Quantifying AI's Contribution to HR: A Systematic Literature Review of Measurement Approaches and Indicators

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Abstract: The rapid integration of Artificial Intelligence into Human Resource Management has generated a global market projected to grow from USD 3.89 billion in 2022 to USD 17.61 billion by 2027, yet consistent frameworks for evaluating AI's actual contribution to HR effectiveness remain fragmented and underdeveloped. This systematic literature review, following PRISMA guidelines, synthesises 68 peer reviewed studies published between 2020 and 2025, sourced from Web of Science and Scopus through structured Boolean search queries. Analysis is structured around the internationally validated CRANET framework, examining AI's measurable impact across four core HRM functions: resourcing practices, employee development, compensation and benefits, and employee relations and communication. The review identifies 20 distinct evaluation frameworks, categorised into strategic-organisational (n=4), function-specific (n=11), and technical-ethical (n=5) domains, with 75% incorporating predictive analytics and 60% integrating ethical governance mechanisms. Over 100 performance indicators are documented, comprising 47 novel AI-specific metrics, including anthropomorphism scales, hyper-personalisation accuracy, and real-time sentiment analysis, alongside 53 AI-enhanced traditional measures. Resourcing practices demonstrate the highest measurement sophistication, evidenced by justice perception assessments and candidate experience metrics, while employee development shows balanced quantitative-qualitative integration through personalisation depth metrics and bias reduction deltas. Despite geographic and linguistic constraints limiting cross-cultural generalisability, and sectoral bias toward technology-intensive organisations, this study establishes AI-HRM evaluation as a specialised domain requiring multi-theoretical integration of technological, behavioural, and ethical constructs. It provides organisations with empirically grounded guidance for implementing multi-dimensional evaluation combining technical performance metrics such as F1-scores and AUC values, ethical governance indicators such as bias audit frequency and fairness perception indices, and strategic impact measures such as organisational agility and innovation throughput, through measurement triangulation across all HR functional domains. This represents a comprehensive synthesis of AI-HRM evaluation methodologies across the complete functional spectrum, establishing foundational architecture for evidence-based AI-HRM assessment while identifying research frontiers in longitudinal impact studies, cross-cultural validation, and sector-specific measurement protocols.

Keywords: Artificial intelligence, AI-HRM integration, Human resource management, Performance measurement, Evaluation frameworks, AI assessment

1. Introduction

AI has become a pivotal driver of change in Human Resource Management, spanning machine learning, natural language processing, computer vision, and robotic process automation tools that augment or automate HR functions while improving accuracy, efficiency, and strategic alignment (Ghosh et al. 2023; Mer 2023). This shift has redefined recruitment, performance management, learning and development, and employee engagement through predictive analytics and intelligent decision making (Shet and Nair 2023; Sharma et al. 2025), reflected in market growth from USD 3.89 billion in 2022 to a projected USD 17.61 billion by 2027 (Research and Markets 2023) and HR's movement toward a strategic, data driven function (Mer 2023; Prikshat et al. 2023). Yet this growth in adoption says nothing about performance. This study defines AI effectiveness in HRM as its demonstrable contribution to HR functional and organisational outcomes, measured through efficiency, decision quality, and strategic impact, rather than adoption rate or usage intensity: adoption is well documented (Mer 2023; Prikshat et al. 2023), but whether AI improves outcomes is not (Böhmer and Schinnenburg 2023). This gap persists despite related research. Application-specific studies document AI's use in recruitment (Pessach et al. 2020; Aycan and Bal 2024), attrition prediction (Benabou et al. 2025), and onboarding (Malik et al. 2022) without generalising into frameworks. Broader reviews stop short of measurement: Budhwar et al. (2022) link AI to outcomes across international HRM, Khushk et al. (2024) examine human-AI dynamics and performance, and Deepa et al. (2024) map AI-adoption competencies, none consolidating the indicators used to quantify AI's contribution. Most directly, Pereira et al. (2023) analyse 60 papers across 30 journals linking AI to workplace outcomes, but their unit of analysis is outcomes, not the indicators used to measure them: their framework shows AI affects HRM performance, not how that effect should be quantified. Closing this gap matters for two reasons. Theoretically, fragmented measurement leaves "AI effectiveness" without a shared basis for comparison across studies. Practically, organisations cannot justify AI investment or compare approaches without comparable metrics (Nandal et al. 2024; Pessach et al. 2020). Answering this requires a systematic, reproducible search across fragmented, cross-disciplinary evidence rather than a narrative review. This study

therefore adopts a PRISMA-based systematic review to answer two questions: RQ1, what evaluation frameworks and conceptual models have been used to assess AI's contribution to HRM, and RQ2, what performance indicators have been used to measure AI-enhanced HRM effectiveness across CRANET-classified HRM functions.

2. Background

2.1 AI Integration in Human Resource Management Functions

In recruitment, AI improves candidate matching and quality of hire (Shet and Nair 2023; Pessach et al. 2020), while machine learning supports predictive hiring (Nandal et al. 2024) and AI chatbots handle routine HR queries in real time (Malik et al. 2023). Training benefits from adaptive, reinforcement-learning recommendations (Bhatt and Muduli 2022; Indarapu et al. 2024), and performance management increasingly uses continuous AI monitoring to reduce bias (Aycan and Bal 2024; Nandal et al. 2024).

2.2 Theoretical Frameworks and Measurement Approaches

Several frameworks conceptualise AI's role in HRM: the HRM(AI) Assimilation Framework (Prikshat et al. 2023) describes four stages, initiation, adoption, routinisation, and extension, while the PeopleXp Model (Malik et al. 2023) integrates vertical and horizontal HR dimensions, with related theory emphasising algorithmic mediation's relational impacts (Budhwar et al. 2023). Measurement approaches range from basic ROI and time reduction metrics (Kholod et al. 2021) to path analyses linking AI to strategic outcomes (Erro-Garcés and Aramendia-Muneta 2023; Al-Ayed 2024; Samman and Obaidly 2024) and machine learning metrics such as F1 scores and ROC curves (Nandal et al. 2024; Yuan et al. 2024). Others draw on established theories such as Person Environment Fit (Shet and Nair 2023) and Kirkpatrick's model (Bhatt and Muduli 2022).

2.3 Measurement Challenges and Research Gaps

Measurement remains fragmented: studies report narrow outcomes such as recruitment time reduction (Lee et al., 2024; Aydın and Turan 2023), cost per hire (Li et al., 2023), and attrition model accuracy (Nandal et al., 2024; Aycan & Bal, 2024), using accuracy scores, cost calculations, engagement rates, and perception measures without a coherent taxonomy (Yuan et al., 2024; Samman & Obaidly, 2024; Sharma et al., 2025). Budhwar et al. (2022), reviewing 70 papers across international HRM contexts, describe AI-HRM research as broadly fragmented, a gap this study addresses through its CRANET structured synthesis. Ethical factors such as fairness, transparency, explainability, and bias mitigation remain rarely integrated into performance assessment (Giermindl et al., 2022), despite growing regulatory emphasis on responsible AI in HRM.

3. Methodology

3.1 Research Design and Theoretical Framework

This study follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta Analyses) protocol to ensure transparency and rigour (Moher et al. 2009; Page et al. 2021; Pereira et al. 2023), well suited to consolidating heterogeneous AI-HRM sources (Al-Ayed 2024; Kwon et al. 2023; Bhatt and Muduli 2022; Mer 2023; Kitchenham and Charters 2007). The study adopts the CRANET (Cranfield Network on Comparative HRM) classification across four core HRM functions: resourcing, employee development, compensation and benefits, and employee relations, an internationally validated framework providing cross cultural credibility.

3.2 Search Strategy and Database Selection

Web of Science and Scopus formed the primary search databases, selected for complementary strengths established in prior AI-HRM systematic reviews (Al-Ayed 2024; Kwon et al. 2023). Web of Science offers rigorous journal curation and mature citation tracking, supporting reproducible, high-quality retrieval; Scopus offers broader interdisciplinary and journal coverage, relevant given AI-HRM spans management, computer science, and psychology, and provides a complementary citation index. Together they yielded 9,647 records through a three block Boolean structure combining AI technology terms (e.g., artificial intelligence, machine learning, predictive analytics), HRM terms (e.g., talent acquisition, workforce planning, compensation), and evaluation terms (e.g., performance measurement, KPI, ROI, benchmarking), with AND across blocks and OR within blocks, following established systematic review protocols (Ghosh et al. 2023; Li et al. 2023; Erro-Garcés and Aramendia-Muneta 2023; Sharma et al. 2025). Google Scholar was not used as a primary search database but supported backward and forward citation chaining and identification of grey literature not indexed in Web of Science or Scopus. To offset its lower precision and indexing transparency, Google Scholar-derived records underwent the

same title, abstract, and keyword screening and independent double screening applied to primary-database records (Section 3.4), with peer-reviewed status verified before inclusion. This process contributed 7 of the 68 included studies, identified through snowball searching after full text retrieval of the primary sample (Section 4.1).

3.3 Inclusion and Exclusion Criteria

Table 1: Inclusion and exclusion criteria

Criterion	Include	Exclude
Topics	AI systems and HRM functions	Unrelated topics
Date	Studies published 2020 onward	before year 2020
Main Source	Scopus, web of science. Google Scholar	from other journals
Area of Research	Business Management Economics, Applied psychology, Computer & Social science	Other areas
Secondary Source	Company documents, websites, and papers on the listed topics.	Unrelated Secondary sources
Geography	Not restriction	NA
Language	English	Studies in other languages

The date limit captures recent technological developments. Primary academic sources provide rigour, supplemented by secondary industry sources for practical insight. The interdisciplinary scope reflects AI-HRM's cross domain nature, and the English language restriction ensures standardisation with no geographic limit (Bhatt & Muduli, 2022; Mer, 2023).

3.4 PRISMA Implementation Process

The process moved through identification (Web of Science and Scopus database searches, supplemented by Google Scholar citation chaining), screening (title, abstract, and keyword filtering against inclusion criteria, with independent double screening and discussion resolved disagreements; Pessach et al. 2020; Yuan et al. 2024; Indarapu et al. 2024), and inclusion (full text assessment of methodological quality, theoretical contribution, and relevance to the research questions).

3.5 Data Extraction and Analytical Approach

Each article was coded for bibliographic details, HRM functions, AI technology type, evaluation frameworks, indicators, methodology, and context. Thematic analysis proceeded through functional mapping, technology identification, framework analysis, and indicator synthesis, ensuring consistent comparison across HR functions and direct alignment with research questions.

4. Results

4.1 PRISMA Results Overview

The search yielded 9,647 articles from Web of Science and Scopus. After removing duplicates and applying inclusion criteria, 9,032 articles were excluded, leaving 615 for title and abstract screening. This produced 113 articles for full text retrieval; 12 could not be retrieved, though their citations informed a snowball search. This process yielded 61 included articles, plus 7 more identified through snowball searching, for a final dataset of 68 studies.

4.2 Evaluation Frameworks and Concepts for Assessing AI Impact in HRM (RQ1)

The systematic review revealed 20 evaluation frameworks across the four core HRM functions, organised into three primary categories.

Table 2: Evaluation Frameworks Mapped to HRM Functions

Framework Category	Framework/Model	HRM Function	Source
Strategic & Organizational	Path Analysis Model	Cross-functional	Al-Ayed (2024)
	HRM(AI) Assimilation + TOP Model		Prikshat et al. (2023)
	AI-Employee Productivity-Performance Mediation Model		Kassa & Worku (2025)
	AI Maturity Models		Sharma et al. (2025)
Function-Specific	Person-Environment Fit Theory	Resourcing Practices	Shet & Nair (2023)
	Framework on Effective Adoption of AI in Talent Acquisition (FEATA)		Roppelt et al. (2024)
	Organizational Justice Theory		Kwon et al. (2023)
	Predictive Modeling Framework		Aycan & Bal (2024)
	ADDIE + Kirkpatrick Model	Employee Development	Bhatt & Muduli (2022)
	Human Capital Theory Integration		Indarapu et al. (2024)
	AI-Mediated Social Exchange Framework		Malik et al. (2022)
	AIHR Construct Evaluation	Compensation & Benefits	Al-Ayed (2024)
	Fair Compensation Assessment		Mer (2023)
	Technology-Mediated Exchange	Employee Relations	Malik et al. (2023)
	Mental Health Monitoring		Mer (2023)
Technical & Ethical	ML Performance Metrics (F1, AUC, ROC)	Cross-functional	Nandal et al. (2024)
	GDPR Compliance Assessment		Indarapu et al. (2024)
	Fairness Audit Framework		Böhmer & Schinnenburg (2023)
	Human-AI Trust Framework		Khushk et al. (2024)
	Financial ROI Models		Chaudhuri et al. (2024)

4.3 Performance Indicators for Measuring AI-enhanced HRM Effectiveness (RQ2)

The review identified over 100 performance indicators across the four core HRM functions.

Table 3: Performance Indicators across HRM Functions

HRM Functions	Traditional Indicators	Novel AI-Specific Indicators	Source
Resourcing Practices	Time-to-hire reduction, Cost-per-hire optimization, Candidate diversity metrics	P-G Fit & P-S Fit assessments, Justice Perception (CASA Theory), Candidate Acceptance Rate (CAR) and Application Response Time (ART)	Shet & Nair (2023); Kwon et al. (2023); Aycan & Bal (2024); Benabou et al. (2025) Nandal et al. (2024) Socoliuc et al. (2025)
Employee Development	Training ROI, Knowledge retention rates, Certification success rates. AI-mediated exchange quality metrics	Personalization accuracy, Engagement retention curves, VR training efficiency, Bias reduction delta Personalized HRM ROI, P-O Fit score,	Bhatt & Muduli (2022); Malik et al. (2023); Dutta & Mishra (2025) Sharma et al. (2025) ;Alexander et al. (2025); Mer (2023);
Compensation & Benefits	Pay equity analysis, Benefits satisfaction, Cost efficiency metrics	Dynamic salary prediction accuracy, Salary range recommendation accuracy AI transparency in pay decisions, Performance-based pay classification accuracy	Mer (2023); Budhwar et al. (2023); Lee et al. (2024)

HRM Functions	Traditional Indicators	Novel AI-Specific Indicators	Source
Employee Relations & Communication	Employee satisfaction, Communication effectiveness	Sentiment analysis (NLP), Chatbot resolution accuracy, eNPS, AI-usage interaction volume, Organizational agility metrics, Privacy compliance index	Dutta & Mishra (2025); Venugopal et al. (2024); Sharma et al. (2025) ; Khushk et al. (2024); Giermindl et al. (2022)

Table 4: Emerging Cross-Functional AI Indicators

Indicator Category	Specific Metrics	Application Context	Sources
Technical Performance	F1-scores, AUC values, Feature importance rankings, Predictive accuracy (80-95%)	Model validation across all functions	Gowrabhathini et al. (2024); Hickman et al. (2024)
Ethical & Compliance	Bias audit frequency, AI transparency indexes, Diversity uplift indexes, Procedural fairness scores Sourcing algorithm fairness index, Algorithmic transparency score	Responsible AI implementation	Indarapu et al. (2024); Kwon et al. (2023); Alexander et al. (2025)
Human-Centered Wellbeing	Mental health improvement scores, Burnout detection accuracy, Emotional intelligence recognition	Employee wellness monitoring	Mer (2023)
Organizational Impact	Task automation rates, Decision-making efficiency, HR strategic value ratios, Innovation throughput	Strategic AI contribution	Samman & Obaidly (2024); Venugopal et al. (2024); Li et al. (2023); Kassa & Worku (2025); Sharma et al. (2025); Aycan & Bal (2024)

4.4 Synthesis and Integration of Findings

The identified frameworks and indicators show HR measurement evolving from operational metrics toward strategic, ethical, and transformational assessment. Of the 20 frameworks, 60% incorporate ethical considerations and 75% employ predictive analytics, while resourcing and employee development show the highest indicator diversity. Growing emphasis on fairness metrics, justice perceptions, and bias audit frequency reflects responsible AI implementation as the field expands beyond efficiency toward engagement, innovation, and workforce agility, indicating AI's potential to transform, not merely optimise, HR practices.

5. Discussion

5.1 Key Findings on Frameworks and Indicators (RQ1, RQ2)

Advanced methodologies include path models (Al-Ayed, 2024), hybrid optimisation systems (Pessach et al., 2020), and assimilation stage models (Prikshat et al., 2023). Novel AI specific indicators, such as anthropomorphism scales, hyper personalisation scores, and real time experience feedback loops (Kwon et al., 2023; Malik et al., 2023), sit alongside technical indicators such as F1 scores, AUC, and prediction accuracy, now standard for validating attrition, promotion, and performance models (Nandal et al., 2024; Hickman et al., 2024).

Framework sophistication varies by function: resourcing shows the highest maturity, moving beyond process efficiency toward fairness, fit, and candidate experience (Kwon et al., 2023; Shet & Nair, 2023). Roppelt et al. (2024), analysing 19 multinational corporations, introduce the Framework on Effective Adoption of AI in Talent Acquisition, mapping adoption motives, barriers, and success factors. Employee development uses ADDIE and Kirkpatrick models combined with AI driven personalisation (Bhatt & Muduli, 2022). Compensation frameworks are less developed but integrate salary range simulation and equity gap detection (Mer, 2023; Budhwar et al., 2023). Lee et al. (2024) found compensation level the strongest predictor of firm sales among 36 HR variables, evidence that AI powered compensation analytics carry strategic value. Communication and engagement models emphasise emotional and relational impacts, including sentiment monitoring and trust building (Malik et al., 2023; Samman & Obaidly, 2024).

Resourcing also leads in quantitative, model driven indicators, including clustering based fit scores and applicant job match models (Shet & Nair, 2023; Pessach et al., 2020). Socoliuc et al. (2025) report a Candidate Acceptance

Rate of 90% through AI assisted pre vetting, and an Application Response Time of 70% within 24 hours, both measurable gains beyond time to hire. Employee development shows balanced quantitative and qualitative approaches, including learning personalisation depth and skill progression tracking (Bhatt & Muduli, 2022). Employee relations increasingly rely on AI enhanced qualitative measures: Malik et al. (2023) report an AI staffing chatbot achieving 90% query resolution and cutting lead times by 20%, confirming these outcomes are now measurable (Sharma et al., 2025).

The reviewed frameworks increasingly integrate classical theories, including Person Environment Fit, Human Capital Theory, and Organisational Justice, alongside ethical indicators such as bias audit frequency, justice perception scales, and AI fairness perception indexes (Indarapu et al., 2024; Böhmer & Schinnenburg, 2023; Giermindl et al., 2022), particularly in resourcing where decisions significantly affect careers and diversity.

5.2 Toward Integrated, Rigorous Measurement

Convergence toward integrated, multi stakeholder assessment is clear: the evolution from simple metrics like time to hire to measures such as perceived interactional justice from AI (Kwon et al., 2023) reflects the need for multi layered assessment pairing quantitative precision with qualitative insight, as shown by Shet and Nair (2023) and Malik et al. (2023) in their integration of user experience into evaluation loops. Indicators such as organisational agility and innovation throughput reflect AI's capacity to enhance enterprise wide performance beyond HR efficiency; Kassa and Worku (2025) confirm this, finding that AI affects organisational performance both directly ($\beta = 0.390$, $p < 0.001$) and indirectly through employee productivity ($\beta = 0.360$, $p < 0.001$), with productivity as a partial mediator, evidence that AI-HRM evaluation must encompass broader organisational outcomes. Integrating technical metrics such as AUC and ROI with perception based measures such as justice perceptions and adoption sentiment reduces over reliance on system generated metrics that lack context (Kwon et al., 2023; Sharma et al., 2025); Dutta and Mishra (2025) show AI based virtual assistants improve engagement both directly and through perceived fairness as a mediator, confirming subjective measures as essential complements to technical metrics.

5.3 Implications for Theory and Practice

This review identifies AI-HRM evaluation as a distinct domain requiring specialised frameworks that integrate technological, behavioural, and ethical considerations, advancing both AI and HRM theory. For practice, organisations must adopt evaluation frameworks aligned with organisational and ethical goals and invest in HR capability to interpret AI outputs responsibly (Sharma et al., 2025). Deepa et al. (2024) show that successful adoption also requires managerial competencies, including cognitive, human, and social capital, so evaluation frameworks must incorporate organisational readiness alongside technical performance

6. Conclusion, Limitations, and Future Research Directions

6.1 Conclusion

This review examined 68 peer reviewed studies to understand how AI's contribution to HRM is evaluated across four core functions. Using PRISMA methodology, it identified 20 evaluation frameworks and over 100 performance indicators, evidencing a shift from descriptive to predictive and prescriptive measurement, though standardisation challenges, sectoral limitations, and implementation gaps remain. This research establishes AI-HRM evaluation as a distinct domain requiring specialised frameworks that integrate technological, behavioural, and ethical considerations, offering organisations evidence-based guidance for balancing technical performance with human centered outcomes. Interdisciplinary research and global benchmarking remain essential to ensure AI in HRM evolves as a force for equitable and sustainable workforce transformation.

6.2 Limitations and Future Research Directions

The formal Boolean search was restricted to Web of Science and Scopus, and to English language publications, potentially excluding non-English and industry sources. Google Scholar's supplementary use for citation chaining and grey literature carries residual selection risk given its lower indexing transparency. Studies predominantly examined large, technology focused organisations using cross sectional designs with short evaluation periods, limiting applicability to smaller enterprises, traditional industries, and understanding of long term effects. Ooi et al. (2022) show that AI implementation across talent acquisition, human capital development, and performance management significantly improves organisational performance in a Southeast Asian context, while Kshetri (2021) shows that AI-HRM applications carry distinct implications in emerging economies, particularly in reducing nepotism and favouritism in recruitment, a dimension absent from current evaluation frameworks and pointing to a clear need for cross cultural measurement validation.

Future priorities cluster into four areas. Methodologically, longitudinal designs and standardised, comparable evaluation protocols are needed to capture both technical and human centred outcomes beyond cross sectional snapshots. Contextually, testing frameworks across underrepresented countries and developing sector specific evaluation methods for manufacturing, healthcare, education, and government would extend generalisability. Technologically, evaluation approaches must keep pace with emerging AI capabilities not yet captured by current indicator sets. Ethically and managerially, priorities include fairness and transparency guidelines, the managerial competencies HR managers need to interpret AI driven systems (Deepa et al. 2024), and the cultural and institutional contexts shaping algorithm transparency (Kim et al. 2025), alongside supporting policy and training infrastructure.

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