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Generative Artificial Intelligence in Human Resource Management: A Critical Systematic Review of Opportunities, Ethical Challenges, Governance, and the Future of Work

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ABSTRACT

Generative artificial intelligence (GenAI), particularly large language models and multimodal foundation models, is reshaping human resource management (HRM) by extending automation from prediction and classification to content generation, conversational support, knowledge synthesis, personalization, and increasingly agentic workflow execution. This review critically synthesizes the emerging literature on GenAI enabled HRM, focusing on opportunities across the employee lifecycle, ethical and organizational risks, human–AI collaboration, workforce transformation, and governance. The review builds on the uploaded manuscripts four research questions concerning HR opportunities, ethical and legal risks, future of work implications, and responsible governance. Rather than treating GenAI as a stand-alone technology, the analysis conceptualizes value as an interaction among model capability, data quality, workflow design, human expertise, organizational culture, and governance.

The review identifies a risk gradient: low risk, reversible activities such as drafting, summarization, learning content development, and routine employee support offer comparatively strong augmentation potential, whereas recruitment ranking, performance evaluation, promotion, compensation, disciplinary action, and termination require substantially stronger controls. A six-stage Responsible GenAI–HRM framework is refined around purpose and impact assessment, data stewardship, fairness by design, accountable human oversight, continuous monitoring, and workforce empowerment. The review further proposes research priorities involving measurable decision quality, employee trust, AI literacy, bounded autonomy, job redesign, cross cultural fairness, and sustainable adoption. The central conclusion is that GenAI should augment HR capability without transferring accountability for consequential employment decisions from people to machines.

Keywords: Generative artificial intelligence; human resource management; large language models; responsible AI; algorithmic fairness; employee experience; future of work

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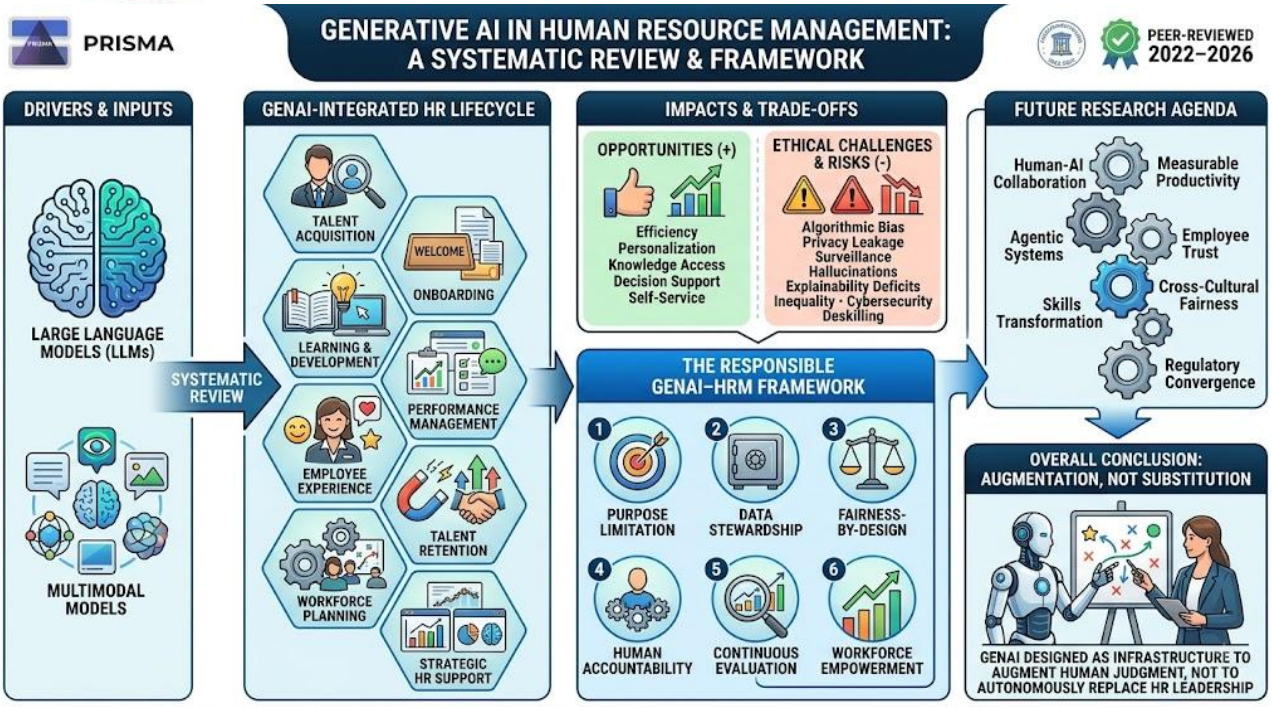

Figure 1. Conceptual graphical abstract linking Gen AI enabled HRM opportunities, ethical risks, future of work transformations, and a responsible human centered governance pathway.

1 Introduction

HRM is undergoing a new era in which AI tool chimes in from predicting to creating content, conversing with and increasingly taking over, tasks. Generative artificial intelligence (GenAI) is a type of AI that creates new textual, image, aural, or code content from prompts or context. Conversational AI has become a reality for employeees and managers with the advent of large language models (LLMs) like those of the GPT family, Claude, Gemini and open weight models, and enterprise platforms are integrating generative AI capabilities into learning, performance and workforce management processes in recruitment. HR activities involve language intensive, judgmental, and repetitive processes, such as creating job descriptions, communicating with candidates, summarizing interviews, creating learning materials, answering employeee questions, drafting policies, and synthesizing information about the workforce: this is important in an HRM context.

The upcoming literature indicates that GenAI can boost HR productivity and personalisation, and yet it presents a paradox. An HR professional can create an emotionally sophisticated communication to hundreds of workers, but generate convincing but wrong communications; a same system can expand access to career counseling services, but also generate stereotypes captured in training data; the same automation that cuts workload of administrative tasks could create the illusion of expanding decision-making authority for managers, which invites poor decisions. The question that needs to be thoroughly discussed with scholarship is not whether AI can be used to do HR work, but when HR work using AI remains fair, transparent, legal, effective and human centered. The implications of the findings are found in the broad spectrum of concepts of employeee relations, well-being, talent, performance, international HRM and sustainable HRM; and the subsequent research has increasingly expanded to encompass the notions of responsible AI, algorithmic inclusion and the ethics of GenAI related HR decisions.

This is a strategic need amidst the labour market environment. An updated global index by the International Labour Organisation (ILO) projects that one in four people employeed around the world have some degree of 'GenAI exposure' in their occupations, with fewer jobs being replaced than transformed, since most occupations consist of tasks that need some human input. The World Economic Forum (WEF) Women in Business and the Economy Report also shows that technological shifts, such as artificial intelligence, are significant factors in workforce transformation to 2030 and new growing emphasis on skills building. This research positions HRM in the heart of company

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adaptation: HR needs not just to utilize AI to employ it, however additionally to restructure work, create abilities, safeguard workers, motivate change and create governance. There is a lack of review on this subject in the ever increasing literature.

There are some existing reviews discussing AI in HRM, responsible AI, algorithmic HRM and the first applications of GenAI to HRM but the evidence is scattered across separate HR domains. This present review combines four aspects in one analytical architecture, namely operational opportunities throughout the entire HR lifecycle; ethical, legal and organizational risks; implications for jobs, skills, and the employeee–AI relationship; and governance mechanisms that can shift the technology potential into responsible value. The review therefore transcends a technology perspective and offers a Responsible GenAI–HRM framework where technology is accompanied by stewarding of data, fairness, human responsibility, ongoing evaluation, and employeee empowerment.

The review answering the four research questions and locations of key opportunities is outlined below: RQ1: What are the principle opportunities created by GenAI across each HRM function? The four research questions are addressed in the review below that outlines the areas of key opportunities created by GenAI in each HRM function. RQ2: What are the ethical, legal and organizational risks that come with the use of GenAI in HRM? RQ3: What are the implications of GenAI for the work, skills and human resource roles and how will they be working with AI? RQ4: How governance and research priorities can help in the responsible, inclusive and sustainable adoption of GenAI in HRM?

2 Novelty and Contribution of the Review

This is where the novelty of this review comes in: The three traditionally disjointed conversations of HR efficiency through AI, responsible and ethical use of HR analytics and transformation of the future of work are now brought into one HRM cosmos with a focus on GenAI. First, a distinction between generative and traditional predictive AI is explained. Predictive HR platforms can predict metrics like attrition risk or candidate fit assessment; GenAI can also generate explanations, communications, learning content, recommendations, and interactive conversation. Second, unlike a compliance check, the review takes ethical issues into account in an architectural manner. Third, it links up AI adoption with the capability building associated with it, positing that the successful use of GenAI does need to involve simultaneous task, skills, controls and employeee re design. Fourth, the framework aims to establish a perpetual human accountability cycle, where the output of AI is evaluated prior to consequential HR decisions, and monitored after its deployment.Fifth, the review singles out the agentic AI, which are systems that navigate multi step HR use cases and can plan, as an area of future AI where more control over the systems is needed than regular chat bots. Finally, and most importantly, the review creates a set of future research priorities that emphasize more realistic and measurable benefits, such as quality of decision making, trust, fairness, improved employee skills, and improved organizational "responsible resilience" instead of adoption only.

2.1 Review Methodology

This systematic review – PRISMA was designed to be as transparent as possible and uses a systematic review design. To discover further use Scopus, Web of Science Core Collection, ScienceDirect, SpringerLink, Wiley Online Library, IEEE Xplore, ACM Digital Library and Google Scholar. For the HR and technology domain, combine terms like "generative AI" with "employee experience," "workforce planning," "learning and development" or "performance management" and "human resource management" or HRM with "ChatGPT" and "foundation model*" or "AI agent*". The publishing window will be opened between two years, 2022 to August 2026, coinciding with the growing number of public GenAI system developments and emphasizing the importance of the AI HRM studies that provide theoretical underpinning or methodological tools prior to the year of 2022. Qualifying literature should cover empirical research undertaken through a peer reviewed process, systematic reviews, conceptual articles, high-quality conference papers and reports from institutions throughout the world, as well as established standards or best practice that are relevant to the applications of AI, AI HRM, responsible AI, forecasting or future of work implications from GenAI.

Materials which are not included in this list are those which are anonymous or are only of a marketing nature; papers which are duplicated, papers which are only of a technical nature and have nothing to do with HR and opinion pieces with no substantive analysis. To complement research published in the peer reviewed literature, a number of authoritative ILO, OECD, WEF, NIST and European Union institutions publish a complementary report, and these

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reports are not to be used as a source of research. For example, in the NIST profile these are all a list of identified risks, and the related actions that can be translated to HR governance.

2.2 The concept of Generative AI in HRM

We can think of GenAI in HRM as a socio technical ability in four dimensions. It automates or augments particular activities like Drafting, Summarizing, Searching, Classification and Conversational Support at the task level. At the process level it links various functions in the recruitment, learning, performance and employee service processes. It's at the decision level that it offers suggestions or comprehensified information to HR professionals and managers. The organizational aspect includes a shift in job design and skills demand, governance and HR strategic role. This multilevel view challenges the notion that the AI model is the driver of value in the organization, rather, the value is enabled by the interplay of capabilities of the AI model, data, workflow design, human expertise, organizational culture and controls.

2.3 Talent Acquisition: From Automation to Augmented Judgment

Recruitment has been one of the most apparent applications of AI in HRM; it has meaningful high volume language tasks. GenAI can compose vacancy descriptions, customize ads addressing different audiences, reply to candidate questions, summarize resumes and interviews, and even create structured interview guides and even assist with recruiter correspondence. These functions can minimize admin and free up bandwidth for recruiters to invest in relationship building and assessing the situation in context. But generative systems do not have to be taken for granted as uninvolved decision makers. Earlier promulgated prompts, training data or criteria for evaluation may contain stereotyping, which can result in recommendations that perpetuate excluding patterns. Studies of algorithmic inclusion, however, highlight that algorithmic bias is caused by data, system design and decisions, and that human review is not guaranteed to correct algorithmic issues.

This distinction should be reflected in the recruitment architecture, and should differentiate between offers of assistance and offers of decision support, both in terms of consequence and in terms of the probability of the same event occurring again. There are distinct differences between preparing a job advertisement and ranking candidates. The former can be reviewed within a short period of time, the latter can dictate employment opportunities. Industry HR practitioners should implement a classification of impact for each use case, provide validation on output that is related to candidates, maintain an audit trail and ensure that applicants are notified when AI has a significant role in assessment. The goal should be structured augmentation rather than a faceless replacement for a substitute for the judgment of a recruiter. 7 Learning, Development and Reskilling Learning and development could be among the most advantageous domains for responsible GenAI, as the technology can produce and provide personalized content, something that HR teams once had a hard time providing since these topics are unique and cater to the needs of their employees.

There are several things GenAI can do with competency frameworks, like making learning plans, generating examples and practice activities, engaging in complex conversations, translating content into multiple languages, designing microlearning and conversational training. This helps the transition from periodic training to ongoing ability development. The impact on the labor market is significant. The WEF Future of Jobs Report 2025 puts the emphasis on skills disruption and the need to build combination of technological adoption, reskilling and upskilling by organizations. Also, 2025 evidence from the ILO suggests that 'occupied, but transformed' is more likely than 'completely replaced'. This is a strategic opportunity for HR to help treat GenAI as a productivity technology, as well as a technology for workforce development. The best implementation model is not, “AI takes the place of educators” but “AI to supplement educators to help them manage greater learning capacity whilst learning professionals supervise competencies, monitor outcomes and oversee sensitive development requirements.” Effective employeee performance management and employeee experience 8 Performance management is a sensitive subject as the wording of AI powered summaries can have an effect on promotion, development, compensation and employment sustainability.

GenAI can actually support managers in structuring notes into feedback and create training questions and recap the common themes from the notes. However, language models can produce convincing stories from incomplete

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bits of evidence, and well placed prose can build up an illusion of objectivity. Therefore, an AI performance narrative should not simply be accepted as a report if the evidence behind it is not verified. This is somewhat linked to employeee experience. Familiarity with policies, advice on benefits, and information on available career options are just a few aspects of HR information that can be delivered by a conversational HR assistant anytime. There has been an initiative to start making connections between perceptions of GenAI, trust and outcomes for the HR. However, care, which requires conversation, is not generated by just talking. There must be transparency regarding what information the AI should use, what happens in the output process and when and how humans can challenge the AI supported decision.The transparency, thus, should be in action, not in information.

2.4 Data Governance, Privacy and Cybersecurity

The sensitivity of HR datasets is exceptional. Personally identifiable information, pay, health related information, disciplinary records, performance reviews, immigration information, biometric or behavioural data, and private company information are a few examples. Therefore, compared to standard productivity software, GenAI adoption necessitates better data control. The first guideline should be data minimisation: a GenAI process should only contain information required for a clearly stated HR goal. The second is environment control: businesses should separate corporate systems with contractual, technological, and administrative protections from public consumer tools. The third is lifecycle governance, which calls for specified preservation, access, and destruction guidelines for prompts, outputs, logs, and embedded documents. NIST's GenAI profile and AI RMF offer a helpful foundation for risk management.

The GenAI profile is specifically made to assist businesses in recognising and controlling risks across. NIST's GenAI profile and AI RMF offer a helpful foundation for risk management. The GenAI profile prioritises reliable AI practices over a onetime compliance review and is specifically made to assist organisations in identifying and managing risks throughout the AI lifecycle. These concepts can be applied to HRM in the form of an AI use case registry, data classification, impact assessment, model/vendor assessment, human supervision needs, monitoring, and incident response. Applicable national and regional data protection regulations should also be taken into consideration by privacy governance, especially where automated decision making or sensitive employee data are involved.

3 Human–AI Collaboration and the Future of Work

A straightforward automation versus human dichotomy is unlikely to be sufficient to characterize the future of HRM. It is more accurate to think of GenAI as a new layer of cognitive infrastructure that modifies the division of labour between humans and machines. While human labour changes to problem framing, contextual judgement, relationship management, ethical reasoning, and exception handling, routine drafting and information retrieval may become more automated. This results in a "judgement premium": the value of knowing what should be produced, whether it is accurate, and how it should influence people increases as routine production becomes less expensive. A transformation viewpoint is strongly supported by the ILO's 2025 analysis. Globally, one in four people have some exposure to GenAI, but as most jobs involve a variety of functions, they are more likely to be changed than destroyed.

As a result, HR directors should rethink positions at the task level. A position that used to be 60% document preparation and 40% interpersonal work might now be 25% document preparation, 25% AI supervision, and 50% relationship and strategy work. New competency models are needed for such developments. Thus, the developing idea of AI literacy ought to be a fundamental HR competency. Prompt and workflow design, output verification, data protection, bias awareness, model limits, source validation, and responsible escalation are all included. Additionally, managers must possess "AI judgement literacy" the capacity to discern when a recommendation from AI is suitable, when more information is required, and when a decision should be made exclusively by humans.

3.1 Agentic AI and the Next Generation of HRM

Agentic AI, which enables computers to plan activities, call tools, retrieve information, and carry out multi step workflows, is the next frontier. In HRM, an agent might find an authorised position, create and post a job description, respond to standard enquiries from candidates, set up interviews, compile structured feedback, and update workflow systems. Although it alters the risk profile, this could result in significant efficiency gains. One issue is a chatbot that

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gives the wrong response; another is an autonomous system that spreads the mistake across several HR systems. Permission limits, tool level authorisation, transaction restrictions, human approval gates, and full audit trails are all necessary for authentic HR. Candidate rejection, suggestions for promotions, changes in salary, disciplinary action, or termination are examples of high impact activities that should typically require express human authorisation.

The "bounded autonomy" design approach should let agents to carry out regular, reversible tasks within predetermined bounds, but human decision-making rights should still apply to important and irreversible actions.

3.2 Responsible GenAI–HRM Framework

The review proposes a six stage Responsible GenAI–HRM framework:

1. Assess purpose and impact: Define the HR problem, intended benefit, affected stakeholders and consequence level before selecting a model.
2. Govern data: Classify inputs, minimize personal data, establish access and retention controls, and document lawful/legitimate processing.
3. Design for fairness: Test representative scenarios, evaluate subgroup performance, inspect prompts and outputs for stereotypes, and monitor adverse impacts.
4. Deploy with human accountability: Assign a named decision owner, define escalation thresholds and require human review for consequential decisions.
5. Monitor continuously: Track accuracy, hallucinations, fairness, privacy incidents, employeee complaints, model drift and unintended use.
6. Empower people: Provide AI literacy, reskilling, transparent communication, appeal mechanisms and employeee participation.

The distinctive feature is that these stages form a loop rather than a linear checklist. HR use cases should be reassessed whenever models, data sources, workflows or regulations change. This is especially important because GenAI capabilities evolve faster than traditional HR policy cycles.

3.3 Theoretical Perspectives for Understanding GenAI HRM

A strong review of GenAI in HRM benefits from combining several theoretical perspectives rather than treating the technology as an isolated technical intervention. The first is the resource based view (RBV), which suggests that competitive advantage arises when organizations develop valuable, rare, difficult to imitate and well organized capabilities. GenAI itself is increasingly accessible, so the model is unlikely to be a sustainable source of advantage on its own. Advantage may instead arise from complementary organizational capabilities: high quality workforce data, domain specific knowledge, skilled HR professionals, effective governance, proprietary workflows and a culture of responsible experimentation. This shifts the research question from "Does an organization have GenAI?" to "What organizational capability has been built around GenAI?" The second perspective is socio technical systems theory.

HR decisions are produced by interactions among people, technologies, rules, organizational structures and institutional environments. A model may be technically accurate but organizationally inappropriate if the workflow encourages managers to over trust it. Conversely, a technically imperfect model may still be useful when deployed as a low stakes drafting assistant with strong human review. Socio technical analysis therefore requires researchers to study the whole decision system rather than model accuracy alone. The third perspective is the automation–augmentation paradox. AI can automate activities while simultaneously creating new forms of human work. GenAI illustrates this paradox strongly: it automates drafting but creates verification work; it accelerates analysis but increases the need for judgment; it reduces search costs but creates source validation requirements. HR research should therefore measure both displaced tasks and newly created oversight tasks.

A narrow productivity metric can miss this redistribution of effort. The fourth perspective is psychological contract theory. Employeees form expectations about fairness, transparency, respect and organizational obligations. Hidden AI monitoring or unexplained algorithmic decisions may violate these expectations even when the technology is legally permissible. Transparent and participatory implementation may strengthen trust, whereas opaque deployment can produce resistance. Future empirical research should therefore examine AI adoption as an employeee

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relations event, not only a technology adoption event. Finally, dynamic capability theory helps explain why organizations differ in their ability to adapt to GenAI. Sensing involves identifying valuable use cases and emerging risks; seizing involves investing in tools, skills and governance; transforming involves redesigning HR processes, roles and competencies.Organizations that develop these capabilities are more likely to convert GenAI into sustainable HR value.

3.4 Conventional AI versus Generative AI in HRM

Conventional AI HRM systems and GenAI HRM systems should not be treated as interchangeable. Traditional machine learning systems often classify, predict, rank or recommend. For example, an attrition model may estimate the probability that an employeee will leave, while a recruitment model may rank candidates according to predefined features. GenAI adds an open ended content generation and interaction layer. It can create a job advertisement, explain a policy, summarize multiple documents, simulate an interview or produce a personalized learning plan. This difference creates both opportunities and risks. Predictive systems are often evaluated using statistical metrics such as accuracy, precision, recall or calibration. Generative systems require additional evaluation dimensions: factuality, groundedness, relevance, toxicity, stereotyping, consistency, provenance and resistance to prompt manipulation.

HRM research therefore needs new measurement frameworks. A system that generates excellent prose but invents facts should not be considered high performing in a consequential HR context. Another difference is accessibility. Many employeees can interact directly with consumer GenAI tools without formal HR approval. This creates "shadow AI" in which staff use unapproved systems for resumes, employeee communications, and policy questions or data analysis. Shadow AI is a governance challenge because organizations may not know what data are being submitted or how outputs are being used. A prohibition only response is unlikely to be effective. Organizations should provide approved alternatives, clear rules and practical training while maintaining strong controls over confidential data. The distinction also matters for accountability. When a predictive model produces a score, organizations may be able to document its input variables.

A conversational model can produce a long form narrative whose reasoning is less directly traceable. Therefore, GenAI governance should preserve the evidence behind a consequential recommendation. Generated prose should be treated as an interpretation layer, not as the underlying evidence itself.

3.5 Sectoral and Organizational Implications

The impact of GenAI on HRM will differ by sector. In technology and professional services organizations, GenAI may be integrated rapidly into recruitment, coding adjacent work, learning and knowledge management. In manufacturing, HR applications may focus more on skills mapping, safety training, workforce scheduling and multilingual employeee support. In healthcare, education and public services, privacy, professional regulation and high stakes decision requirements may impose stronger controls. In retail and hospitality, conversational employeee support and scheduling assistance may offer immediate operational value, but workforce monitoring and job quality concerns require careful governance. Organization size also matters. Large organizations can establish dedicated AI governance teams, enterprise licenses, security controls and model evaluation programs. Small and medium sized enterprises may depend on external vendors and consumer facing tools.

Their risk is not necessarily lower; governance capacity may simply be weaker. Scalable governance is therefore essential. A practical SME model could use a small approved tool list, standardized data rules, a high risk use case register and mandatory human review for employment decisions. Geography creates another layer of variation. Employment law, data protection, collective bargaining and AI regulation differ across countries. A multinational organization should avoid assuming that one global AI policy automatically satisfies every jurisdiction. Instead, a global baseline can be supplemented with local requirements. This is particularly relevant for recruitment and workforce management, where emerging AI regulation increasingly treats certain employment uses as high risk. Organizational culture is also likely to influence outcomes. A culture emphasizing experimentation may accelerate adoption but increase unmanaged risk.

A highly risk averse culture may protect against misuse but fail to realize productivity and learning opportunities. The optimal culture is neither unrestricted experimentation nor blanket prohibition. It is controlled

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experimentation: low risk pilots, explicit success criteria, rapid evaluation, employeee feedback and documented decisions about scaling.

3.6 Measurement Framework for Gen AI HRM Outcomes

Future studies should move beyond adoption frequency and perceived usefulness. A multidimensional evaluation framework can classify outcomes into six categories. First, operational outcomes include cycle time, administrative workload, cost per transaction and response time. Second, decision outcomes include accuracy, consistency, fairness, calibration and quality of human judgment. Third, employeee outcomes include engagement, trust, autonomy, learning, job satisfaction and perceived dignity. Fourth, organizational outcomes include retention, productivity, internal mobility, innovation and strategic agility. Fifth, risk outcomes include privacy incidents, hallucination rates, adverse impact indicators, complaints and policy violations. Sixth, workforce transition outcomes include reskilling rates, task redistribution and changes in occupational composition. An important methodological issue is the difference between output quantity and outcome quality.

GenAI can increase the amount of HR content produced without improving HR decisions. For example, a manager may generate more performance feedback but still provide less accurate or less meaningful feedback. Research should therefore compare baseline and AI assisted conditions using objective and subjective indicators. Experimental designs can be particularly valuable. Randomized or quasi experimental studies could compare recruitment teams with and without GenAI assistance, controlling for vacancy complexity. Field experiments could assess whether AI supported learning improves skill acquisition relative to conventional programs. Longitudinal studies could examine whether employeees who receive AI assisted career recommendations actually experience better mobility and retention. Qualitative research remains important because many GenAI effects are difficult to capture numerically. Interviews and ethnographies can reveal how managers negotiate AI recommendations, how employeees interpret disclosure, and how new forms of hidden work emerge around verification and correction. Mixed method studies are therefore especially appropriate for GenAI HRM research.

3.7 Implementation Roadmap for Organizations

A practical implementation roadmap can be organized into seven phases. Phase 1 is discovery: map existing HR processes and identify repetitive, language intensive tasks. Phase 2 is risk classification: distinguish administrative assistance from uses that influence employment opportunities. Phase 3 is controlled experimentation: pilot low risk applications with measurable objectives. Phase 4 is evaluation: assess productivity, quality, fairness, security and employeee experience. Phase 5 is governance: formalize policies, approval mechanisms, vendor requirements and accountability. Phase 6 is capability building: train HR professionals, managers and employeees in AI literacy and responsible use. Phase 7 is continuous improvement: monitor model updates, emerging risks, regulation, employeee feedback and business outcomes. The implementation sequence matters. Organizations should not begin with the question "Which GenAI platform should we buy?" The better question is "Which HR problem are we trying to solve, what is the consequence of failure, and what level of automation is justified?" Technology selection should follow this analysis.

For high impact uses, an AI impact assessment should document purpose, affected groups, data sources, model/provider, known limitations, fairness risks, human decision rights, security controls, appeal mechanisms and monitoring indicators. This document can become a living record that is updated when the model or workflow changes. Employeee participation is another critical implementation factor. Employeees should have meaningful opportunities to ask questions, provide feedback and challenge harmful use. Where collective representation exists, consultation should be integrated into implementation. Participation can improve legitimacy and help identify practical risks that technical teams overlook.

3.8 Research Propositions

Based on the synthesis, the following propositions provide a useful agenda for empirical testing: P1. GenAI adoption improves HR process efficiency more strongly when HR professionals possess high levels of AI literacy. P2. The positive relationship between GenAI assistance and HR decision quality is stronger when AI outputs are grounded in verified organizational data. P3. Human oversight moderates the relationship between GenAI use and employment

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decision fairness, with stronger oversight reducing the probability of harmful automation bias. P4. Perceived transparency and employeee control positively influence trust in GenAI enabled HR services. P5. Perceived organizational support for reskilling strengthens the positive relationship between GenAI adoption and employeee acceptance. P6. The productivity benefits of GenAI are greater for language intensive HR tasks than for context dependent interpersonal tasks P7. The risk of algorithmic discrimination increases when generated recommendations are derived from historical HR data containing structural inequalities. P8. Responsible AI governance mediates the relationship between GenAI capability and sustainable organizational value. P9. Bounded autonomy produces better HR outcomes than unrestricted autonomy for high consequence employment workflows. P10. Cross functional governance involving HR, legal, privacy, cybersecurity and employeee representatives reduces implementation risk more effectively than HR only governance. These propositions can be operationalized through surveys, field experiments, case studies, longitudinal panels and comparative multi country research.

3.9 Additional Synthesis: Opportunities versus Risks

The evidence indicates that GenAI value is not uniformly distributed across HR functions. The highest opportunity to risk ratio is generally found in drafting, summarization, learning content creation, routine employeee service interactions and knowledge navigation. These tasks are repetitive, relatively reversible and easily reviewed. The risk profile increases when AI outputs influence candidate selection, performance evaluation, promotion, compensation, disciplinary action or termination. These activities involve fundamental rights, livelihood and organizational trust. This suggests a practical "risk gradient" rather than a binary permitted/prohibited model. Low risk uses can be scaled quickly with basic controls. Moderate risk uses require stronger validation and monitoring. High risk uses require impact assessment, documented human decision rights, fairness evaluation and appeal mechanisms.

Some uses may be unacceptable if the organization cannot establish a defensible purpose, data basis and accountability structure. The review also identifies an important distinction between assistance and delegation. Assistance means that the human retains responsibility and uses AI to expand cognitive capacity. Delegation means that the human effectively transfers a decision to the system. The same technical tool can therefore be low risk or high risk depending on workflow design. For example, a GenAI model may safely draft five interview questions, but it should not autonomously decide which applicant is suitable for employment. This distinction should be reflected in organizational policies. Policies that merely say "AI may be used" or "AI may not be used" are too coarse. Effective policies specify tasks, data classes, decision consequences, required oversight and documentation. They also need mechanisms for employeees to report inappropriate use without fear of retaliation.

4 Implications for HR Professionals and HR Education

The HR profession itself will evolve. Recruiters will increasingly need skills in structured assessment design, prompt and workflow engineering, candidate experience and algorithmic fairness. Learning specialists will become curators and evaluators of AI generated content. HR business partners will need stronger data literacy and the ability to translate AI outputs into organizational decisions. HR analytics professionals will increasingly work with natural language interfaces but will remain responsible for methodological validity. HR leaders will need governance literacy covering privacy, employment law, cybersecurity and responsible AI. Universities and professional bodies should respond by integrating AI HRM modules into HR curricula. Core topics should include LLM fundamentals, prompt design, hallucination detection, data protection, algorithmic fairness, AI assisted recruitment, workforce transformation, AI governance and human centered design.

Students should learn not only how to use GenAI but how to challenge it. Professional development should also emphasize human capabilities that become more valuable as generative tools improve: empathy, negotiation, ethical reasoning, contextual judgment, facilitation, conflict resolution, coaching and strategic thinking. A future ready HR professional is therefore not the person who can generate the most text with AI, but the person who can combine AI speed with human judgment and accountability.

4.1 Final Integrated Model

The overall synthesis can be represented as a three layer model. Layer 1 is capability: GenAI provides generation, summarization, conversational interaction, personalization and increasingly agentic execution. Layer 2 is

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organizational translation: HR processes convert these capabilities into recruitment, learning, employeee service, performance, talent and workforce planning applications. Layer 3 is responsible value: governance mechanisms determine whether technological activity produces trustworthy outcomes. The model can be expressed as: GenAI capability → HR task redesign → Human–AI collaboration → Responsible decision process → Employeee and organizational outcomes. At each arrow, a potential failure can occur. Capability can be misapplied; task redesign can create hidden workload; collaboration can produce automation bias; decision processes can reproduce discrimination; and organizational outcomes can become unequal.

Governance therefore cannot be positioned only at the end. It must operate at every transition. The framework also suggests that "human centered AI" should not mean keeping humans nominally in the loop. A human who merely clicks approve after receiving an AI recommendation is not meaningful oversight. Human oversight requires sufficient time, information, authority and competence to challenge the system. Future research should therefore measure the quality of human oversight rather than merely whether a human was technically present. In conclusion, responsible GenAI HRM is best understood as an organizational capability. Organizations that combine technological adoption with strong data stewardship, fairness, transparency, employeee participation and reskilling are more likely to achieve sustainable value. Those that treat GenAI as a cheap substitute for HR expertise may obtain short term efficiency while increasing long term legal, ethical and organizational risk.

4.2 Emerging Ethical Issues in Multimodal and Personalized HR

The next generation of GenAI will be increasingly multimodal, combining text with speech, images, video and potentially behavioral signals. This creates new possibilities for recruitment, training and employeee assistance, but it also expands the ethical surface of HRM. A voice enabled assistant may infer emotional states from speech, a video system may generate or analyze training simulations, and multimodal systems may integrate documents, images and audio records. HR organizations should resist the assumption that greater data richness automatically creates better HR decisions. More data can also create more opportunities for intrusive inference, discrimination and privacy loss. Personalization introduces a similar tension. A GenAI system may tailor learning content to an employeee's role, experience and goals, but increasingly granular personalization can become profiling. The boundary between helpful personalization and unwanted surveillance should therefore be explicit.

Employeees should understand what information is used to personalize services and should have meaningful choices where appropriate. Synthetic media also creates a new authentication problem. GenAI can generate highly convincing messages, voices and documents. HR departments are frequent targets for impersonation because recruitment, payroll and employeee communication involve financial and identity information. Security procedures should therefore combine technical detection with human verification. High impact changes such as bank account updates, termination instructions or executive requests should not rely solely on generated messages. These developments reinforce the need for principle based governance. The organization should evaluate not only whether a system can perform a task, but whether the task is appropriate to automate, whether the data required are proportionate, whether affected employeees can contest the outcome and whether the organization can explain and reverse errors.

4.3 Generative AI, Inclusion and the Digital Divide

GenAI has the potential to improve inclusion by providing multilingual assistance, accessible explanations, personalized learning and support for employeees who may have limited access to specialist HR resources. For example, an employeee in a geographically remote location could use a conversational HR assistant to understand benefits or career development opportunities without waiting for an HR appointment. Employeees with different language backgrounds may receive information in accessible formats. However, inclusion is not guaranteed. Models can perform differently across languages, dialects and cultural contexts. A recruitment communication optimized for one population may not be equally appropriate for another. Training data can underrepresent minority groups, and generated language can contain subtle stereotypes. Organizations should therefore evaluate outputs across relevant demographic, linguistic and cultural contexts.

The digital divide can also become an AI divide. Employeees with higher digital literacy may use GenAI to

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increase productivity while others receive fewer benefits. If organizations measure only aggregate productivity, they may overlook unequal distribution of gains. HR should monitor access, training participation and outcomes across workforce groups. AI literacy should be treated as an organizational capability available to all employeees, not as a privilege for technical specialists. Inclusion also requires preserving human alternatives. Some employeees will prefer human interaction for sensitive HR issues. A responsible system should make escalation easy rather than forcing employeees to interact with an AI assistant. The most inclusive HR technology is therefore not necessarily the most automated one; it is the one that gives employeees appropriate choices.

4.4 Toward Sustainable and Human Centered GenAI HRM

Sustainability should be incorporated into GenAI HRM discussions more explicitly. AI systems require computational infrastructure, energy and data center resources. Although an HR department may not control model training, it can influence the amount and type of inference used. Repeatedly generating unnecessary content, processing large confidential documents without purpose or deploying complex models for simple tasks may increase resource use without corresponding value. A sustainable HR approach therefore applies proportionality: use the smallest suitable model and the least amount of data for the task; avoid unnecessary repeated generation; use retrieval and templates when they provide equivalent quality; and evaluate whether AI is actually improving outcomes. Sustainability should also include social dimensions. If automation increases productivity but produces excessive work intensification, reduced autonomy or unequal job security, the system cannot be considered socially sustainable.

Human centered GenAI HRM should therefore pursue four simultaneous outcomes: productivity, employeee well-being, fairness and organizational resilience. These outcomes may sometimes conflict. Faster automated performance monitoring, for example, may increase managerial efficiency while reducing employeee autonomy. A responsible HR leader must evaluate the tradeoff rather than optimizing a single metric. The future of HRM should consequently be framed as augmentation with accountability. GenAI can expand human capacity, but humans must retain responsibility for the social consequences of HR decisions. Organizations that adopt this principle can use GenAI to reduce administrative burden while redirecting human capability toward coaching, inclusion, workforce development and strategic organizational design.

5 Overall Evidence Synthesis

Across the reviewed evidence, five broad conclusions emerge. First, the strongest near term GenAI applications in HRM are language intensive, repetitive and relatively reversible tasks. Second, the largest ethical risks occur when generated outputs influence consequential employment decisions or use sensitive employeee data. Third, employeee trust is a central mediating condition: technically capable systems may fail if employeees perceive them as opaque, intrusive or unfair. Fourth, workforce transformation requires reskilling and job redesign rather than simple headcount substitution. Fifth, governance must be continuous because model capabilities, organizational uses and regulatory expectations evolve rapidly. The literature also reveals a methodological imbalance. There is substantial conceptual discussion about what GenAI could do, but fewer longitudinal field studies measuring what it actually does to HR outcomes.

Many claims about efficiency, engagement or fairness are based on expected benefits rather than controlled evidence. Future research should therefore distinguish capability from realized impact. A model may be capable of producing personalized learning, for example, without evidence that employeees learn more effectively. Another gap concerns negative cases. Research often focuses on successful adoption, while failed implementations, employeee resistance, hallucination incidents and unintended consequences receive less attention. Publishing negative evidence would help the field develop more realistic implementation theories. Researchers should report not only performance improvements but also failure modes, mitigation costs and residual risks. Finally, there is a need for interdisciplinary collaboration. GenAI HRM is simultaneously a management, information systems, organizational behavior, legal, ethical, cybersecurity and labor market issue.

High quality research will benefit from combining these perspectives rather than evaluating AI solely through technical performance or managerial efficiency.

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5.1 Implications for Policy and Organizational Regulation

Policy makers and organizational leaders should treat employment related GenAI as a high consequence application domain. Regulation is increasingly moving toward risk based approaches in which AI used for recruitment, worker management and other employment decisions can attract stronger obligations than low risk productivity applications. For organizations operating across jurisdictions, this means that compliance should be integrated into procurement, HR policy, privacy management and vendor governance rather than handled after deployment. A practical policy architecture should define minimum requirements for transparency, documentation, data protection, fairness testing, human oversight and contestability. It should also establish responsibility across the AI supply chain. HR cannot assume that responsibility disappears because an external vendor provides the model. The deploying organization remains responsible for understanding how the tool is used, what decisions it influences and whether its implementation creates unacceptable risk.

At organizational level, boards and senior leaders should receive periodic reports on material AI use cases, incidents, workforce effects and governance performance. This elevates GenAI from an experimental IT issue to a strategic human capital issue. The most mature organizations will measure not only financial return on AI investment but also employeee trust, fairness, capability development and responsible use indicators. Such a balanced scorecard is more consistent with the long term purpose of HRM and with the human centered future of work proposed in this review.

5.2 Conclusions

HRM is evolving from a largely administrative support role to a more intelligent, conversational, and data rich organisational capability thanks to generative AI. Enhancing language intensive work, tailoring employee services and learning, speeding up talent acquisition, and increasing access to decision support are its best prospects. When created outputs impact job possibilities, employee evaluations, or sensitive personal information without sufficient controls, it poses the most significant concerns. The data points to a change in perspective on work rather than its replacement. It is anticipated that HR professionals will devote more time to judgement, relationship management, governance, workforce development, and organisational strategy than to routine content production. Only if businesses make concurrent investments in technology, data governance, AI literacy, ethical controls, and employee involvement will this shift be effective.

Purpose, data, justice, accountability, monitoring, and human empowerment are at the core of the proposed Responsible GenAI HRM paradigm. The fundamental strategic idea is straightforward: GenAI should increase HR's capabilities without diminishing its humanity. Therefore, rather than focusing only on technology adoption, future research should prioritise quantifiable improvements in decision quality, employee trust, fairness, skills, and organisational resilience.

5.3 Critical Synthesis and Novel Contribution

The principal contribution of this review is an integrated explanation of why GenAI outcomes in HRM differ across tasks even when organizations use similar models. The review distinguishes capability from value and assistance from delegation. GenAI capability includes generation, summarization, retrieval oriented interaction, personalization, and agentic execution; HR value depends on how these capabilities are translated into tasks and decisions. The proposed Responsible GenAI–HRM framework therefore places governance at every transition from technology to task redesign, from task redesign to human–AI collaboration, and from collaboration to organizational outcomes. This perspective extends conventional AI HRM reviews by connecting operational use cases with responsible AI, employee relations, future of work transformation, and measurable organizational outcomes. It also identifies bounded autonomy as a key design principle for agentic HR systems: autonomous execution may be acceptable for routine, reversible actions, while consequential employment decisions should remain subject to explicit human authorization. The framework additionally treats employee participation, reskilling, accessibility, and trust as performance conditions rather than peripheral ethical considerations.

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5.4 Declarations

Funding: This review did not receive any specific grant from public, commercial, or not for profit funding agencies. Conflict of interest: The author declares no conflict of interest. Data availability: No new primary dataset was generated for this review. The evidence base should be documented through the final database search exports and screening records before submission. Author contributions: Conceptualization, literature synthesis, framework development, writing, and revision were undertaken by the author. Generative AI disclosure: If generative AI or AI assisted tools are used in preparing the submitted manuscript, the author should follow the target journal's disclosure policy and independently verify all generated text, claims, citations, and references before submission.

Credit authorship contribution statement

Venkateswarlu.B: Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Suresh Kumar Gundeboina**: Writing – review & editing, Writing – original draft, Visualization, Supervision, Formal analysis. **Dhanunjhay Gangineni** Writing – review & editing, Writing – original draft, Supervision.

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References

1. Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. Journal of Economic Perspectives, 33(2), 3–30. https://doi.org/10.1257/jep.33.2.3
2. Amershi, S., Weld, D., Vorvoreanu, M., Fourney, A., Nushi, B., Collisson, P., Suh, J., Iqbal, S., Bennett, P. N., Inkpen, K., Teevan, J., Kikin-Gil, R., & Horvitz, E. (2019). Guidelines for human-AI interaction. Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, 1–13. https://doi.org/10.1145/3290605.3300233
3. Andrieux, P., Johnson, R. D., Sarabadani, J., & Van Slyke, C. (2024). Ethical considerations of generative AI-enabled human resource management. Organizational Dynamics, 53(1), 101032. https://doi.org/10.1016/j.orgdyn.2024.101032
4. Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. Journal of Economic Perspectives, 29(3), 3–30. https://doi.org/10.1257/jep.29.3.3
5. Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, 610–623. https://doi.org/10.1145/3442188.3445922
6. Bondarouk, T., & Brewster, C. (2016). Conceptualising the future of HRM and technology research. The International Journal of Human Resource Management, 27(21), 2652–2671. https://doi.org/10.1080/09585192.2016.1232296
7. Brynjolfsson, E., Li, D., & Raymond, L. R. (2025). Generative AI at work. The Quarterly Journal of Economics, 140(2), 889–942. https://doi.org/10.1093/qje/qjae044
8. Budhwar, P., Chowdhury, S., Wood, G., Aguinis, H., Bamber, G. J., Beltran, J. R., Boselie, P., Lee Cooke, F., Decker, S., & others. (2023). Human resource management in the age of generative artificial intelligence: Perspectives and research directions on ChatGPT. Human Resource Management Journal, 33(3), 606–659. https://doi.org/10.1111/1748-8583.12524
9. Bujold, A., Roberge-Maltais, I., Parent-Rocheleau, X., Boasen, J., Sénécal, S., & Léger, P. M. (2024). Responsible artificial intelligence in human resources management: A review of the empirical literature. AI and Ethics, 4, 1185–1200. https://doi.org/10.1007/s43681-023-00325-1
10. Chui, M., Hazan, E., Roberts, R., Singla, A., Smaje, K., Smit, S., & others. (2023). The economic potential of generative AI: The next productivity frontier. McKinsey Global Institute.
11. European Union. (2024). Regulation (EU) 2024/1689 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). Official Journal of the European Union. No DOI; use the official EUR-Lex legislation reference.

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Vol. 01, Issue 7, November2026, pp :1-18

12. Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. Business & Information Systems Engineering, 66, 111–126. https://doi.org/10.1007/s12599-023-00834-7
13. George, G., Osinga, E. C., Lavie, D., & Scott, B. A. (2024). Sociotechnical implications of generative artificial intelligence for organizations. Journal of Management.
14. Gmyrek, P., Berg, J., Kamiński, K., Konopczyński, F., Ładna, A., Nafradi, B., & others. (2025). Generative AI and jobs: A refined global index of occupational exposure. International Labour Organization Working Paper No. 140. https://doi.org/10.54394/HETP0387
15. International Labour Organization. (2023). Generative AI and jobs: A global analysis of potential effects on job quantity and quality. ILO. https://doi.org/10.54394/FHEM8239
16. International Labour Organization. (2025). Generative AI and jobs: A 2025 update. ILO. https://doi.org/10.54394/HETP0387
17. Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007
18. Ji, Z., Lee, N., Frieske, R., Yu, T., Su, D., Xu, Y., Ishii, E., Bang, Y., Madotto, A., & Fung, P. (2023). Survey of hallucination in natural language generation. ACM Computing Surveys, 55(12), 1–38. https://doi.org/10.1145/3571730
19. Kelan, E. K. (2024). Algorithmic inclusion: Shaping the predictive algorithms of artificial intelligence in hiring. Human Resource Management Journal, 34(3), 694–707. https://doi.org/10.1111/1748-8583.12511
20. Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. Academy of Management Annals, 14(1), 366–410. https://doi.org/10.5465/annals.2018.0174
21. Liang, P., Bommasani, R., Lee, T., Tsipras, D., Soylu, D., Yao, D., & others. (2023). Holistic evaluation of language models. Correction needed: The published journal version is: Bommasani, R., Liang, P., & Lee, T. (2023). Holistic evaluation of language models. Annals of the New York Academy of Sciences, 1525(1), 140–146. https://doi.org/10.1111/nyas.15007
22. Marler, J. H., & Boudreau, J. W. (2017). An evidence-based review of HR analytics. The International Journal of Human Resource Management, 28(1), 3–26. https://doi.org/10.1080/09585192.2016.1244699
23. Minbaeva, D. (2021). Disrupted HR? Human resource management in the digital age. Human Resource Management Review, 31(4), 100820. https://doi.org/10.1016/j.hrmr.2020.100820
24. Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. Science, 381(6654), 187–192. https://doi.org/10.1126/science.adh2586
25. OECD. (2023). OECD employment outlook 2023: Artificial intelligence and the labour market. OECD Publishing. https://doi.org/10.1787/08785bba-en
26. Prasad, K. D. V., & De, T. (2024). Generative AI as a catalyst for HRM practices: Mediating effects of trust. Humanities and Social Sciences Communications, 11, 1362. https://doi.org/10.1057/s41599-024-03842-4
27. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. Academy of Management Review, 46(1), 192–210. https://doi.org/10.5465/amr.2018.0072
28. Raji, I. D., Smart, A., White, R. N., Mitchell, M., Gebru, T., Hutchinson, B., Smith-Loud, J., Theron, D., & Barnes, P. (2020). Closing the AI accountability gap. Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency, 33–44. https://doi.org/10.1145/3351095.3372873
29. Selbst, A. D., Boyd, D., Friedler, S. A., Venkatasubramanian, S., & Vertesi, J. (2019). Fairness and abstraction in sociotechnical systems. Proceedings of the Conference on Fairness, Accountability, and Transparency, 59–68. https://doi.org/10.1145/3287560.3287598
30. Shneiderman, B. (2022). Human-centered AI. Oxford University Press. https://doi.org/10.1093/oso/9780192845290.001.0001
31. Stone, D. L., Deadrick, D. L., Lukaszewski, K. M., & Johnson, R. D. (2015). The influence of technology on the future of human resource management. Human Resource Management Review, 25(2), 216–231. https://doi.org/10.1016/j.hrmr.2015.01.002

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32. Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. California Management Review, 61(4), 15–42. https://doi.org/10.1177/0008125619867910
33. Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. The International Journal of Human Resource Management, 33(6), 1237–1266.

5.5 Submission note

The uploaded manuscript describes a PRISMA oriented systematic review, but it does not contain verified database search counts, screening counts, or a completed PRISMA flow diagram. Those elements must be generated from the author's actual searches before submission. The present document therefore presents the review as a critical systematic review draft and does not invent PRISMA numbers.

6 PRISMA 2020–ALIGNED SYSTEMATIC REVIEW METHODOLOGY

Important methodological note. PRISMA counts must come from the author's actual final database searches. The manuscript therefore uses verification fields rather than invented numbers.

6.1 Review objective and research questions

The objective was to critically synthesize peer reviewed evidence on applications, benefits, risks, governance requirements and future of work implications of generative artificial intelligence in human resource management (GenAI HRM).

- RQ1. What opportunities and applications of GenAI are reported across the HR lifecycle?
- RQ2. What ethical, legal, privacy, fairness, transparency and accountability risks are associated with GenAI enabled HRM?
- RQ3. How may GenAI reshape HR roles, skills, jobs, and employee experience and human–AI collaboration?
- RQ4. What governance and implementation practices can support responsible, human centered GenAI HRM?

6.2 Information sources and search strategy

The final systematic search should be conducted in Scopus and Web of Science Core Collection, with supplementary backward/forward citation searching where permitted. The principal search window should cover 2020 through the final search date, while seminal earlier studies may be retained when theoretically necessary.

Recommended core search string:

("generative artificial intelligence" OR "generative AI" OR GenAI OR "large language model" OR LLM* OR ChatGPT OR "foundation model*") AND ("human resource management" OR HRM OR "human resources" OR "people management" OR recruitment OR "talent management" OR "performance management" OR "learning and development" OR reskilling OR "employee experience")*

6.3 Inclusion and exclusion criteria

Criterion	Include	Exclude
Publication type	Peer reviewed journal articles; selected scholarly reviews and authoritative policy reports	Editorials, news, blogs, marketing content
Topic	GenAI/LLMs/foundation models with substantive HRM, workforce or people management relevance	GenAI studies unrelated to HR/workforce
Language	English	Non English unless reliably translated
Period	Primarily 2020–final search date; seminal earlier studies retained where necessary	Older papers without essential theoretical relevance

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Evidence	Empirical, conceptual, theoretical and systematic review studies answering the research questions	Insufficiently relevant or methodologically unusable records
Full text	Full text available for eligibility assessment	Unretrievable after reasonable attempts

6.4 PRISMA 2020 study selection process

Records should be exported to a reference manager; duplicates removed using DOI, database identifiers and title/author checks; titles/abstracts screened against predefined criteria; potentially eligible reports assessed in full text; and final included studies documented in a study characteristics table. PRISMA 2020 recommends reporting the numbers at each stage and principal reasons for exclusion.

PRISMA stage	Verified count
Scopus records identified	n = _____
Web of Science records identified	n = _____
Additional citation search records, if used	n = _____
Duplicates removed	n = _____
Records screened	n = _____
Records excluded after title/abstract screening	n = _____
Full text reports sought	n = _____
Reports not retrieved	n = _____
Full text reports assessed	n = _____
Full text reports excluded	n = _____
Studies included in qualitative synthesis	n = _____

Figure X. PRISMA 2020 flow diagram template. Replace all blanks with verified counts before submission.

IDENTIFICATION

Scopus: n=___ | Web of Science: n=___ | other sources: n=___

↓

Duplicates removed: n=___

↓

SCREENING

Records screened: n=___

Records excluded: n=___

↓

ELIGIBILITY

Full text reports assessed: n=___

Full text reports excluded with reasons: n=___

↓

INCLUDED

Studies included in qualitative synthesis: n=___

6.5 Data extraction framework

For each included study extract: author/year, country or setting, study design, sample/data source, HR function, GenAI application, theoretical perspective, principal opportunity/outcome, ethical/legal risk, human oversight mechanism, limitations and future research implications.

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Study	Year	Design/setting	HR function	GenAI application	Benefits/outcomes	Risks/governance	Limitation
To be completed	To be completed	To be completed	To be completed	To be completed	To be completed	To be completed	To be completed
To be completed	To be completed	To be completed	To be completed	To be completed	To be completed	To be completed	To be completed
To be completed	To be completed	To be completed	To be completed	To be completed	To be completed	To be completed	To be completed
To be completed	To be completed	To be completed	To be completed	To be completed	To be completed	To be completed	To be completed
To be completed	To be completed	To be completed	To be completed	To be completed	To be completed	To be completed	To be completed

6.6 Evidence synthesis

Because the literature is heterogeneous in design, context and outcomes, the primary synthesis should be thematic and narrative rather than a statistical meta analysis. Studies should be grouped by HR function, opportunity/risk domain, human–AI relationship and governance mechanism.

6.7 Quality and bias appraisal

Quality appraisal should be matched to study design and consider research question clarity, sampling/data adequacy, methodological transparency, measurement quality, analytical rigor, limitations and conflicts of interest. A consistently applied higher/moderate/lower confidence scheme may be used if justified.

6.8 Required supplementary material

Before submission provide: (i) completed PRISMA 2020 checklist; (ii) final flow diagram; (iii) complete database search strings and dates; (iv) deduplicated screening dataset; and (v) final study characteristics table. PRISMA S may be used to report literature search details.

Table: GenAI HRM opportunity–risk synthesis

HR domain	Potential uses	Principal risks	Governance
Recruitment & selection	Job descriptions, candidate communication, interview support	Bias, privacy, explainability	Human decision authority; bias testing; audit trail
Learning & development	Personalized content, tutoring, skills gap analysis	Hallucination, privacy, inappropriate	Content validation; privacy; AI literacy

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		personalization	
Performance management	Feedback drafting, evidence summarization	Surveillance, opacity, unfair evaluation	Human review; contestability; minimum necessary data
Employee experience	HR assistants, policy Q&A, onboarding	Incorrect advice, confidentiality, over reliance	Approved knowledge base; escalation
Workforce planning	Scenario generation, skills mapping, job redesign	Inaccurate forecasts, automation bias	Scenario validation; workforce consultation
Compensation & promotion	Analytical decision support	High consequence discrimination	Strict human authorization; fairness audits

Final PRISMA submission checklist

- Run final Scopus and Web of Science searches and record exact search dates.
- Export records and preserve the raw database exports.
- Remove duplicates and document the method used.
- Screen titles/abstracts using the predefined criteria.
- Record full text exclusion reasons.
- Replace every PRISMA placeholder with actual verified counts.
- Generate the final PRISMA 2020 flow diagram.
- Complete the PRISMA 2020 checklist.
- Complete the study characteristics and evidence synthesis tables.
- Verify every DOI and bibliographic detail.
- Update the search immediately before submission because GenAI HRM evidence is rapidly changing.

PRISMA references

1. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372, n71. https://doi.org/10.1136/bmj.n71
2. Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., et al. (2021). PRISMA 2020 explanation and elaboration: Updated guidance and exemplars for reporting systematic reviews. BMJ, 372, n160. https://doi.org/10.1136/bmj.n160
3. Rethlefsen, M. L., Kirtley, S., Waffenschmidt, S., Ayala, A. P., Moher, D., Page, M. J., & Koffel, J. B. (2021). PRISMA S: An extension to the PRISMA Statement for Reporting Literature Searches in Systematic Reviews. Systematic Reviews, 10, 39. https://doi.org/10.1186/s13643 020 01542 z
4. Nyberg, A. J., Schleicher, D. J., Bell, B. S., Boon, C., Cappelli, P., Collings, D. G., et al. (2025). A brave new world of human resources research: Navigating perils and identifying grand challenges of the GenAI revolution. Journal of Management.
5. Naoum, R. F., Szakadáti, T., & Balogh, G. (2026). Artificial intelligence (AI) in human resource management (HRM): A systematic review of its dual impact on diversity, equity, and inclusion (DEI). Management Review Quarterly.