Artificial Intelligence Adoption in Human Resource Practices: A Review of Literature Across Educational and Corporate Sectors

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Abstract: *Artificial intelligence (AI) has become a transformative force in human resource management (HRM), reshaping practices across corporate and educational contexts. Despite a growing body of empirical work, no prior systematic review has directly compared AI adoption in HRM across these two distinct yet converging sectors. Guided by the SPAR-4-SLR search protocol, reported according to PRISMA 2020 standards, and grounded in the 5W+H framework for research question formulation, this systematic review synthesises 62 peer-reviewed studies published in Scopus and Web of Science between 2015 and 2024. How results appear follows the TCCM blueprint, yet trust checks rely on five distinct POWER signs. Four questions steer the research - how AI steps into HR across areas comes first; what benefits and snags tag along with AI-HR tools shows up next; differences in how schools use AI-HR compared to businesses takes third place; last is where researchers might look later. Findings point to faster HR work - hiring times drop by about 75 percent, profits climb close to 20 percent - even as intelligent tutors boost learning outcomes between 20 and 30 percent. Still, problems linger - biased systems, shaky data protection, murky decision paths, resistance among workers. Viewed through TCCM lenses, hidden gaps emerge, hinting strongly at future efforts cantered on fair standards, extended cross-sector studies, experimental models, and places usually ignored.*

Keywords: Artificial intelligence; human resource management (hrm); systematic literature review(slr); TCCM; SPAR-4-SLR; PRISMA; educational sector; corporate sector; AI adoption; POWER framework

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Introduction

Where machines meet people practices, a shift unfolds quietly inside modern workplaces. Because digital tools now shape choices once made by hand, hiring, reviews, training, morale checks, and staffing forecasts change form slowly over time (Guo, 2018); (Vrontis et al., 2022). Though first named during a summer gathering in New Hampshire decades ago, the idea of thinking machines drifted through theory until real-world uses took hold much later. After years of quiet progress, breakthroughs in pattern recognition, speech understanding, and forecasting models around 2015 pushed these systems into daily HR routines (Haenlein & Kaplan, 2019). *These days, cash pouring into artificial intelligence reveals just how quickly change is happening. By 2021, global spending on AI reached almost $85.3 billion, according to IDC - yet that number might exceed $204 billion by 2025, rising around twenty-five percent annually. Research from groups such as PwC, IBM, Deloitte, and Gartner hints machines could add nearly $16 trillion to the world's economic output within ten years, equalling about one-seventh of total global income. 1Workforce structures transform because World Economic Forum research indicates seventy five million positions vanish while one hundred thirty million unique jobs appear within seasons demanding organizations educate staff immediately regarding modern technical necessities so human resource leads prevent major professional performance loss problems*

Need for This Review

Despite significant research momentum, the existing AI–HRM literature remains fragmented in three important respects. First, most prior reviews focus narrowly on specific HR functions—such as recruitment (S. K. Banerjee et al., 2015) or learning and development (Zawacki-Richter et al., 2019)— Although scholars publish much research today, current studies about AI inside human resource departments suffer from fragmentation regarding three key factors. Primarily, authors analyze particular tasks like recruitment. Because real-world training happens in classrooms, that gap matters more than it seems at first glance (Akhmadieva et al., 2024). Third, the methodological rigour of existing reviews varies considerably: few apply structured protocols such as SPAR-4-SLR (Siddaway et al., 2026) or report findings according to PRISMA 2020 (Page et al., 2021), and even fewer employ established analytical frameworks such as TCCM (Paul et al., 2024) to organise and synthesise findings systematically. This review addresses all three gaps.

Comparison with Previous Reviews

Several existing reviews have advanced the AI–HRM literature but each has important limitations that the present work addresses. Looking at 85 studies, researchers found AI helps HR work better when people and machines collaborate - results improve compared to using just one or the other. Still, they mixed school-based and business HR settings without separating them. The analysis skipped TCCM for organizing findings. It also missed using SPAR-4-SLR to guide how studies were searched (Vrontis et al., 2022). A closer look at how artificial intelligence shapes jobs emerged from reviewing 63 separate studies, applying a method that tracks multiple effects at once. Automation showed up clearly, along with ways machines boost human work, sometimes stepping in fully where people used to operate. Still, the whole picture focused only on employment settings - schools and learning environments were left out completely (Pereira et al., 2023).

(Hmoud, 2021) investigated AI adoption in HRM conceptually in Forum Scientiae economia, establishing a foundational understanding of adoption drivers and barriers but without a systematic search protocol or sector comparison. (Zawacki-Richter et al., 2019) conducted a systematic review of 146 AI studies in higher education, finding that AIED research focused predominantly on learner-facing applications, leaving the institutional HRM perspective largely unaddressed. (Pedrami & Vaezi, 2025) Lately added a meta-synthesis about what drives AI use in HRM, showing adoption jumped by 70 percent in half a decade - yet still missed comparisons between fields or any TCCM context. Research scholars view this work as unique, applying SPAR-4-SLR frameworks and PRISMA 2020 protocols simultaneously. Authors integrate TCCM, POWER, and 5W+H structures into unified methodology instead of separate segments. These investigators contrast academic sector findings with private firm personnel policies for identifying gaps where digital tools affect talent acquisition through machine learning.

Scope of This Review

Research published from 2015 to 2024, in Scopus and Web of Science, reveals that 2015 was chosen as the starting date for this work because it marked when deep learning became mainstream, resulting in many of the tasks once considered impossible for neural networks and machines (such as language comprehension) becoming possible; as well as improvements in the accuracy of projections for many tasks; and many of these developments were happening outside of laboratories, as they were quickly developing into practical HR technologies (Haenlein & Kaplan, 2019); (Pedrami & Vaezi, 2025). Companies and educational institutions around the globe utilize Human Resource Technology (HR Tech) to evaluate key components of their business, including how they attract, onboard and train new employees; monitor and provide ongoing employee engagement; and how they plan their teams. The starting point for this analysis is through the lens of shifting concepts related to artificial intelligence (AI). Column one provides a map of the major elements of HR Tech as identified in various management literature to provide context for this analysis.

Table 1: Evolution of Artificial Intelligence Definitions in the Management and HRM Literature (2018–2021)

Year	Author(s)	Definition
2018	(Guo, 2018)	“A conceptual framework enabling machines to mimic human cognitive capabilities for organisational decision-making.”
2019	(Haenlein & Kaplan, 2019)	“A system's ability to correctly interpret external data, learn from it, and use those learnings to achieve specific goals through flexible adaptation.”

2019	Dwivedi et al.	"The increasing capability of machines to perform roles currently performed by humans within the workplace and society."
2020	Malik et al.	"Development of intelligent machines or computerised systems that can learn, react, and perform activities like humans across a range of business tasks."
2020	(Makarius et al., 2020)	"A system's capability to correctly interpret external data, learn from it, and use those learnings to achieve specific goals through flexible adaption."
2020	(Tykkyläinen Saila, 2020)	"Use of computer to model intelligent behaviour with minimal human intervention; a general term encompassing a range of machine-based intelligence systems."
2021	(Mikalef & Gupta, 2021)	"The ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organisational and societal goals."

Note. Compiled by the authors from primary sources cited above. Definitions selected based on citation frequency (>50 Scopus citations) and direct relevance to HRM applications.

Research Questions

To ensure clarity; the procedure was developed by combining 6 essential components: who, what, where, when, how and why; which have also resulted in the development of 4 specific questions. These questions provide guidance for the overall analytical process and are non-overlapping/non-gapping in their respective analytical processes. The analytical process uses these questions to develop an analytical framework that defines how data will be measured, evaluated and used through the analytical process and ultimately leads to future paths of investigation. The questions are also mutually supportive to one another and are therefore aligned with their individual purposes (Paul et al., 2024).

RQ1: How has the artificial intelligence been adopted in HR management practices across the educational and corporate sectors between 2015 and 2024? (What/How dimension — mapping adoption patterns)

RQ2: What are the primary benefits and challenges associated with AI adoption in HRM across both sectors? (What dimension — documenting outcomes and barriers)

RQ3: How do AI-based HR strategies and outcomes differ between educational institutions and corporate organisations? (Where/Who dimension — sector comparison)

RQ4: What are the key future research directions warranted by the current state of the AI–HRM literature? (Why/Where-next dimension — knowledge gaps and agenda)

Coherence throughout all following sections will be maintained through these four questions: review methodology operationalizes search to address all four; literature synthesis will substantiate RQ1 through RQ3; and future research agenda will provide a direct response to RQ4.

Review Methodology

Looking at past studies, this review uses several different structures to stay organized. One type focuses on steps taken during the work, shaping how tasks unfold. Another shapes how results get shared, centring clarity in presentation. A third checks depth and care in execution, making sure nothing gets overlooked. Each choice appears in the table ahead, explained by reasoning behind it, then discussed one by one after.

Framework	Type	Purpose in This Review	Citation
SPAR-4-SLR	Process-oriented	Search protocol design; ensuring replicability and reduced selection bias	(Siddaway et al., 2026)
PRISMA 2020	Process-oriented	Transparent reporting of study selection and flow	(Page et al., 2021)
5W+H	Process-oriented	Establishing the four research questions (Who, What, Where, When, How, Why of AI–HRM adoption)	(Rosado-Serrano, 2023)
TCCM	Outcome-oriented	Structuring findings across Theory, Context, Characteristics, and Methodology; generating future research agenda	(Rosado-Serrano, 2023)
POWER	Quality-oriented	Five quality parameters: Purpose, Organisation, Width (scope), Evidence, Rigour — applied as self-audit checklist during manuscript preparation	(Bandara et al., 2015)

Note. SPAR-4-SLR = Searching, Practical screen, Analytical screen, Reading, Evaluating, Reporting, for Systematic Literature Reviews; TCCM = Theory–Context–Characteristics–Methodology; POWER = Purpose, Organisation, Width, Evidence, Rigour.

2.1 Process Framework: SPAR-4-SLR

To shape how the search unfolded, the SPAR-4-SLR method guided everything from start to finish. Stage one involved gathering - pinpointing the field of interest, key queries, along with what would count in or out. Next came organizing - building structured keyword chains plus planning where searches would run. Then followed reviewing - using set rules to sort relevant items while weeding out weak ones. Finally, insights were pulled together under the TCCM lens, leading into clear reporting of outcomes (Siddaway et al., 2026).

2.2 Database Selection and Base Year Justification

Among available options, Scopus plus Web of Science stood out - not due to popularity but based on clear support from prior studies. The first reason ties to size: it holds more records than any other system, pulling data from above twenty-five thousand reviewed publications, especially those central to management and human resource fields - titles released by major publishers like Elsevier, Emerald, Springer, Sage, Taylor & Francis appear regularly inside it (Burnham, 2006). Another layer comes through Web of Science, which picks up titles missed elsewhere, particularly ones listed in the Social Sciences Citation Index; key names such as International Journal of Human Resource Management along with Human Resource Management Review fall into that net, widening reach across disciplines without leaning too heavily on one area. Functionality matters just as much - both platforms allow complex searches using precise logic rules, follow where citations lead, sort findings by topic zones, capabilities needed if a study follows the SPAR-4-SLR method correctly. To keep standards high, only journals rated two stars or higher in the ABS Academic Journal Guide 2021 made it into the final pool.

It began in 2015 because that year sat just after deep learning took off - thanks to breakthroughs seen between 2012 and 2014 in image recognition contests. After those advances, use of neural nets spread fast through many real-world areas. Around 2015, tools for understanding human language started working well enough, alongside forecasting systems and cloud-powered machine learning setups. These together made it possible to start using AI meaningfully in managing people work tasks. Studies later showed AI use jumped by 70 percent within five years past 2015, proving that moment marked a turning point (Pedrami & Vaezi, 2025).

2.3 Search Protocol

The following Boolean search string was applied across title, abstract, and keyword fields in both Scopus and WoS:

> *("Artificial Intelligence" OR "AI" OR "Machine Learning" OR "Natural Language Processing") AND ("Human Resource Management" OR "HRM" OR "Talent Management" OR "Recruitment" OR "Employee Training" OR "Performance Management") AND ("Corporate" OR "Educational" OR "Organisation" OR "Workplace")*

Eight more articles made it into the review after clearing the full check. These came from tracking earlier and later works linked to heavily referenced papers - those with over fifty Scopus mentions - that predate organized AI–HRM cataloging.

2.4 Inclusion and Exclusion Criteria

Table 2 presents the structured inclusion and exclusion criteria applied during the screening phase.

Table 2: Inclusion and Exclusion Criteria for the Systematic Review

Criterion	Inclusion	Exclusion
Publication type	Peer-reviewed journal articles	Conference papers, dissertations, grey literature
Language	English-language publications only	Non-English publications

Time span	2015–2024 (post-deep-learning era in AI; see §1.3 for base-year rationale)	Studies published before 2015
Topic relevance	AI applications in HRM in corporate or educational settings	Studies unrelated to HRM; pure computer-science papers without HR application
Database & quality	Scopus and Web of Science; journals ranked 2* and above per ABS Academic Journal Guide 2021	Predatory, unverified, or non-indexed journals
Availability	Full-text accessible	Abstract-only or paywalled without institutional access

Note. Criteria developed following SPAR-4-SLR guidelines (Siddaway et al., 2026) and PRISMA 2020 standards (Page et al., 2021). ABS = Association of Business Schools Academic Journal Guide 2021.

2.5 Study Selection: PRISMA 2020 Flow

The PRISMA 2020 process appears in Figure 1, outlining how studies were selected. Database queries returned 1,247 entries - 712 from Scopus, 535 from Web of Science. Duplicates made up 189 of those, leaving 1,058 to be reviewed via titles and abstracts. From that group, researchers evaluated 312 papers in full. Most of the 312 did not meet standards: 98 lacked an HRM emphasis, 34 were not in English, 61 had no accessible full version, while 57 came from questionable journals. Eight more articles met the criteria, found through citation tracking. The synthesis brought together 62 published studies in total.

IDENTIFICATION

Records identified through database search Scopus: n = 712 | Web of Science: n = 535 Total: n = 1,247

▼

SCREENING

After duplicates removed n = 1,058	Duplicates removed: n = 189

▼

Records screened by title & abstract n = 1,058	Records excluded (off-topic / non-English): n = 746

▼

ELIGIBILITY

Full-text articles assessed for eligibility n = 312	Full-text excluded (n = 250): • No HRM focus: n = 98 • Non-English: n = 34 • No full text: n = 61 • Predatory journal: n = 57

▼

INCLUDED

Studies included in final synthesis n = 62	Citation search additions: n = 8 (forward + backward searches on highly cited papers >50 citations)

Figure 1. PRISMA 2020 flow diagram for study selection and screening (Page et al., 2021).

2.6 Quality Assurance: POWER Framework

For solid methods, we used the five POWER criteria (Bandara et al., 2015) as a personal audit tool while drafting The purpose of the paper is clearly defined in terms of intent, limitations, and relevance as outlined between sections 1.1–1.3; whereas, the logical arrangement of information is assessed through the relationship of all, including how questions relate to design, results, and next steps in section 2. The broad applicability of the information was supported by using a variety of sources, which consisted of two databases (with multiple cited references), along with articles published over a period of ten years. The result of this study was based upon the analysis of 62 peer-reviewed publications, with additional sources obtained by relying on trusted industry reports from organisations such as International Data Corporation (IDC), World Economic Forum (WEF), Learning and Development Benchmarking initiatives. The procedures for conducting this research were consistent with the SPAR-4-SLR guidelines and complied with the PRISMA-2020 reporting standards, therefore providing a framework to replicate/repeat all steps in this process, without difficulty.

Analytical Framework: TCCM

The TCCM approach is used to guide an analysis by identifying four 'paths' that lead to clear research outcomes. Instead of summarizing the previous studies under each path, the approach organizes the findings according to theory, setting, characteristics of the studies, and methodology. One of the paths includes looking at the foundational concepts of research, while another focuses on where research has been conducted. Study traits - what they test, improve, or struggle with - are mapped alongside patterns in design choices. Because it emphasizes results, TCCM fits well with reviews aiming to shape future management scholarship. Its role here responds directly to RQ4, building a forward-looking direction anchored in existing knowledge.

Shown in Figure 2 is the TCCM framework adjusted to fit the AI–HRM analysis, mapping out four key areas alongside their associated topics drawn from the set of 62 reviewed papers.

AI in HRM: TCCM Analytical Framework	
(T) Theory Technology Acceptance Model (TAM) · Resource-Based View (RBV) · Institutional Theory · Human Capital Theory · Critical Management Studies	**(C) Context** Corporate MNCs (North America, Europe, East Asia) · Indian SMEs · UAE energy sector · K-12 & higher education · EdTech platforms
(C) Characteristics AI applications: Recruitment · L&D · Performance Mgmt · Engagement · Workforce Planning · Compensation Benefits & challenges documented	**(M) Methodology** SLRs & meta-analyses dominant · Survey-based quantitative research · Case studies · Conceptual frameworks · Limited longitudinal designs

***Figure 2. TCCM analytical framework adapted for the AI–HRM systematic review* (Rosado-Serrano, 2023)**

Literature Synthesis: Contributions of Key Studies

What stands out in this review is clarity on how every analyzed study shapes the final interpretations - a response to the editor's note about tracking sources. Shown in Table 3, a breakdown links seventeen core works to their focus within human resource functions, methodological approach, role in shaping results here, and alignment with targeted research queries. Context for these entries unfolds across sections 6 through 8, where analysis weaves each work into broader argumentation. Reading them together brings coherence.

Table 3: Literature Contributions Synthesis — How Key Studies Form Review Results (Selected from n = 62)

Author(s) & Year	Study Type	HR Function Focus	Key Contribution to This Review	RQ
(S. K. Banerjee et al., 2015)	Empirical (India survey)	Recruitment	First India-specific study; identifies adoption barriers in SMEs vs. large corporates; supports base-year selection	RQ1, RQ3
(Guo, 2018)	Conceptual framework	All HRM functions	Proposes AI–HRM application framework; foundational for AI classification in HR operations	RQ1
(Haenlein & Kaplan, 2019)	Conceptual review	General AI	Defines AI capability spectrum; justifies 2015	RQ1

			base year (deep learning onset)	
(Black & van Esch, 2020)	Critical analysis	Recruitment	Identifies ethical risks as AI shifts from administrative to prescriptive recruitment; informs bias challenge discussion	RQ2
(Makarius et al., 2020)	Conceptual	Organisational AI adoption	Sociotechnical framework for AI integration; informs theoretical grounding via TCCM T-dimension	RQ1, RQ2
(Broadbent & Laughlin, 2009)	Theoretical model	Performance management	Links AI to AI-enabled HRM for performance; supports Section 6.3	RQ1
(Zawacki-Richter et al., 2019)	Systematic review (n=146)	L&D / educational AI	Largest AIED systematic review; reveals learner-centric focus gap in institutional HRM; informs sector comparison	RQ1, RQ3
(Lepenioti et al., 2020)	Literature review	Workforce analytics	Extends AI discussion to prescriptive analytics; supports workforce planning and performance management sections	RQ1, RQ2
(Hmoud, n.d.)	Conceptual study	All HRM functions	Establishes adoption driver–barrier framework; foundational for challenges section (§8)	RQ2
(Mikalef & Gupta, 2021)	Empirical	Organisational AI capability	Outcome-centric AI definition; validates AI capability as organisational performance driver	RQ1
(Vrontis et al., 2022)	Systematic review (n=85)	All HRM functions	Confirms human–AI collaboration outperforms either alone; 24% profit margin advantage; validates L&D AI ROI	RQ1, RQ2, RQ3

(Gupta, n.d.)	Empirical review	Employee engagement	Documents chatbot and sentiment analysis tools in HR engagement; supports Section 6.4	RQ1
(Akhmadieva et al., 2024)	Empirical (education sector)	Educational HR/L&D	Tracks AI trends in higher education HRM; essential for educational sector analysis	RQ3
(Pereira et al., 2023)	SLR (n=63)	Workplace AI outcomes	Documents algorithmic bias in recruitment; proposes explainability standards; informs ethics discussion	RQ2, RQ4
(Cappelli et al., n.d.)	Empirical / policy	HRM strategy	Identifies organisational inertia and change resistance as adoption barriers; informs Section 8.4	RQ2
(Pedrami & Vaezi, 2025)	Meta-synthesis & SLR	AI adoption in HRM	Most recent comprehensive review; validates 70% AI adoption growth; highlights skill gap; confirms research gaps	RQ2, RQ4
(Hassan et al., n.d.)	Empirical (UAE)	Recruitment / HR tech	Emerging-market (UAE) evidence for AI–HRM; supports contextual diversity in TCCM analysis	RQ3

Note. SLR = Systematic Literature Review; L&D = Learning and Development; RQ = Research Question. Studies selected based on citation frequency, methodological contribution, and thematic coverage across all four RQs.

Artificial Intelligence in HRM: Applications Across HR Functions

Beginning with digital tools, AI in HRM means using smart technologies - like machine learning, language analysis, predictive models, and automated workflows - to handle or assist human resources duties throughout an employee's time at a company (Guo, 2018). Instead of acting all at once, its use unfolds step by step: first comes gathering information such as job applications, work ratings, and feedback forms; next, software detects trends or oddities within that data; finally, decisions emerge - from suggested actions to automatic steps or alerts needing manager attention. Underpinning much of this shift, the Human Resource Information System functions as the base layer making connections possible (S. K. Banerjee et al., 2015)

As displayed in Figure number 3 is how the 62 reviewed studies break down by the six core HR areas, anchoring the discussion in sections 6.1 through 6.4 with actual data patter ns observed.

HR Function	Research Share (proportional)	%
Talent Acquisition & Recruitment		38%
Learning & Development		22%
Performance Management		17%
Workforce Planning		11%
Employee Engagement		8%
Compensation Management		4%

Figure 3. Distribution of AI–HRM research focus across HR functions in the reviewed literature (n = 62 studies, 2015–2024). Percentages reflect proportion of studies addressing each function as primary focus.

5.1 Talent Acquisition and Recruitment (38% of Studies)

One reason talent hiring draws so much AI research attention lies in how heavily companies invest here, along with clear time and cost improvements tech enables. Early evidence from India, examined by (A. Banerjee et al., 2025), showed major firms bringing automation into hiring well ahead of smaller ones. Slower uptake among midsize businesses tied to limited systems and lack of trained personnel stood out clearly.

(Nawaz, 2024) The utilization of AI to screen candidates greatly reduces the length of the hiring process (75% less) owing to the fact that machine learning systems compare applicant skill sets with valid indicators of success rather than relying on simple keyword scans. However, given the fact that the use of AI will move from providing clerical assistance to actively recommending candidates, (Black & van Esch, 2020) caution that an increase in the possibility of disadvantageous existing workplace bias (in particular, those experienced by women and individuals from ethnic minorities) may occur if equity audit systems and fairness checks are not implemented prior to making decisions on candidates using AI. Talent management assisted by AI occurs in four main stages: locating candidates using meaningful searches; filtering based on automated analysis of resumes and recorded interviews; estimating who is likely to accept job offers made during the selection; and, assisting candidates with digital documents and virtual support services to ultimately begin the start of work.

5.2 Learning and Development (22% of Studies)

(Zawacki-Richter et al., 2019) Looking across 146 studies on AI in education, one pattern stands out - most tools are built for students, not staff. Instead of shaping hiring or workforce planning, these systems focus on adjusting lessons, guiding learners, or scoring work automatically. Because of this tilt, insights into how AI might reshape school personnel practices remain scarce. That gap matters. It means earlier research has overlooked a key part of organizational function.

In corporate L&D, (Vrontis et al., 2022) the L&D Benchmarking Report (2025), there has been a reduction of training expenses by nearly 28% as a result of using virtual teachers in place of physical trainers. Furthermore, those companies employing AI-based learning systems get 24% more revenue compared to other types of learning content. As a consequence of this development due to artificial intelligence, multinational corporations have increased their application of microlearning technology by 31% when compared to previous trends, particularly because of their inclination towards mobile-based and relatively short learning content accessible by smartphones. These developments are not necessarily a result of any change in governing policies but rather an inevitable trend towards new types of digital learning in response to employee requirements.

5.3 Performance Management (17% of Studies)

AI enables real-time, continuous performance monitoring through dashboard analytics, natural language processing of qualitative feedback, and predictive identification of high performers and attrition risks (Lepenioti et al., 2020). (Pereira et al., 2023), More than one perspective on a particular study topic has yielded evidence suggesting that through the use of algorithms, together with statistics, it will be possible to pinpoint individuals likely to become stars or those considering switching jobs (if certain measures are implemented in regard to the protection of data quality and testing for algorithm fairness). The new ways of evaluating employees' work annually will mean a different set of beneficiaries or victims of unfairness related to HR procedures (promotions, pay raises, etc.).

5.4 Employee Engagement, Compensation, and Workforce Planning (23% Combined)

AI-powered chatbots and sentiment analysis tools have emerged as significant instruments for employee engagement, enabling real-time monitoring of workplace morale and proactive issue identification (Gupta, n.d.). More than one perspective on a particular study topic has yielded evidence suggesting that through the use of algorithms, together with statistics, it will be possible to pinpoint individuals likely to become stars or those considering switching jobs (if certain measures are implemented in regard to the protection of data quality and testing for algorithm fairness). The new ways of evaluating employees' work annually will mean a different set of beneficiaries or victims of unfairness related to HR procedures (promotions, pay raises, etc.).The advent of artificial intelligence has enabled pay equity systems to identify unjust pay patterns based upon characteristics that do not relate to an employee’s performance on the job. As a result, users will now obtain personalised rewards from machine learning-based incentives, which will be based upon each employee’s individual behaviour rather than pre-defined benchmarks. The flexibility of reward programmes increases as they no longer rely upon rigid annual adjustments, but can be adjusted continually as changes occur based upon real-time data trends. Forecasting tools can now be used to plan for workforce needs, allowing employers to anticipate potential areas of skill shortages across various departments. Additionally, employers are able to use simulations of probable organisational changes to evaluate the replacement of leadership positions (Cappelli et al., n.d.).

Sector-Wise Comparative Analysis: Educational vs. Corporate Contexts

A key outcome here involves organizing comparisons across fields to respond to RQ3. Although both areas aim at drawing in, growing, alongside keeping skilled individuals, their paths diverge clearly when it comes to oversight methods, financial frameworks, ways of measuring results, plus how quickly new tools are taken up. Found within Table 4 is a synthesis built using insights from the 62 selected works together with trusted background materials.

Table 4: Comparative Analysis of AI–HRM Adoption Across Educational and Corporate Sectors

Parameters	Educational Sector	Corporate Sector
Market size (2024)	USD 3.71 trillion; EdTech sub-segment USD 163.49 billion; CAGR 13.3% (Akhmadieva et al., 2024)	USD 412.83 billion; projected USD 808.89 billion by 2033; CAGR 7.76% (L&D Benchmarking Report, 2025)
Primary objective	Holistic intellectual, social, and civic development; credentialling and lifelong learning	Employee performance improvement, skills gap filling, regulatory compliance, and ROI maximisation
Funding model	Predominantly government-funded; growing private EdTech investment	Internally funded L&D budgets; average USD 16.1 million for large US organisations (2025)
AI technology adoption	86% of students use AI in coursework; adaptive learning in 47% of institutions (Digital Education Council, 2024)	93% of organisations using eLearning; 50% use AI analytics for performance evaluation (L&D Benchmarking Report, 2025)
Primary AI applications	Adaptive learning, AR/VR simulations, intelligent tutoring systems, automated assessment	AI-driven recruitment, predictive workforce analytics, chatbots for engagement, vILT, microlearning
Key AI challenges	Institutional inertia, funding constraints, digital divide, student data privacy (FERPA, DPDP Act)	Algorithmic bias, high implementation costs, employee resistance, evolving regulatory compliance

Performance metrics	Academic outcomes, enrolment rates, learning progression, student satisfaction	ROI, time-to-hire, retention rates, profit margin improvement (up to 24%; (Vrontis et al., 2022)
Strategic AI orientation	Learner-centric; focused on pedagogy and student outcomes	Efficiency-centric; focused on organisational productivity and workforce cost optimisation
Convergence trend	Corporate L&D logic imported via EdTech platforms; growing focus on skills-based credentialling	Corporate universities drawing on educational pedagogical frameworks; growth of AI upskilling (85% of firms by 2030)

Note. Secondary data from IDC (2021), World Economic Forum (2020), Digital Education Council (2024), L&D Benchmarking Report (2025), and (Akhmadieva et al., 2024). All figures cross-referenced against included study evidence.

Despite similar access, progress differs sharply across sectors. Where profit drives decisions, tools follow quickly. By 2025, nearly all large firms used digital learning platforms. Schools show strong student-level engagement - most learners already interact with AI daily. Yet leadership structures there remain unchanged. Institutional adoption lags behind individual use. Financial backing shapes outcomes. Corporate departments integrate new systems as standard practice. In education, such shifts stay isolated, not embedded.

Examining the utilisation of artificial intelligence more closely reveals a significant divergence in focus from traditional business orientation toward an education-based approach to the utilisation of artificial intelligence. Business generally designs its artificial intelligence tools to meet the needs of businesses in terms of speed and return on investment (ROI). That is, companies focus on using technology to recruit faster or reduce the cost of training new employees. Education makes much more of an effort to develop the use of technology in general to meet the needs of students and improve their learning. The difference also highlights two ways in which these two lines of business will eventually intersect: Schools may begin using the same processes as companies for managing the talent of their employees, and companies may expand their employee-training processes by applying education-based processes to training.

Challenges in AI Adoption in HRM

In relation to RQ2, a review of the 62 chosen articles indicates that there are five categories of challenges common to both domains. The problems are not purely technical, but also have important social and organizational implications. Due to the complexity of the problems, the solution will require changes in governance processes, as well ((Cappelli et al., 2019.); (Pereira et al., 2023)).

7.1 Algorithmic Opacity and Trust Deficits

Machine learning systems in HR function as opaque 'black boxes': their decision logic is neither visible nor interpretable to HR professionals or affected employees (Black & van Esch, 2020). This opacity erodes institutional trust and complicates accountability when algorithmic decisions produce adverse outcomes in recruitment, performance evaluation, or compensation. (Pereira et al., 2023)argue that mandatory explainability standards and third-party algorithmic audits are necessary structural remedies, not optional enhancements.

7.2 AI Literacy Gaps and Awareness Deficits

To deploy AI effectively, able HR practitioners to interpret AI results critically, configure algorithms, and identify model boundaries are needed. Many human resources executives do not understand AI well enough for it to help them with decision-making; this lack of understanding is one of the reasons why widespread adoption of AI has not occurred to date. If decisions are made without sufficient input from human resources staff on automated recommendations that do not align with their experience and judgment, the outcome may not be positive. Schools also have additional impediments to progressing with the use of AI; one key impediment is the lack of adequate education for teachers about AI; thus, teacher scepticism towards AI affects the pace of progress. In addition, there is very little technology training on how to become technologically ready throughout many colleges (Pedrami & Vaezi, 2025).

7.3 Data Privacy and Cybersecurity Risks

Since AI programs in HRM deal with vast amounts of data, they deal with sensitive information such as personality tests, performance evaluations, health problems, and compensation history. Since companies do not have adequate security, employee data, which is helpful to create positions in the market, may accidentally be leaked. Educational institutions have to deal with regulations as well; laws such as FERPA in the USA and the Digital Personal Data Protection Act in India from 2023 regulate how learner data is handled (Almarashda et al., 2021).

7.4 Resistance to Change and Organisational Inertia

AI adoption requires a fundamental shift in work practices and organisational culture. (Cappelli et al., n.d.) The opposition shown by line managers, HR personnel, and union representatives to the adoption of AI technology is generally similar to the technical obstacles. This opposition is primarily fueled by the concern for job loss. From the start, plans to adopt artificial intelligence should include strategies for guiding people through change. Clear messaging helps, but so do opportunities to learn new skills. Shared decision-making structures also ease tensions. How organizations handle these human factors shapes overall success more than code alone.

7.5 Algorithmic Bias and Ethical Violations

Though designed to streamline hiring, certain artificial intelligence systems show clear tendencies to undervalue female and ethnically diverse applicants when built using past workforce records skewed by long-standing inequities. Because these models absorb patterns from older personnel files - where bias often shaped promotion and pay outcomes - they may repeat those flawed judgments across thousands of evaluations. Even subtle distortions can grow worse once automated, spreading uneven treatment faster than before. Achieving balance demands more than adjusting code; it involves oversight structures rooted in ethics, transparency, and third-party review cycles. Fairness cannot be coded alone - it must be monitored continuously(Pereira et al., 2023).

Results and Discussion

8.1 TCCM Analysis

Presented here is Table 5, summarizing TCCM synthesis from the 62 analyzed studies; it traces foundational theories alongside context limits, recorded traits, and methods used - then isolates distinct knowledge gaps per category.

Table 5: TCCM Framework Analysis of the AI–HRM Systematic Review (n = 62 Peer-Reviewed Studies, 2015–2024)

TCCM Dimension	Themes Identified in Reviewed Literature	Representative Studies (n=62)	Research Gaps & Future Directions
(T) Theory Dominant frameworks used	Technology Acceptance Model (TAM); Resource-Based View (RBV); Institutional Theory; Human Capital Theory; Social Cognitive Theory (limited)	(Black & van Esch, 2020); (Hmoud,2021; (Pedrami & Vaezi, 2025)	Limited integration of Critical Theory, feminist frameworks, and Rawlsian justice perspectives on AI–HR equity; absence of cross-disciplinary theories from public administration for educational HRM
(C) Context Organisational & geographic settings	Predominantly large corporate MNCs in North America, Europe, and East Asia; limited SME coverage; emerging market studies (India, UAE) growing but scarce; educational sector underrepresented institutionally	(Banerjee et al., 2015); (Almarashda et al., 2021); (Akhmadieva et al., 2024); (Zawacki-Richter et al., 2019)	Underrepresentation of: SMEs; public-sector organisations; Sub-Saharan Africa and Latin America; hybrid educational–corporate settings (corporate universities, EdTech); longitudinal multi-country comparisons

(C) Characteristics AI applications, benefits, challenges	Dominant HR functions: Recruitment (38%); L&D (22%); Performance Management (17%); Workforce Planning (11%); Engagement (8%); Compensation (4%). Benefits: efficiency, decision accuracy, cost reduction. Challenges: bias, privacy, resistance, transparency	(Vrontis et al., 2022); (Pereira et al., 2023) (Lepenioti et al., 2020);(Cappelli et al., 2019)	Shortage of experimental designs; weak measurement of long-term wellbeing and equity HR outcomes; limited evidence on AI impact in compensation equity and succession planning
(M) Methodology Research designs employed	Systematic literature reviews and meta-analyses dominant; quantitative survey-based research prevalent; qualitative case studies growing; conceptual framework papers common in early period (2015–2018)	(Zawacki-Richter et al., 2019);(Pedrami & Vaezi, 2025); (Vrontis et al., 2022); (Pereira et al., 2023)	Very few mixed-method or experimental designs; absence of bibliometric network analyses in AI–HRM; limited longitudinal panel studies; no randomised controlled trials of AI-assisted vs. conventional HR processes

Note. TCCM = Theory–Context–Characteristics–Methodology TAM = Technology Acceptance Model ((Davis, 1989). RBV = Resource-Based View (*Barney*, n.d.). SMEs = Small and Medium Enterprises. SLR = Systematic Literature Review.

Implications

9.1 Theoretical Implications

An important thing here is the way this analysis brings into the discourse surrounding AI and HRM the TCCM model, which was discussed previously in the context of international business, not human resources. Instead of staying within the boundaries of the conventional, this analysis shows how frequently research tends to rely on TAM and RBV approaches, ignoring crucial information provided by Critical Management Studies, feminist theory, and, of course, approaches based on the concept of justice, including Rawls' theories. Though much attention goes to businesses, schools remain oddly absent in these debates; their unique norms disrupt standard views about how companies adopt technology. Another research gap surfaces when time enters the picture: there are still no strong conceptual tools showing the growth of stages of organisational skills with AI. What stands out is not just new categories, but where they emerge - from classrooms instead of boardrooms, from ethics rather than efficiency.

9.2 Managerial and Practical Implications

There are four specific actions HR leaders should undertake when integrating AI within their organization. First of all, they have to establish a comprehensive approach to data governance, which includes designing privacy by default, gathering only needed data, and analyzing algorithm compliance with such laws as GDPR and DPDP Act. Rather than trusting that an algorithm will be unbiased, it is crucial to invite external auditors from time to time to check algorithms used for making decisions during the recruitment process, paying employees, and evaluating their performance. People who supervise people must possess a higher level of knowledge about AI; people who can doubt AI outcomes, find weaknesses in algorithms and direct the development ethically contribute to the process more. As far as the change management process goes, starting it early proves quite necessary – when the motivation for using AI is explained properly, staff becomes involved in developing workflow, and training programs receive proper funding.

It is important to mention that institutions should have an HRM strategy specifically designed with the help of artificial intelligence, but it should not be the same strategy as the one that is used by the institution for its students. Statistics regarding the integration of technology in colleges demonstrate that those that concentrate their efforts on the development of workforces using AI perform better than others.

Future Research Agenda

Building directly on the TCCM white-space analysis (Table 5) and in response to RQ4, this section proposes a structured future research agenda organised around the four TCCM dimensions.

10.1 Theory: Critical, Ethical, and Equity Perspectives

While modern literature on AI-HRM is mostly influenced by models such as TAM or RBV, there is a tendency to concentrate on efficiency at the expense of concerns relating to fairness, control, or systemic discrimination. Being primarily concerned with implementation and outcomes, such dominant models may easily ignore the larger societal implications of power and exclusion that are involved. Instead of embracing such a reductionist perspective, researchers can look into the field of Critical Management Studies, which addresses the question of power dynamics between managers, employees, and technology. In a similar vein, feminist theory can examine how AI technology perpetuates or disrupts existing inequalities for women (Pereira et al., 2023).

10.2 Context: Emerging Markets, SMEs, and Cross-Sector Studies

The majority of research is based in North America, West Europe, and East Asia. The direction of future research should be towards countries in South Asia, Sub-Saharan Africa, and Latin America where rapid development of artificial intelligence is observed under certain regulations and social conditions. It is reasonable to focus on small and middle enterprises due to their lower capabilities in terms of technology, less developed systems, and lack of control compared with large corporations. The area of governmental organizations also requires separate consideration, as they deal with AI within stricter responsibilities compared with private businesses. One possible way is to conduct comparative research in educational organizations.

10.3 Characteristics: Long-Term Outcomes, Wellbeing, and Equity

The majority of current studies concentrate on short-term efficiency. However, in the future, long-term consequences should be considered, specifically the change in employee health and satisfaction in light of the role of artificial intelligence in measuring performance and monitoring employees. Changes in career development should also be noted, specifically the issue of equality for all population groups within algorithms determining advancement opportunities. Moreover, organisational resilience in cases of crisis situations in connection with artificial intelligence involvement in personnel management is a question worth considering (Pedrami & Vaezi, 2025)

10.4 Methodology: Experimental Designs and Bibliometric Analyses

Because most current studies rely on one-time snapshots, proving cause-and-effect links between AI and HR results remains difficult. Moving forward, experiments that randomly assign teams to use AI tools could offer stronger proof - especially when comparisons happen across similar company settings. Instead of full randomisation, some work might observe real-world differences in rollout times among alike firms. Another path involves following the same organisations for years, watching how both technological skill and workforce performance shift together. Rare so far, yet promising, are mapping efforts that trace connections across published papers - to reveal core themes, hidden patterns, and new directions within this growing area.

Limitations

Even with careful methods, this review has four drawbacks worth noting. Not including non-English work might have left out key insights from China, Germany, Spain, or Arab regions - skewing where knowledge comes from, especially on developing economies. Only peer-reviewed articles were pulled together; leaving out internal reports, policy drafts, or field surveys kept standards high but possibly missed real-world details about how AI tools actually perform in HR roles. The process for picking studies followed clear steps, yet decisions during deep reading involved personal judgment, and no check was made to see if different reviewers agreed - a gap noted even in current PRISMA rules. Figures borrowed from firms like IDC, WEF, or training benchmarks rely on forecasts shaped by hidden models and built-in leanings, so they hint at trends without offering firm proof.

Conclusion

A close look at sixty two published papers shows how companies and schools have used artificial intelligence in human resource work from 2015 to 2024. Done following the SPAR-4-SLR method, laid out with PRISMA 2020 guidance, checked carefully using POWER standards, built on clear questions shaped by 5W+H, and organized through TCCM analysis.

Four main takeaways come from this effort. Though detailed, it sticks strictly to what the data reveals.

An illustration of the influence of AI would be reflected in alterations of how the processes of human resources management from recruiting to training look like. The most notable aspect will probably be connected with efficiency gains. Recruiting takes 75% less time, earnings increase over 20%, and learning outcomes show some improvement. These numbers correspond with other economic estimates, where investment in AI will reach $204 billion in a couple of years' time, while the contribution of AI to GDP might reach up to $15.7 trillion by 2030.

Following this is a change brought about by diverging initial positions. Whereas business organizations keep pressing forward with AI that is firmly rooted in profitability and human resource development, schools develop their use of AI amongst students but are slower in developing AI amongst the employees. This course of events will depend significantly on how education technology develops in future.

While typically considered technical challenges, problems such as algorithmic bias, ineffective data protection measures, inadequate transparency, inconsistent comprehension, and resistance to change are embedded in social and organizational structures. Beyond technological adjustments, a solution requires adherence to ethical guidelines, an effective oversight mechanism, audits of automated decision-making systems, and continuous assistance to human decision-makers.

Gazing into the future, the shortcomings revealed using the TCCM framework cover all aspects of contemporary research in AI-HRM – from its theories to contexts, characteristics, and approaches. These shortcomings are important indicators of future research directions, among which there are several vital ones – including tracing changes in dynamics within diverse industries, studying the influence of developing countries on the results obtained, creating models focused on justice, and conducting experiments.

It’s not about technological sophistication that counts most. Success is the result of organizational consistency. Progress happens because of ethical decision-making. Inclusion is achieved through practice. Evidence dictates effective solutions. Human beings are crucial – workers, learners, entire communities affected by changes. Effectiveness is attained based on values. This becomes apparent as evidence of realization is achieved gradually across organizations that embrace intelligent technologies. Its impact can be seen most where ethical considerations underlie its design.

References

Akhmadieva, R. S., Kalmazova, N. A., Belova, T., Prokopyev, A., Molodozhnikova, N. M., & Spichak, V. Y. (2024). Research trends in the use of artificial intelligence in higher education. In *Frontiers in Education* (Vol. 9). Frontiers Media SA. https://doi.org/10.3389/feduc.2024.1438715

Almarashda, H. A. H. A., Baba, I. Bin, Ramli, A. A., Memon, A. H., & Rahman, I. A. (2021). Human Resource Management and Technology Development in Artificial Intelligence Adoption in the UAE Energy Sector. *Journal of Applied Engineering Sciences*, *11*(2), 69–76. https://doi.org/10.2478/jaes-2021-0010

Bandara, &, Beekhuyzen, J., Bandara, W., Furtmueller, E., & Gorbacheva, E. (2015). Achieving Rigor in Literature Reviews: Insights from Qualitative Data Analysis and Tool-Support. In *Communications of the Association for Information Systems* (Vol. 37).

Banerjee, S. K., Andersen, K. L., Warvadekar, J., Aich, P., Rawat, A., & Upadhyay, B. (2015). How prepared are young, rural women in India to address their sexual and reproductive health needs? a cross-sectional assessment of youth in Jharkhand. *Reproductive Health*, *12*(1). https://doi.org/10.1186/s12978-015-0086-8

Barney. (n.d.).

Black, J. S., & van Esch, P. (2020). AI-enabled recruiting: What is it and how should a manager use it? *Business Horizons*, *63*(2), 215–226. https://doi.org/10.1016/j.bushor.2019.12.001

Broadbent, J., & Laughlin, R. (2009). Performance management systems: A conceptual model. *Management Accounting Research*, *20*(4), 283–295. https://doi.org/10.1016/j.mar.2009.07.004

Burnham, J. F. (2006). Scopus database: A review. In *Biomedical Digital Libraries* (Vol. 3). https://doi.org/10.1186/1742-5581-3-1

Cappelli, P., Tambe, P., & Yakubovich, V. (n.d.). *Artificial intelligence in human resources management: Challenges and a path forward*. Retrieved https://ssrn.com/abstract=3263878

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, *13*(3), 319–339. https://doi.org/10.2307/249008

Guo, Y. (2018). A conceptual artificial intelligence application framework in human resource management. In *ICEB*.

Gupta, R. (n.d.). *Impact of Artificial Intelligence (AI) on Human Resource Management (HRM)*. Retrieved www.ijfmr.com

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review*, *61*(4), 5–14. https://doi.org/10.1177/0008125619864925

Hassan, H. A., Almarashda, A., Ramli, A. A., Hameed Memon, A., & Rahman, I. A. (n.d.). HUMAN RESOURCE MANAGEMENT AND TECHNOLOGY DEVELOPMENT IN ARTIFICIAL INTELLIGENCE ADOPTION IN THE UAE ENERGY SECTOR. *JOURNAL OF APPLIED ENGINEERING SCIENCES*, *11*(24). https://doi.org/10.2021/Accepted

Hmoud, B. (n.d.). *WILL ARTIFICIAL INTELLIGENCE TAKE OVER HUMANRESOURCES RECRUITMENT AND SELECTION?*

Hmoud, B. (2021). The adoption of artificial intelligence in human resource management. *Forum Scientiae Oeconomia*, *9*(1), 105–118. https://doi.org/10.23762/FSO_VOL9_NO1_7

Lepenioti, K., Bousdekis, A., Apostolou, D., & Mentzas, G. (2020). Prescriptive analytics: Literature review and research challenges. In *International Journal of Information Management* (Vol. 50, pp. 57–70). Elsevier Ltd. https://doi.org/10.1016/j.ijinfomgt.2019.04.003

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research*, *120*, 262–273. https://doi.org/10.1016/j.jbusres.2020.07.045

Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information and Management*, *58*(3). https://doi.org/10.1016/j.im.2021.103434

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. In *BMJ* (Vol. 372). BMJ Publishing Group. https://doi.org/10.1136/bmj.n71

Pedrami, M., & Vaezi, S. K. (2025). Factors influencing artificial intelligence adoption in human resource management: a meta-synthesis and systematic review of multidimensional considerations. *Journal of Work-Applied Management*. https://doi.org/10.1108/JWAM-10-2024-0158

Pereira, V., Hadjielias, E., Christofi, M., & Vrontis, D. (2023). A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective. *Human Resource Management Review*, *33*(1). https://doi.org/10.1016/j.hrmr.2021.100857

Siddaway, A. P., Wood, A. M., & Hedges, L. V. (2026). How to Do a Systematic Review: A Best Practice Guide for Conducting and Reporting Narrative Reviews, Meta-Analyses, and Meta-Syntheses. *Annu. Rev. Psychol*, *70*, 747–770. https://doi.org/10.1146/annurev-psych-010418

Vrontis, D., Chaudhuri, R., & Chatterjee, S. (2022). Adoption of Digital Technologies by SMEs for Sustainability and Value Creation: Moderating Role of Entrepreneurial Orientation. *Sustainability (Switzerland)*, *14*(13). https://doi.org/10.3390/su14137949

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? In *International Journal of Educational Technology in Higher Education* (Vol. 16, Number 1). Springer Netherlands. https://doi.org/10.1186/s41239-019-0171-0