 7404 455
DOI: https://doi.org/10.38035/jemsi.v8i1

Artificial Intelligence in Human Resource Management: A Systematic Literature Review of Drivers, Barriers, and Outcomes

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Abstract: This review systematically maps the determinants, constraints, and consequences of artificial intelligence (AI) use in human resource management (HRM). A Scopus search for 2021-2026 publications produced 608 records. Sequential screening of titles, abstracts, and available full texts resulted in 44 eligible studies, including 33 empirical investigations and 11 secondary or conceptual works. The synthesis shows that leadership commitment, strategic alignment, employee trust, human capabilities, digital preparedness, resources, perceived usefulness, and institutional conditions support AI adoption and integration. Major obstacles include implementation difficulty, ethical and fairness issues, algorithmic bias, privacy and security exposure, employee anxiety or resistance, and weak governance. Reported benefits include better recruitment, operational efficiency, analytical decision support, employee-related outcomes, innovation, and organizational performance, although risks of unfairness and dehumanization persist. Sustainable AI-HRM therefore depends on technological capacity combined with organizational readiness, workforce competence, and responsible governance.

Keywords: Artificial Intelligence, Human Resource Management, Drivers, Barriers, Outcomes

INTRODUCTION

Artificial intelligence (AI) is increasingly embedded in organizational digital transformation because it can process extensive datasets, identify patterns, produce predictive information, and augment managerial decisions (Dwivedi et al., 2021; Jarrahi, 2018). Within human resource management (HRM), its use now extends across recruitment and selection, talent acquisition, learning and development, performance management, workforce analytics, engagement, and retention (Garg et al., 2022; Vrontis et al., 2022). Thus, AI-HRM is broader than routine automation. It can reshape how HR processes are designed, how managerial judgement is exercised, and how organizations interact with employees.

The arrival of generative artificial intelligence (GenAI) has further widened the range of possible HRM applications. Systems capable of producing text, recommendations, summaries, and related outputs can assist candidate communication, job-material preparation, learning activities, employee development, and HR decision processes (Budhwar et al., 2023). These possibilities also introduce questions about decision accuracy, personal-data protection, accountability, workforce capability, employment effects, and the redistribution of responsibilities between people and intelligent systems. AI-HRM should consequently be understood as a socio-technical and organizational change process, not simply as the installation of a new technology (Bujold et al., 2024; Chowdhury et al., 2023).

Merely possessing AI technology does not mean that an organization will adopt it effectively or continue using it. Prior evidence points to the combined influence of technological preparedness, organizational capability, perceived usefulness, managerial backing, regulation, and contextual conditions. In recruitment, for example, technological competence and supportive regulation can facilitate adoption, whereas perceived complexity can work in the opposite direction (Pan et al., 2022). It is also necessary to distinguish adoption from assimilation. Adoption concerns the initial decision to employ AI, while assimilation concerns its incorporation into established HR routines and organizational processes (Prikshat et al., 2023). Effective implementation therefore requires capability building as well as technological acquisition.

AI-HRM implementation is accompanied by technological, organizational, human, ethical, and governance challenges. Research points to system complexity, insufficient skills and training, algorithmic bias, privacy and data-security exposure, limited transparency, governance weaknesses, employee resistance or anxiety, and fears of job displacement (Bujold et al., 2024; Meijerink & Bondarouk, 2023). These issues are especially important in HRM because AI-supported decisions can influence applicants and employees directly. Fairness, explainability, accountability, and substantive human oversight are therefore central requirements for legitimate AI-supported HR practices rather than optional additions.

The effects of AI in HRM are similarly mixed. Studies associate AI use with automation, efficiency, personalization, decision support, improved recruitment, better employee experiences, and organizational performance (Nawaz et al., 2024; Pereira et al., 2023). When appropriately aligned with HR processes, AI can also expand analytical capacity and contribute to innovation. Yet reported drawbacks include perceived unfairness, algorithmic discrimination, privacy concerns, employment insecurity, diminished autonomy, and unfavorable employee reactions. The value of AI-HRM therefore depends not only on technical functionality but also on how the technology is designed, introduced, interpreted, accepted, and governed.

A substantial body of scholarship already examines AI in HRM. Reviews have considered applications across the HR life cycle, strategic HRM, organizational AI capability, workplace implications, and responsible AI and governance (Bujold et al., 2024; Chowdhury et al., 2023; Gélinas et al., 2022; Malik et al., 2022). Other studies have focused on antecedents of adoption, consequences of AI use, and the organizational process through which AI becomes embedded in HRM (Pereira et al., 2023; Prikshat et al., 2023). Nevertheless, the evidence is spread across functions, contexts, theoretical perspectives, and outcome categories, making an integrated reading difficult.

A remaining gap concerns the limited integration of adoption drivers, implementation barriers, and outcomes within one analytical perspective. Much of the literature isolates these dimensions: some studies explain why organizations adopt AI, others examine implementation problems, and still others evaluate consequences. Such separation obscures how technological, organizational, individual, and institutional conditions interact with barriers during adoption and assimilation and how those interactions shape both favorable and unfavorable HRM consequences. Although prior systematic work has highlighted contextual and governance influences on AI adoption and organizational responses, a synthesis explicitly organized around drivers, barriers, and outcomes can consolidate the dispersed evidence (Basu et al., 2023).

To address this gap, the present study systematically reviews Scopus-indexed research on AI in HRM published during 2021-2026. The review integrates evidence on conditions that encourage adoption, obstacles that may impede implementation and organizational integration, and consequences associated with AI use. Considering these dimensions together allows the study to explain why organizations move toward AI, which conditions may prevent effective incorporation into HR practices, and how adoption may affect HR activities, employees, and organizational performance.

Accordingly, the review is guided by the following research questions:

RQ1. What technological, organizational, individual, and institutional conditions encourage AI adoption and assimilation in HRM?

RQ2. What technological, organizational, human, ethical, and governance-related obstacles hinder AI adoption and assimilation in HRM?

RQ3. Which positive and negative consequences are reported when AI is adopted and assimilated in HRM?

RQ4. In what ways do enabling factors and barriers jointly influence the link between AI adoption, AI-HRM assimilation, and HRM outcomes?

Taken together, these questions support an integrated interpretation of the conditions enabling AI-HRM, the constraints surrounding implementation, and the consequences that follow. Instead of treating adoption, implementation difficulties, and outcomes as unrelated topics, the review connects them along the pathway from initial use of AI to its incorporation into established HRM practices. This approach also highlights areas where additional empirical evidence and theoretical development are needed.

METHOD

Research Design

The study uses a Systematic Literature Review (SLR) to identify, assess, and synthesize published evidence on artificial intelligence (AI) in human resource management (HRM). Its analytical focus covers adoption enablers, implementation and assimilation barriers, contextual conditions, and HRM consequences. The review followed an ordered sequence of identification, screening, eligibility assessment, data extraction, and thematic synthesis, with study selection reported according to PRISMA 2020 (Page, 2021). For synthesis, evidence was grouped into three dimensions: drivers, referring to conditions that promote adoption or integration; barriers, covering technological, organizational, human, ethical, governance, and resource constraints; and outcomes, referring to consequences for HR processes, employees, and organizations. Scopus was used as the sole bibliographic database. A thematic rather than statistical synthesis was appropriate because the studies varied substantially in setting, design, measurement, and reported results.

Literature Search Strategy

Relevant publications for 2021-2026 were identified through Scopus. The search was built around the two central concepts of artificial intelligence and human resource management, supplemented by terms representing adoption, implementation, assimilation, drivers, determinants, barriers, challenges, outcomes, consequences, acceptance, readiness, and capability. This broader vocabulary was intended to capture the multiple dimensions reflected in the research questions rather than focusing on one particular HRM function.

The Boolean search string was: (""artificial intelligence"" OR ""generative artificial intelligence"" OR ""generative AI"") AND (""human resource management"" OR HRM OR ""human resources"") AND (adoption OR implementation OR assimilation OR drivers OR determinants OR barriers OR challenges OR outcomes OR consequences OR acceptance OR readiness OR capability). The retrieved records were subsequently assessed against the predefined Scopus criteria.

Open-access status was deliberately not used as an eligibility requirement. Accessibility alone does not establish substantive relevance or methodological suitability. The final export from Scopus contained 608 records, which then underwent bibliographic and substantive screening; the stage-by-stage results are presented in the Results section and PRISMA flow diagram.

Table 1. Literature Search Strategy

Database source	Scopus
Publication window	2021-2026
Core concepts	Artificial Intelligence; Human Resource Management
Additional dimensions	Adoption; Implementation; Assimilation; Drivers; Determinants; Barriers; Challenges; Outcomes; Consequences; Acceptance; Readiness; Capability
Boolean query	("artificial intelligence" OR "generative artificial intelligence" OR "generative AI") AND ("human resource management" OR HRM OR "human resources") AND (adoption OR implementation OR assimilation OR drivers OR determinants OR barriers OR challenges OR outcomes OR consequences OR acceptance OR readiness OR capability)
Subject areas	Business, Management and Accounting; Social Sciences; Economics, Econometrics and Finance
Document category	Article
Language	English
Source category	Journal
Publication status	Final
Open-access criterion	Not used as a screening criterion

The Scopus export yielded 608 records that were processed through sequential bibliographic and substantive screening. The successive counts and changes at each stage are reported in the Results section and represented in the PRISMA 2020 flow diagram.

Inclusion and Exclusion Criteria

Eligibility requirements were defined in advance to maintain consistency during study selection. A publication qualified when it was indexed in Scopus, appeared between 2021 and 2026, was written in English, was a journal article at the final publication stage, and addressed artificial intelligence within HRM. Eligible studies needed to contribute evidence on at least one of the following: adoption, implementation, assimilation, drivers, barriers, acceptance, readiness, capability, or outcomes in HRM.

Records were removed when they failed the bibliographic requirements, fell outside the HRM setting, or lacked substantive evidence relevant to the research questions. Papers discussing general technology acceptance without a clear relationship to AI implementation in HRM were also excluded. Review and conceptual papers were retained where they met the substantive criteria, but their evidence type was kept distinct from primary empirical research in the synthesis.

Table 2. Inclusion and Exclusion Criteria

Criterion	Included	Excluded
Database indexing	Indexed in Scopus	Not indexed in Scopus
Publication period	2021-2026	Before 2021 or after 2026
Subject area	Business, Management and Accounting; Social Sciences; Economics, Econometrics and Finance	Outside the specified subject areas
Document type	Article	Conference paper, book, editorial, or other non-article document types
Language	English	Non-English
Source type	Journal	Non-journal
Publication stage	Final	Other than final publication
Topic	Artificial intelligence in human resource management	AI outside the HRM context
Substantive focus	Drivers, barriers, adoption/implementation/assimilation, acceptance/readiness/capability, and/or AI-HRM outcomes	No substantive relevance to the research focus

Criterion	Included	Excluded
Open access	Not restricted	Not used as a basis for exclusion

Screening followed a staged procedure. First, bibliographic filters specified in Scopus were applied. Titles and abstracts were then examined for substantive relevance, after which potentially eligible records were assessed through full-text review when the article could be retrieved. Final decisions reflected both bibliographic eligibility and alignment with the AI-HRM framework of drivers, barriers, adoption or implementation, and outcomes.

Information Sources and Study Selection Process

Scopus served as the single bibliographic source for the review. Using one database established a uniform indexing basis for the retrieved literature and allowed all records to be assessed against identical publication criteria. The process began with filters for publication year, subject area, document type, language, source type, and publication stage, followed by title and abstract assessment.

Potentially relevant articles were subsequently evaluated in full text when the complete document was obtainable. Eligibility at this stage depended on whether the study examined AI use, adoption, implementation, or assimilation in HRM and contributed evidence to at least one of the three review dimensions. Studies outside HRM or without adequate substantive relevance were excluded. Reports whose full texts could not be obtained were retained as not retrievable rather than being treated as substantive exclusions.

The title stage retained 62 records, and abstract screening left 57 records for retention or additional verification. Fifty-five reports were provisionally eligible for retrieval. Full texts were obtained for 46 reports; assessment of those articles resulted in 44 included studies, while 2 were excluded after full-text evaluation. Nine additional reports remained unavailable. The complete sequence was documented using PRISMA 2020.

Quality Assessment

Methodological quality was appraised with criteria suited to each study design. Empirical studies were considered separately from secondary and conceptual contributions because their evidentiary bases differ. The assessment considered clarity of research objectives, appropriateness of design, adequacy of data or evidence, transparency of analysis, agreement between findings and conclusions, and reporting of limitations.

Quality appraisal was used to support interpretation rather than as an automatic exclusion rule. Its role was to indicate the relative evidentiary strength and contribution of studies within the thematic synthesis.

Data Extraction and Thematic Synthesis

For each eligible study, information relevant to the research questions was systematically extracted. The extraction form captured bibliographic details, geographic or organizational context, AI application, HRM function, research method, and theoretical basis where available. It also recorded adoption drivers, implementation barriers, adoption or assimilation conditions, reported outcomes, evidence type, and the study's substantive relevance to the review framework.

Table 3. Data Extraction Components

Component	Information Recorded
Study identification	Author(s) and year of publication
Research context	Country, industry or sector, and organizational setting
AI application	Type and specific form of AI utilization
HRM function	Recruitment, talent management, performance management, learning and development, HR analytics, employee relations, or other HR functions
Research method	Research approach, study design, sample or data source, and analytical procedure
Theoretical perspective	Theory, model, or conceptual framework reported in the study

Component	Information Recorded
Drivers	Conditions that facilitate AI adoption, implementation, or assimilation
Barriers	Factors that impede or restrict AI implementation and organizational integration
Adoption/assimilation	Stage, pattern, or form of AI adoption and its integration into organizational practices
Outcomes	Effects identified at the level of HR processes, employees, or organizations
Evidence role	Classification as primary empirical or secondary/conceptual evidence
Substantive relevance	Degree of relevance to AI-HRM and the research questions

The extracted evidence was organized thematically into drivers, barriers, and outcomes. Driver findings were grouped as organizational, individual, technological, resource, and institutional factors. Barriers were coded as implementation challenges; ethical, fairness, and bias concerns; human resistance; privacy and security problems; governance limitations; skills deficiencies; and resource constraints. Outcomes were classified into recruitment and talent management, efficiency and productivity, decision quality, employee effects, organizational performance, innovation, fairness and compliance, and sustainability.

This coding structure made it possible to identify recurring patterns, compare findings across contexts, and trace links between adoption, organizational assimilation, and subsequent consequences. The thematic approach was appropriate because the selected studies differed in research design, organizational setting, HRM application, and measurement. Quantitative, qualitative, conceptual, and review evidence could therefore be compared at the substantive level without erasing differences in their methodological foundations or improperly combining heterogeneous results.

RESULTS AND DISCUSSION

Identification and Selection of Literature

The search initially identified 608 Scopus records. These records were processed according to the predefined bibliographic and substantive criteria. No duplicate records were identified in the exported dataset, so the complete set moved to title screening. Sixty-two records were retained after title assessment, while 546 were removed because their titles did not establish sufficient relevance to AI and HRM.

Abstract assessment then retained 57 records or flagged them for further verification. Fifty-five reports were classified as provisionally eligible for full-text retrieval. Complete texts were available for 46 reports, whereas 9 could not be obtained. The latter were recorded as not retrievable rather than as evidence of substantive ineligibility.

The 46 accessible reports underwent full-text assessment. Reviewers considered their connection with the study scope, including AI use, adoption, implementation, or assimilation in HRM and contribution to drivers, barriers, or outcomes. Forty-four studies satisfied the substantive criteria, while two were removed because the eligibility requirements were not adequately met.

The PRISMA flow diagram summarizes this pathway. Separating non-retrievable reports from substantively excluded studies preserves the distinction between an inability to obtain a paper and a decision that its content was outside the review scope. Consequently, the final evidence base contains 44 studies that were retrievable and sufficiently relevant to the review objectives.

Table 4. Literature Screening Results Based on Search Criteria

Screening stage	Number	Change
Scopus records identified	608	Baseline
Title-screened records	608	0 removed before screening
Title-selected records	62	546 excluded
Abstract/eligibility candidates	57	5 removed at abstract stage
Potentially eligible reports	55	2 not retained before retrieval
Full texts retrieved	46	9 not retrievable
Full texts included	44	2 excluded after full text

The selection procedure progressively reduced the initial Scopus set through bibliographic filtering, title and abstract assessment, full-text retrieval, and substantive eligibility review. Forty-four studies remained for thematic synthesis; unavailable reports and excluded articles were maintained as separate screening outcomes.

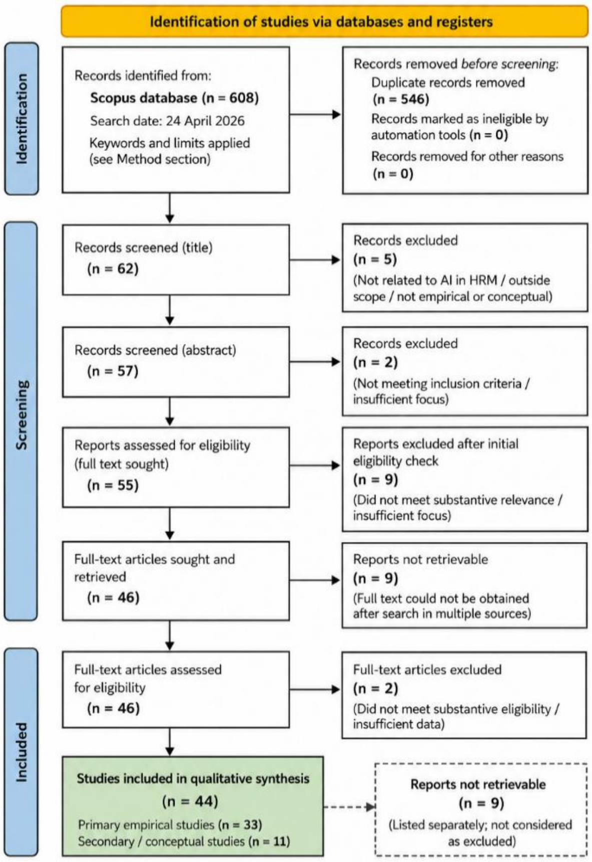

Figure 1. PRISMA 2020 Flow Diagram of the AI-HRM Study Selection Process

Figure 1 depicts the complete evidence-selection pathway, beginning with 608 Scopus records and moving through title screening, abstract assessment, retrieval of full texts, and final eligibility evaluation. Nine reports could not be retrieved and two retrieved articles were excluded after full-text review, leaving 44 studies for qualitative synthesis. These studies were subsequently characterized by context, AI application, HRM function, research design, and reported drivers, barriers, and outcomes.

Characteristics of the Included Studies

The final sample contains 44 eligible studies: 33 primary empirical investigations and 11 secondary or conceptual contributions. The evidence spans quantitative surveys and statistical models, qualitative interviews, phenomenological work, experiments, case-based research, systematic and scoping reviews, and conceptual analyses. This diversity reflects the interdisciplinary character of AI-HRM scholarship and allows adoption, implementation, assimilation, and organizational consequences to be viewed from several methodological perspectives.

Recruitment and talent acquisition receive substantial attention in the selected literature. Other applications include HR analytics, performance management, learning and development, employee engagement and well-being, HR operations, sustainable HRM, and AI-supported decision-making. The distribution indicates a shift from viewing AI primarily as an administrative automation mechanism toward broader analytical, strategic, and employee-facing uses.

The studies cover organizational and geographic settings in Asia, Africa, the Middle East, and Europe, together with sector-specific and organization-specific investigations. Such variation matters because digital maturity, institutional arrangements, regulatory environments, organizational capabilities, and workforce characteristics can influence how AI is adopted and assimilated.

The publication profile also signals rapid expansion of the field. Seventeen of the included studies were published in 2025, with several addressing newer AI and GenAI applications in HRM. The concentration of recent studies reinforces the value of systematic synthesis because organizational experimentation with increasingly capable AI continues to enlarge the evidence base.

Table 5. Characteristics of the Included Studies

Study characteristic	Synthesis of included evidence
Evidence base	44 included studies: 33 primary empirical studies and 11 secondary/conceptual studies
Primary empirical designs	Quantitative surveys/SEM, qualitative interviews, phenomenological studies, experiments, case-based and applied empirical studies
Secondary/conceptual designs	Systematic reviews, scoping reviews, conceptual models, theoretical frameworks, and review-oriented studies
Publication pattern	17 studies published in 2025, indicating strong recent growth in AI-HRM research
Dominant HRM areas	Recruitment and talent acquisition, HR analytics, performance management, employee engagement and well-being, learning and development, and HR decision-making
Geographic/contextual diversity	Studies conducted across Asia, Africa, the Middle East, Europe, and sector- or organization-specific settings
Core AI-HRM phenomena	AI adoption, implementation, assimilation, AI augmentation, generative AI, algorithmic HRM, predictive analytics, and AI-supported HR decision-making

Table 5 organizes the included evidence by study characteristics, distinguishing empirical and secondary/conceptual designs, publication pattern, dominant HRM areas, contextual diversity, and the principal AI-HRM phenomena examined. This classification clarifies the methodological and substantive breadth of the literature used in the thematic analysis.

Table 6. Summary of the Included Studies on Artificial Intelligence in Human Resource Management

No.	Author(s) & Year	Study focus	Evidence Type	HRM Function
1.	Ncube et al. (2025)	AI effects on HRM practices	Primary empirical	Recruitment/Talent
2.	Gayathiri & Prabu (2025)	AI-HR practices and employee well-being	Primary empirical	HR practices/Well-being
3.	Ali et al. (2025)	AI capabilities, digital literacy and green HRM	Primary empirical	Green HRM
4.	Böhmer & Schinnenburg (2023)	Critical exploration of AI-driven HRM to build up organizational capabilities	AI-driven HRM and organizational capabilities	General HRM
5.	Islam et al. (2023)	Artificial intelligence adoption among human resource professionals: Does market turbulence play a role?	AI adoption by HR professionals	General HRM
6.	Kumar & Pathak (2026)	Algorithmic HRM and GenAI assimilation	Primary empirical	General HRM
7.	Shin et al. (2025)	AI, dehumanization and employee reactions	Primary empirical	HR Operations
8.	Grigoryan et al. (2025)	Challenges and opportunities of artificial intelligence adoption in human resources management within the ICT industry in Armenia	AI adoption challenges in ICT-sector HRM	General HRM

9.	Daueshova et al. (2026)	AI adoption determinants in public HRM	Primary empirical	Public HRM
10.	Devi et al. (2026)	AI-augmented HR practices and employee outcomes	Secondary	General HRM
11.	Ketchiwou & Ngulube (2026)	Prerequisites for successful AI-HRM implementation	Secondary	General HRM
12.	Li et al. (2023)	AI and HR performance in healthcare	Primary empirical	HR Performance
13.	Radonjić et al. (2024)	HR managers' views on AI decisions	Primary empirical	HR Decision-making
14.	Sony et al. (2025)	Bias risks in AI recruitment and analytics	Primary empirical	Recruitment/HR Analytics
15.	Fadi (2025)	AI-HRM and organizational performance	Primary empirical	Strategic HRM
16.	Ali et al. (2026)	AI-HRM digitization and employee outcomes	Primary empirical	HR Digitization
17.	Prasad & De (2024)	GenAI, trust and HRM practices	Primary empirical	General HRM
18.	Adabala (2026)	AI-enabled talent acquisition	Secondary	Talent Acquisition
19.	Nawaz et al. (2024)	The adoption of artificial intelligence in human resources management practices	AI adoption in HRM practices	General HRM
20.	Chilunjika et al. (2022)	AI in South African public HRM	Secondary	Public HRM
21.	Suseno et al. (2022)	Beliefs, anxiety and change readiness for artificial intelligence adoption among human resource managers: The moderating role of high-performance work systems	AI beliefs, anxiety and change readiness	General HRM
22.	Xin et al. (2022)	HR-AI implementation and organizational performance	Primary empirical	Talent Acquisition/HCD/Performance
23.	Basu et al. (2023)	AI-HRM interactions and outcomes	Secondary	General HRM
24.	Arslan et al. (2022)	Human-AI interaction at team level	Conceptual	Team/HRM
25.	Isrososiawan et al. (2025)	Enhancing Talent Retention Through AI-Driven Employer Branding	AI employer branding and talent retention	Recruitment/Talent
26.	Benabou & Touhami (2025)	AI integration and human-AI collaboration	Secondary	General HRM
27.	Kevin Durai & Anbu (2026)	AI adoption determinants in Indian IT	Primary empirical	HRM
28.	Choudhari et al. (2025)	AI impact on talent acquisition	Primary empirical	Talent Acquisition
29.	Khdour et al. (2025)	AI adoption challenges for HR managers	Primary empirical	Recruitment/HRM
30.	Cao & Nguyen (2025)	AI adoption in Vietnamese talent acquisition	Primary empirical	Talent Acquisition
31.	Najam Shaikh et al. (2025)	AI adoption, green HRM and sustainability	Primary empirical	Green HRM
32.	Nyberg et al. (2025)	GenAI opportunities and HR research challenges	Secondary	General HRM
33.	Mahade et al. (2025)	Leveraging AI-driven insights to enhance sustainable human resource management performance: Moderated mediation model	AI insights and sustainable HRM performance	Sustainable HRM

34.	Mwita & Kitole (2025)	AI benefits and challenges in public institutions	Primary empirical	Public HRM
35.	Pan et al. (2022)	Contextual factors in AI recruitment adoption	Primary empirical	Recruitment
36.	Prikshat et al. (2023)	AI-HRM antecedents and assimilation	Conceptual	General HRM
37.	Al Qahtani & Alsmairat (2023)	AI adoption drivers in HRM	Primary empirical	General HRM
38.	Ore & Sposato (2022)	AI opportunities and risks in recruitment	Primary empirical	Recruitment/Selection
39.	Khalifa et al. (2022)	AI in HR crisis management	Primary empirical	HR Crisis Management
40.	Basri (2023)	Impact of AI-Based Recruitment Systems on Human Resource Professionals Ability Practices	AI recruitment systems and HR professionals	Recruitment
41.	Cai et al. (2024)	AI replacement in HR decisions and fairness	Primary empirical	Recruitment/Selection
42.	Mollah et al. (2024)	AI-augmented HRM and sustainable performance	Primary empirical	Sustainable HRM
43.	Malik et al. (2022)	AI-HRM interactions and causal outcomes	Secondary/conceptual	General HRM
44.	He et al. (2025)	AI adoption, innovation and big-data HR capability	Primary empirical	General HRM

Across the 44 studies, the evidence varies in authorship, publication year, methodological status, and HRM application. Recruitment and talent acquisition remain prominent, but the literature also addresses HR analytics, performance, employee outcomes, sustainable HRM, and general AI-HRM integration. These study-level differences form the basis for interpreting the drivers, barriers, and outcomes synthesized below.

Drivers of Artificial Intelligence Adoption and Implementation in HRM

Seven recurring driver categories were identified. Organizational support and strategic orientation appeared most often, followed by employee attitudes and trust, skills and capability development, technological readiness, financial and other resources, perceived value or usefulness, and external or institutional pressure. The counts overlap because a single study can report several enabling factors; therefore, the categories are not mutually exclusive.

Table 7. Drivers of AI Adoption and Implementation in HRM

Driver Theme	Studies (n)	Share of 44	Interpretation
Organizational support and strategy	10	22.7%	Top management support, organizational culture, strategic alignment, governance, leadership, and organizational coordination
Individual attitudes and trust	9	20.5%	AI beliefs, trust, anxiety, willingness, innovativeness, and individual acceptance
Skills and capability development	8	18.2%	AI literacy, training, reskilling, technical competence, and human capability development
Technological readiness and capability	6	13.6%	Infrastructure, technology competence, digital readiness, AI capability, and task-technology fit
Financial and resource availability	6	13.6%	Budget, financial capacity, resources, and organizational investment required for implementation
Perceived value and usefulness	5	11.4%	Perceived usefulness, expected benefits, perceived value, ease of use, and performance expectations
External/institutional pressure	3	6.8%	Regulatory support, competitive pressure, market conditions, and broader contextual influences

Organizational conditions represent the most frequently observed foundation for AI-HRM adoption. Leadership commitment, strategic alignment, governance structures, organizational culture, and coordination help convert technological availability into usable HR capability. The AI capability perspective likewise emphasizes employee competence, leadership, collaboration, culture, innovation orientation, governance, and effective human-AI interaction as complementary elements of value creation (Chowdhury et al., 2023). AI adoption is therefore better interpreted as capability development than as a simple technology-purchasing decision.

Employee perceptions and trust constitute another important enabling mechanism. HR professionals' willingness to use AI is influenced by beliefs about the technology, confidence, anxiety, perceived competence, and expected usefulness. Suseno et al. (2022) found that favorable AI perceptions were associated with stronger change readiness, whereas anxiety was associated with lower readiness. Evidence from Saudi banking also shows positive roles for perceived usefulness and trust, with trust mediating the usefulness-adoption relationship (Al Qahtani & Alsmairat, 2023). Acceptance is consequently more likely when AI is viewed as useful, dependable, and suitable for professional work.

Human capability is a further prerequisite for implementation. AI changes the knowledge and skill profile expected of HR professionals, increasing the relevance of AI literacy, technical knowledge, training, and reskilling. These capabilities enable practitioners to interpret AI-generated information, question algorithmic recommendations, and interact responsibly with intelligent systems. Capability development thus connects technological resources with practical HRM value.

Technological preparedness also determines whether AI can be incorporated into HR processes. Digital infrastructure, technological competence, organizational digital maturity, AI capability, and task-technology alignment influence implementation feasibility. Pan et al. (2022) found that technological competence can facilitate recruitment-related adoption, while perceptions of complexity can inhibit it. Readiness should therefore be evaluated in terms of an organization's ability to integrate, operate, and manage AI rather than merely whether an AI tool has been acquired.

Sustained implementation also depends on financial and organizational resources. Moving from experimentation to established AI-HRM practice can require investment in infrastructure, software, data management, cybersecurity, employee development, and change management. Adoption becomes more attractive when organizations expect concrete returns, such as faster processes, reduced routine work, stronger decision support, and measurable performance gains. Perceived usefulness, ease of use, and trust are consistent considerations in this decision (Al Qahtani & Alsmairat, 2023).

External conditions appear less frequently than internal organizational and individual drivers but remain relevant. Regulatory support, competitive pressure, and changing market conditions can encourage organizations to develop AI capability when doing so is viewed as necessary for competitiveness or compliance. Pan et al. (2022), for example, identified regulatory support as a facilitating condition in AI-supported employee recruitment.

Overall, adoption and implementation emerge from a combination of mutually reinforcing conditions. Strategy and leadership establish direction; employee trust and perceptions affect acceptance; skills determine effective use; technological readiness supports integration; resources sustain implementation; and institutional conditions can strengthen the incentive to act. These relationships also clarify the movement from initial adoption toward assimilation, in which AI becomes part of established organizational routines and HRM practices (Prikshat et al., 2023).

Barriers and Challenges in AI-HRM Implementation

Seven broad barrier categories were identified in the thematic synthesis. Implementation complexity and organizational readiness were most prevalent, appearing in 27 of the 44 studies. Ethical, fairness, and algorithmic-bias concerns formed the next largest category. Other reported obstacles included employee resistance and anxiety, possible job displacement, governance and transparency weaknesses, privacy and data protection, financial and resource limitations, and specialized-skill shortages. Because studies may report multiple obstacles, the frequencies overlap.

Table 8. Barriers and Challenges in AI-HRM Implementation

Barrier Theme	Studies (n)	Share of 44	Typical Manifestations
Implementation complexity/readiness	27	61.4%	Integration difficulties, organizational readiness gaps, assimilation problems, system complexity, and implementation challenges
Ethics/fairness/bias	16	36.4%	Algorithmic bias, discrimination, fairness concerns, ethical dilemmas, and unequal treatment
Human resistance/anxiety/job displacement	8	18.2%	Fear, distrust, anxiety, resistance to change, and concerns about job displacement
Governance/transparency	7	15.9%	Limited oversight, explainability problems, accountability gaps, and inadequate policies
Privacy/data security	7	15.9%	Employee-data privacy, information protection, cybersecurity, and data-security concerns
Cost/resources	7	15.9%	Financial constraints, implementation costs, limited resources, and competing organizational priorities
Skills/expertise gap	1	2.3%	Insufficient specialized expertise and limited AI-related competencies

The evidence indicates that the principal implementation problem is not simply access to AI but successful integration with existing HR systems, workflows, routines, and managerial decisions. High implementation complexity and readiness gaps can prevent an adopted system from becoming assimilated. Organizations may need to modify HR information systems, improve data quality, redesign workflows, and determine how AI recommendations should complement managerial judgement. Without these capabilities, AI may remain an isolated application rather than an embedded HRM practice (Prikshat et al., 2023).

Ethics, fairness, and algorithmic bias are especially consequential because AI may support decisions concerning recruitment, selection, evaluation, and promotion. Automated outputs can reproduce existing inequalities, and applicants may judge algorithmic screening differently from human judgement. Resistance and anxiety add a human dimension to these difficulties, particularly when employees fear displacement or loss of control. Since positive AI perceptions support change readiness while anxiety can weaken it (Suseno et al., 2022), training, communication, and meaningful employee involvement are important implementation conditions.

Governance, transparency, privacy, and cybersecurity create further constraints. Limited explainability or oversight can reduce accountability and trust, while HR applications frequently handle sensitive information about applicants and employees. Effective deployment therefore requires explicit governance arrangements, human supervision, data-protection practices, and adequate cybersecurity. Financial constraints can simultaneously restrict investment in technology, training, and organizational change. Although an explicit skills gap was coded in only one study, AI literacy and technological competence remain practically important. Overall, the barriers operate across technological, organizational, human, ethical, and institutional levels, so technical solutions alone cannot secure effective AI-HRM (Basu et al., 2023).

Outcomes of Artificial Intelligence Implementation in HRM

The evidence indicates that AI-HRM produces a combination of favorable and unfavorable consequences. Recruitment and talent management, operational efficiency, productivity, decision support, employee-related outcomes, and organizational performance are the most frequently reported benefit areas. At the same time, studies identify possible problems involving fairness, trust, anxiety, autonomy, and dehumanization. Outcome frequencies overlap because individual studies can address several consequences at once.

Table 9. Outcomes of AI Implementation in HRM

Outcome Theme	Studies (n)	Share of 44	Typical Outcomes
Recruitment/talent outcomes	13	29.5%	Screening, candidate matching, hiring, recruitment marketing, talent management, and retention
Efficiency/productivity/cost	11	25.0%	Automation, time savings, productivity improvement, process efficiency, and cost reduction
Decision quality/effectiveness	8	18.2%	Decision support, analytical capability, accuracy, and HR effectiveness
Employee attitudes/well-being	5	11.4%	Employee engagement, well-being, commitment, and negative employee reactions
Organizational performance	5	11.4%	Workforce productivity and broader organizational performance
Fairness/equity/compliance	5	11.4%	Fairness, inclusion, accountability, and compliance-related outcomes
Innovation/adaptability/capability	4	9.1%	Innovation, employee agility, organizational adaptation, and HR capability development
Sustainability/green HRM	2	4.5%	Environmental sustainability through AI-enabled HRM
Crisis management/resilience	1	2.3%	AI-supported human-resource crisis management and organizational response

Recruitment and talent management are the most commonly reported areas of benefit. AI can accelerate screening, candidate matching, information handling, and hiring while reducing administrative effort. Additional effects have been reported in candidate experience, employer branding, and retention. Efficiency gains arise from automating repetitive activities, shortening processing time, and analyzing large volumes of employee and applicant information. Applications in talent acquisition, human-capital development, and performance management can consequently support broader organizational performance.

AI can also strengthen HR decision processes through predictive techniques and HR analytics, enabling managers to organize evidence and evaluate alternatives more systematically. The magnitude and direction of these effects depend on the organizational and governance context in which AI is used (Basu et al., 2023). Employee engagement and well-being may improve when AI enhances HR services or reduces unnecessary workload. AI-enabled analytics can likewise support innovation, adaptability, and organizational capability when connected to strategic HRM priorities.

The evidence does not, however, support an exclusively positive interpretation. AI use can raise concerns about fairness, equity, transparency, compliance, privacy, trust, autonomy, anxiety, and dehumanization. Experimental work on automated resume screening indicates that applicants may regard AI-based decisions as less fair than comparable human decisions, showing that operational efficiency does not automatically establish legitimacy. AI use in HR operations has also been associated with negative employee reactions and turnover concerns. Sustainability is an emerging outcome, with some studies linking AI-enabled HR practices to green HRM and environmental objectives.

The overall pattern is therefore one of simultaneous value creation and risk. AI can deliver operational and strategic gains while also generating human and ethical consequences. Evaluation of AI-HRM effectiveness should consequently consider both organizational performance and employee experience. Positive effects are more likely when technological capability is supported by workforce competence, organizational preparedness, responsible governance, and meaningful human participation.

Integrated Synthesis of Drivers, Barriers, and Outcomes

Drivers, barriers, and outcomes are best interpreted as connected components of an adoption-to-assimilation process rather than as isolated themes. Organizational support, technological capability, employee trust, skills, resources, and institutional conditions can establish the basis for adoption. The subsequent transition toward routine use may nevertheless be interrupted by implementation complexity, ethical concerns, algorithmic bias, privacy risks, resistance, or weak governance.

Table 10. Integrated Synthesis of Drivers, Barriers, and Outcomes

Stage	Key Mechanisms	Implications
Drivers	Organizational support and strategy; technological readiness and capability; trust and positive attitudes; skills and capability development; financial and organizational resources; institutional support	Strengthen organizational and individual readiness to adopt AI in HRM
Adoption/assimilation	AI implementation, system integration, diffusion, routinization, and human-AI interaction	Determine whether AI becomes embedded in HRM practices and organizational routines
Barriers/conditions	Implementation complexity; algorithmic bias; ethical concerns; privacy and data security; resistance and anxiety; governance and transparency; resource constraints	Condition the extent to which expected AI-HRM benefits can be realized and accepted
Positive outcomes	Recruitment and talent management; process efficiency; productivity; decision support; employee outcomes; innovation; organizational performance	Generate operational and strategic value when AI is appropriately implemented and governed
Adverse outcomes	Perceived unfairness; anxiety; distrust; dehumanization; exclusion; job-displacement concerns; reduced autonomy	Require human oversight, responsible governance, ethical safeguards, and inclusive implementation

The synthesis in Table 10 indicates that readiness at organizational and individual levels is necessary but not sufficient for successful AI-HRM. Adoption marks the initial decision or action to use AI, whereas assimilation reflects the degree to which AI becomes embedded in HR processes, organizational routines, and managerial decision-making. An organization can therefore introduce an AI system without possessing the technological, organizational, human, or governance capabilities needed for sustained use.

Barriers can influence both the initial decision and the quality and durability of subsequent AI use. Where integration is supported by adequate capability and responsible governance, organizations may obtain gains in recruitment, efficiency, decision support, employee experience, innovation, and performance. If ethical, human, privacy, or governance problems remain unresolved, acceptance may weaken and adverse consequences may emerge. The relationship is consequently dynamic: enabling conditions facilitate adoption, implementation conditions shape assimilation, and observed outcomes feed back into perceptions of effectiveness and legitimacy.

The evidence suggests that the critical issue is not whether AI is adopted but whether adoption is converted into responsible, durable assimilation. Technology creates the possibility of value, whereas organizational readiness, employee capability, trust, resources, ethical safeguards, and governance determine whether that possibility becomes realized. This interpretation is aligned with the adoption assimilation distinction developed by Prikshat et al. (2023).

Research Gaps

Several unresolved issues remain in AI-HRM research. First, empirical attention is still concentrated on recruitment and talent acquisition, whereas performance management, learning and development, compensation, employee relations, and strategic workforce planning receive less coverage. Similar concentration has been noted in earlier reviews (Garg et al., 2022; Verma et al., 2023). Future studies should test whether the drivers, barriers, and outcomes identified in recruitment also hold across these less-studied HRM functions.

Second, the literature provides more evidence about adoption, implementation, and immediate benefits than about longer-term consequences. Efficiency, automation, recruitment, decision support, and productivity are frequently assessed, while durable effects on autonomy, trust, well-being, fairness, and human-AI relationships remain less established. Because implementation challenges can persist after an initial adoption decision (Prikshat et al., 2023), longitudinal designs are needed to observe how AI-HRM practices and their effects develop over time.

Third, theoretical perspectives remain fragmented. Existing studies draw on different explanations of technology acceptance, organizational readiness, AI capability, assimilation, employee responses, and strategic outcomes, while empirical tests of models combining technological, organizational, individual, and institutional variables are still limited. Pan et al. (2022) similarly identify interdisciplinary fragmentation and methodological limitations as continuing constraints. Future research should therefore examine multilevel models that connect these factors throughout adoption and assimilation.

Fourth, evidence at the organizational level is comparatively weaker than evidence focused on employees or individual HR processes. Prior work has highlighted the limited empirical basis for connecting AI-HRM with broad organizational outcomes (Verma et al., 2023). Greater attention to strategic capability, resilience, financial performance, and sustained competitive advantage is needed to determine whether improvements in HR processes translate into measurable long-term organizational value.

Fifth, more longitudinal and comparative research across countries, sectors, and organizational contexts is warranted. Much existing evidence is tied to specific industries, organizations, or national environments, which makes it difficult to separate context-specific effects from more general patterns. Comparisons across organizational size, sector, country, and digital maturity could clarify which adoption drivers and barriers are broadly applicable and which depend strongly on context.

Finally, the rapid diffusion of Generative AI creates a distinct research agenda. Traditional AI, predictive analytics, algorithmic HRM, and GenAI differ in capability, interaction, autonomy, and risk. Combining them under one label may hide differences in adoption, assimilation, trust, human-AI collaboration, and governance. Evidence on GenAI assimilation points to the relevance of technological infrastructure, task-technology fit, top-management support, personal innovativeness, and openness to experience. Future research should therefore distinguish AI technologies according to their characteristics when analyzing adoption, implementation barriers, and HRM consequences.

Collectively, these gaps indicate that AI-HRM scholarship should move beyond asking whether organizations adopt AI and instead examine how it is assimilated, governed, experienced, and maintained. Future work should broaden coverage across HRM functions, use longitudinal and comparative designs, test integrated multilevel explanations, and assess both organizational value and human consequences. Such an agenda can clarify when AI contributes to sustainable HRM value while limiting unintended harm.

CONCLUSION

This systematic review synthesized evidence on the drivers, barriers, and outcomes surrounding AI adoption and assimilation in HRM. The search identified 608 Scopus records, from which 44 studies with retrievable full texts satisfied the substantive criteria. The final evidence base contained 33 empirical studies and 11 secondary or conceptual contributions. Across the literature, AI-HRM adoption is shaped by a combination of technological, organizational, individual, resource, and institutional conditions rather than by technology availability alone.

The synthesis identifies organizational support and strategic direction, employee attitudes and trust, skills development, technological readiness, resources, perceived usefulness, and institutional pressure as important enabling conditions. Conversely, implementation complexity, ethical and fairness concerns, algorithmic bias, privacy and data-security risks, employee resistance or anxiety, governance limitations, and resource constraints can obstruct effective integration. AI-HRM is associated with gains in recruitment and talent management, efficiency, decision support, employee outcomes, innovation, and organizational performance, but it can also create perceived unfairness, dehumanization, employment insecurity, and reduced autonomy. AI-HRM should therefore be treated as an ongoing socio-technical transformation in which technological capability must be accompanied by organizational preparedness, human competence, and responsible governance to produce sustainable value.

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