

AI and Generative AI for Recruitment and Talent Management: A PRISMA-Based Systematic Literature Review

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Abstract—The rapid emergence of Artificial Intelligence (AI) and Generative Artificial Intelligence (GenAI) is reshaping Human Resource Management (HRM), transforming traditional recruitment and talent management processes into intelligent, data-driven ecosystems. Recent advances in Natural Language Processing, transformer architectures, Large Language Models (LLMs), and Retrieval-Augmented Generation (RAG) have enabled significant improvements in resume understanding, semantic candidate-job matching, workforce analytics, and decision support. However, despite the growing number of studies in this domain, a comprehensive synthesis of the latest developments and emerging paradigms remains limited. This paper presents a PRISMA-based systematic literature review of 21 studies published between January 2025 and May 2026, focusing on AI-driven recruitment, resume information extraction, semantic matching, workforce forecasting, Generative AI, and responsible AI. The included studies are analyzed to identify prevailing techniques, applications, limitations, and research trends. Based on the reviewed literature, a taxonomy of AI and Generative AI techniques in Human Resource Management is proposed, together with a structured comparison of the included studies and an overview of major open challenges. The findings reveal a clear transition from conventional keyword-based Applicant Tracking Systems toward transformer-based architectures, LLM-powered frameworks, RAG-enhanced systems, and emerging agentic AI paradigms. Although these technologies demonstrate remarkable capabilities in semantic understanding and decision support, several challenges remain unresolved, including algorithmic bias, explainability, privacy preservation, hallucination phenomena, and the lack of standardized benchmarks. This review highlights the evolution of Human Resource Management toward autonomous, explainable, and human-centric ecosystems. It provides researchers and practitioners with a structured overview of the current landscape and identifies promising future directions involving multimodal AI, knowledge-enhanced systems, Agentic AI, and collaborative human-AI frameworks for next-generation talent management.

Keywords—Human resource management; artificial intelligence; generative AI; large language models; recruitment; semantic matching; retrieval-augmented generation; agentic AI; explainable AI; systematic literature review

I. INTRODUCTION

The rapid evolution of Artificial Intelligence (AI) and Generative Artificial Intelligence (GenAI) is profoundly transforming Human Resource Management (HRM), particularly

recruitment and talent management processes [2], [1]. This transformation is highlighted in [3], which demonstrates the growing adoption of machine learning and semantic matching techniques for employment prediction and recruitment decision support. Similarly, [4] illustrates how AI-based profile classification and recommendation techniques improve recruitment efficiency by automating candidate evaluation and reducing mismatches between professional profiles and job requirements.

Traditional recruitment systems mainly rely on keyword-based Applicant Tracking Systems (ATS), manual screening, and rule-based approaches, which struggle with heterogeneous resumes and semantic matching [8], [5]. Recent advances in NLP, transformer architectures, and Large Language Models (LLMs) enable more intelligent recruitment systems for semantic information extraction, candidate-job matching, and decision support [16], [19]. Recent approaches combine BERT-based representations and explainable NLP pipelines to improve resume understanding and job recommendation [3], [5]. Generative AI and Retrieval-Augmented Generation (RAG) further extend these capabilities through automated resume analysis, personalized recommendations, and conversational recruitment, while raising challenges related to transparency and accountability [21].

Despite these promising developments, several challenges remain unresolved [7]. Algorithmic bias, fairness, explainability, privacy preservation, and transparency have become critical concerns for AI-driven recruitment systems. These issues are comprehensively addressed in [9], which investigates fairness-aware resume-job matching, bias mitigation strategies, and human-in-the-loop auditing mechanisms for trustworthy hiring systems. In parallel, [12] demonstrates that explainable multi-agent AI systems combined with human validation can improve recruitment efficiency while maintaining transparency and human oversight during candidate evaluation. Furthermore, organizations are increasingly adopting predictive analytics and AI-powered workforce planning to anticipate talent needs and support strategic Human Resource Management. [13] illustrates how AI and big data infrastructures enable proactive workforce forecasting and intelligent talent pipeline management, highlighting the growing role of AI beyond candidate screening toward strategic workforce planning.

Several literature reviews have already examined the inter-

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section of AI and Human Resource Management. Vrontis et al. [29] reviewed 45 articles on AI, robotics and advanced technologies in HRM; Votto et al. [30] surveyed AI applications in tactical HR processes; and Pan and Froese [31] synthesized 184 articles across management, computer science and engineering. Hunkenschroer and Luetge [32] focused specifically on the ethics of AI-enabled recruiting, while Budhwar et al. [33] outlined research directions for HRM in the age of generative AI. These reviews cover literature published up to 2022–2023 and therefore predate the widespread adoption of Retrieval-Augmented Generation, preference-optimized ranking and agentic architectures in recruitment. The present review complements them by covering the January 2025 – May 2026 window and by focusing explicitly on generative, retrieval-augmented and agentic AI in recruitment and talent management.

Although recent studies have investigated individual aspects of AI-enabled recruitment, including semantic matching, explainable hiring, workforce analytics, professional profile recommendation, and AI-assisted decision support, the literature remains fragmented and often focuses on isolated recruitment tasks rather than integrated Human Resource Management ecosystems. Therefore, this paper presents a PRISMA-based systematic literature review of studies published between January 2025 and May 2026 to synthesize recent advances in AI and Generative AI for recruitment and talent management. The review identifies dominant AI techniques, emerging application domains, current limitations, and future research directions, while proposing a taxonomy that captures the evolution of intelligent HR systems toward LLM-based, explainable, and agentic AI architectures.

II. RESEARCH METHODOLOGY: PRISMA

A. Research Method

This study adopts the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework [14] to ensure a transparent, rigorous, and reproducible review process. PRISMA provides an established methodology for identifying, screening, evaluating, and selecting scientific publications, reducing selection bias and improving the reliability of systematic reviews [28]. Following this framework, the review investigates recent advances in Artificial Intelligence (AI) and Generative Artificial Intelligence (GenAI) for recruitment and talent management, focusing on semantic job-candidate matching, resume understanding, Large Language Models (LLMs), workforce analytics, and responsible AI. Four research questions guide the review, addressing the main AI techniques used in Human Resource Management, the impact of LLMs and GenAI on recruitment, the ethical and technical challenges of AI-driven HR systems, and future research directions for intelligent HR ecosystems.

RQ1: What AI techniques are currently used in recruitment and talent management?

RQ2: How are Generative AI and LLMs transforming recruitment and talent management?

RQ3: What ethical and technical challenges affect AI-driven HR systems?

RQ4: What emerging research directions are shaping next-generation intelligent HR ecosystems?

B. Information Sources and Search Strategy

The literature search was conducted across eight scientific databases: ACM Digital Library, ScienceDirect, SpringerLink, Frontiers, Sage Journals, Inderscience, arXiv, and OpenReview. Queries were executed on the title, abstract and keyword fields. These sources were selected because they provide high-quality peer-reviewed publications and recent preprints covering the latest developments in Artificial Intelligence and Human Resource Management. To retrieve the most relevant studies, combinations of keywords related to Artificial Intelligence, Machine Learning, Large Language Models, Generative AI, recruitment, talent management, semantic job matching, resume analysis, workforce analytics, Natural Language Processing (NLP), transformer models, and Retrieval-Augmented Generation (RAG) were used. The following search strings were employed: ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Large Language Models" OR "Generative AI") AND ("Recruitment" OR "Talent Acquisition" OR "Talent Management" OR "Human Resource Management") AND ("Resume Analysis" OR "Candidate Matching" OR "Job Matching" OR "Workforce Analytics" OR "Career Recommendation") AND ("Semantic Similarity" OR "NLP" OR "Transformer" OR "RAG")

The search strategy was designed to capture studies addressing both technical innovations and practical applications of AI throughout the recruitment lifecycle. The results of these searches were then subjected to a multistage selection process, following the PRISMA flow shown in Fig. 1.

C. Study Selection

To ensure the quality, relevance, and methodological reliability of the selected literature, explicit inclusion and exclusion criteria were defined prior to the screening process. Only studies published between January 2025 and May 2026, written in English, and focusing on Artificial Intelligence, Machine Learning, Deep Learning, Large Language Models, or Generative AI applied to Human Resource Management were considered. Eligible studies addressed topics such as recruitment, talent acquisition, resume analysis, semantic candidate-job matching, workforce analytics, and career recommendation. Peer-reviewed journal articles, conference papers, and high-quality preprints were included. Publications released before 2025, duplicate records, editorials, tutorials, non-scientific documents, inaccessible studies lacking sufficient methodological detail, and works unrelated to Human Resource Management were excluded. Studies exclusively focused on educational applications without direct HR relevance were also discarded.

D. PRISMA Screening Process

The study selection followed the four successive phases recommended by PRISMA 2020 [14]: identification, screening, eligibility, and inclusion. Records retrieved from all sources were first pooled and de-duplicated. Titles and abstracts of the remaining records were then screened against the inclusion criteria. Reports passing this stage were retrieved in full text and assessed for eligibility. Fig. 1 summarizes the

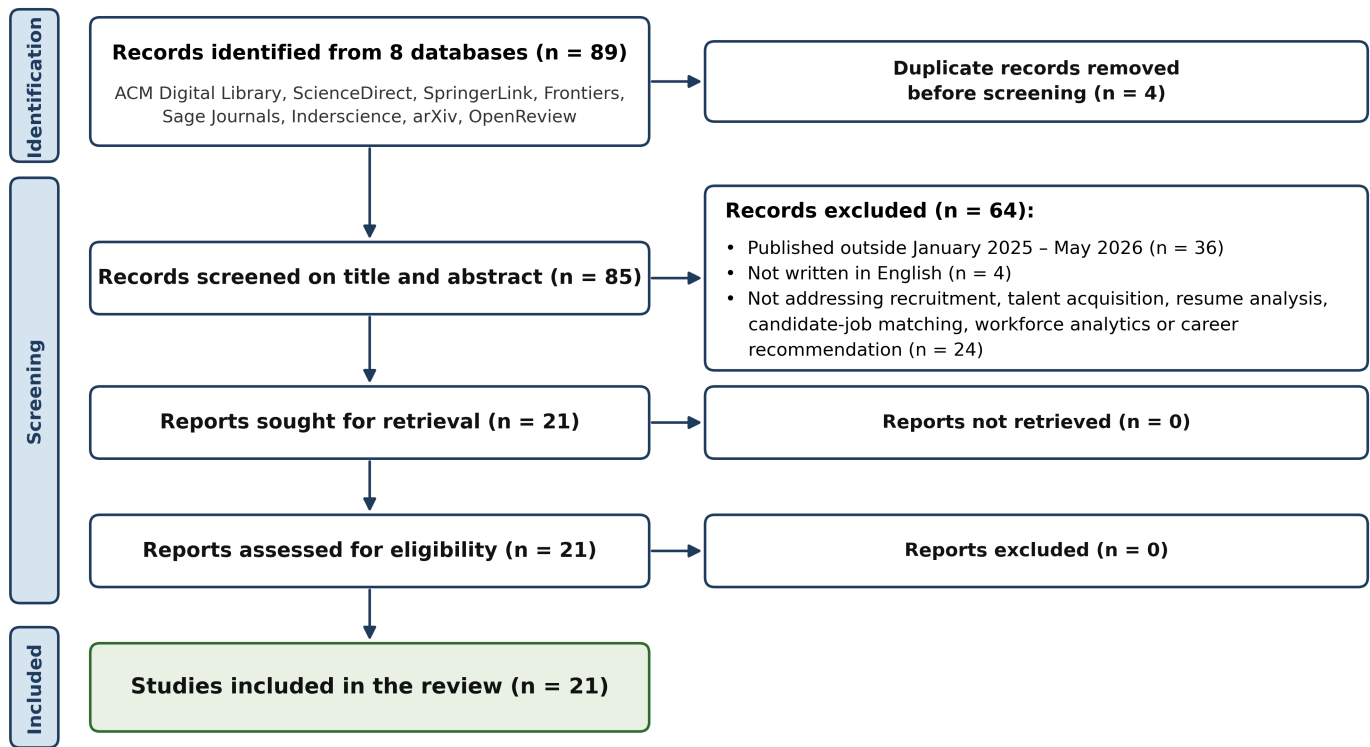


Fig. 1. Systematic filtering and selection of articles following the PRISMA methodology.

number of records retained at each phase, from the records initially identified to the 21 studies included in the review.

The final corpus comprises 21 studies: [1], [2], [3], [4], [5], [6], [8], [9], [10], [11], [12], [13], [15], [16], [18], [19], [20], [21], [22], [23], and [26]. Sections III to VII synthesize these studies exclusively. A limited number of additional references are cited as methodological, historical or technical background only, and are not part of the synthesized corpus.

E. Data Extraction and Analysis

A structured data extraction protocol was applied to ensure consistent analysis across the selected studies. For each publication, information regarding the publication year, source, application domain, AI techniques, datasets, evaluation metrics, principal contributions, reported limitations, and future research directions was systematically collected. This information enabled a comparative analysis of existing approaches, facilitated the identification of technological trends, and supported the development of a unified view of recent advances in AI-powered Human Resource Management.

F. Research Framework

The included studies were analysed using a thematic synthesis procedure: each study was first coded openly on its application domain, techniques and reported limitations; codes were then grouped axially into candidate themes; and the resulting themes were reviewed by all authors until agreement was reached. This analysis revealed six major research themes

that characterize the current landscape of AI-driven Human Resource Management. These themes include AI for recruitment and talent acquisition, resume understanding and information extraction, semantic job-candidate matching, workforce analytics and talent forecasting, Generative AI and Large Language Models, and ethical, explainable, and responsible AI. Together, these research domains form the basis of the taxonomy proposed in this review and provide a coherent framework for organizing the subsequent sections while highlighting the evolution of Human Resource Management toward intelligent, collaborative, and human-centered AI ecosystems.

III. AI FOR RECRUITMENT AND TALENT ACQUISITION

Recruitment and talent acquisition have experienced a profound transformation over the past decade, evolving from traditional keyword-based Applicant Tracking Systems (ATS) toward intelligent systems capable of understanding candidate profiles, predicting workforce needs, and supporting human decision-making. Conventional recruitment methods are often limited by manual screening, subjective evaluation, and their inability to process the growing volume and heterogeneity of resumes and job descriptions. The emergence of Artificial Intelligence (AI), Machine Learning (ML), and, more recently, Generative Artificial Intelligence (GenAI), has introduced new opportunities to improve efficiency, objectivity, and scalability throughout the recruitment lifecycle [3], [4].

Recent studies reveal that AI-driven recruitment systems are no longer restricted to automating repetitive tasks but increasingly act as decision-support tools capable of assisting

recruiters in candidate sourcing, screening, ranking, and workforce planning [15]. The work published in [13] highlights the growing role of AI and Big Data technologies in talent analytics and workforce forecasting, demonstrating how data-driven approaches contribute to strategic human resource management by improving prediction capabilities and facilitating long-term talent acquisition strategies. Similarly, recent studies on workforce pipelines emphasize the integration of predictive analytics and AI techniques to anticipate labor market demands and optimize talent management processes [11].

The integration of Generative AI has further accelerated this transformation. The study [2] shows that large language models and conversational AI systems are reshaping recruitment practices by enabling personalized candidate interactions, automated information extraction, and enhanced decision-making. These findings are consistent with recent investigations conducted in the IT sector, which demonstrate that AI-based recruitment solutions significantly improve recruiter productivity while reducing screening time and enhancing matching accuracy [17]. Such systems increasingly support recruiters rather than replacing them, creating collaborative human-AI decision-making environments [24], [12].

Beyond efficiency considerations, several studies have investigated the impact of AI on ethical and responsible hiring. The work in [22] argues that AI systems can contribute positively to recruitment by reducing cognitive biases [9] and improving consistency when human judgment and algorithmic recommendations are combined. Similarly, recent studies addressing fair and transparent AI for hiring advocate for explainable and human-centered recruitment [9] frameworks capable of balancing algorithmic performance with fairness and accountability requirements. These findings align with the human-centric organizational perspective [23] proposed by recent research, which emphasizes that successful AI adoption in organizations depends not only on technological performance but also on trust, transparency, and the preservation of human agency.

Recent contributions from ACM and ScienceDirect [3], [26] further demonstrate that AI-powered recruitment systems are progressively evolving toward intelligent ecosystems integrating predictive analytics, semantic understanding, and Generative AI capabilities. Rather than relying exclusively on rule-based mechanisms, these systems combine machine learning [4], natural language processing, and contextual information to provide more comprehensive assessments of candidate suitability. Such developments suggest a transition from conventional recruitment automation toward cognitive recruitment systems capable of continuously learning and adapting to changing organizational needs.

Despite these advances, several challenges remain. The reliability of AI recommendations, the presence of algorithmic bias [9], privacy concerns, explainability issues, and regulatory requirements continue to limit the widespread adoption of autonomous recruitment systems. Furthermore, most existing approaches focus primarily on candidate screening [5] and ranking, while fewer studies address end-to-end recruitment processes involving resume understanding, semantic job matching, workforce forecasting [13], and continuous talent development. These limitations have motivated the emergence of more sophisticated architectures based on transformer mod-

els, Large Language Models, and Generative AI, which are discussed in the following sections.

IV. RESUME UNDERSTANDING AND INFORMATION EXTRACTION

Resume understanding constitutes one of the fundamental components of intelligent recruitment systems, as the quality of downstream tasks such as candidate ranking, semantic matching, and talent recommendation largely depends on the ability to accurately extract and represent information contained in resumes and job descriptions. Traditional Applicant Tracking Systems (ATS) mainly rely on keyword-based approaches and manually defined rules, which often fail to capture implicit competencies, contextual relationships between skills, and semantic similarities across heterogeneous candidate profiles [5]. The increasing diversity of resume formats and the growing complexity of labor market requirements have therefore stimulated the development of more sophisticated information extraction techniques based on Natural Language Processing (NLP), machine learning, and deep learning.

Early AI-driven resume analysis systems primarily focused on parsing structured information such as education, work experience, certifications, and technical skills using rule-based approaches and Named Entity Recognition (NER) techniques [5]. However, these approaches often suffer from limited generalization capabilities and struggle with unstructured and highly variable resume formats. Recent advances in NLP have enabled the transition toward context-aware extraction methods capable of identifying latent skills, semantic relationships, and transferable competencies. In particular, transformer-based architectures and contextual embeddings have significantly improved the understanding of candidate profiles by capturing richer semantic representations compared to conventional keyword matching techniques.

Recent studies have further demonstrated the potential of lightweight NLP frameworks such as spaCy for skill extraction and resume-job matching. The study in [6] illustrates how entity recognition and linguistic processing techniques can automatically identify relevant competencies and facilitate candidate classification. Although these approaches provide satisfactory performance and low computational complexity, their dependence on predefined vocabularies and handcrafted rules limits their adaptability to dynamic labor market environments characterized by evolving skill requirements.

To overcome these limitations, more advanced architectures integrating semantic embeddings and transformer models have emerged. The study in [8] proposes a multi-stage framework combining semantic similarity measures, Sentence-BERT embeddings, and fuzzy matching techniques to evaluate candidate suitability. Unlike conventional ATS solutions, such systems exploit contextual representations to identify similarities beyond exact keyword correspondence, thereby improving the robustness of candidate evaluation. Nevertheless, the relatively limited size of the experimental datasets used in these studies raises concerns regarding scalability and generalization across diverse domains and industries.

The growing availability of Large Language Models (LLMs) has further transformed information extraction in recruitment systems. Recent studies published in arXiv [5], [12],

[20] and OpenReview demonstrate that LLM-based architectures are capable of understanding complex resume structures, extracting implicit competencies, and generating contextual representations that significantly improve downstream matching tasks. These models enable the identification of semantic relationships between experiences and soft skills that are often overlooked by traditional approaches. Moreover, recent works investigating resume understanding emphasize the ability of LLMs to handle multilingual and heterogeneous documents while reducing manual feature engineering requirements.

Another emerging trend concerns the integration of Retrieval-Augmented Generation (RAG) frameworks [37] into recruitment pipelines. Recent studies in [21] demonstrate that combining vector databases, semantic retrieval mechanisms, and generative models enables more explainable and context-aware candidate assessments. By enriching large language models with external knowledge sources and dynamically retrieved information, these systems improve response reliability and reduce hallucination phenomena commonly associated with generative models. Such architectures represent a promising direction for developing intelligent recruitment assistants capable of providing more transparent.

Beyond textual information extraction, several recent studies have highlighted the importance of multimodal resume understanding. Modern resumes increasingly contain graphical layouts, tables, icons, certifications, and heterogeneous formatting structures that challenge traditional parsing systems. Consequently, multimodal architectures combining computer vision, optical character recognition, and layout-aware language models [39] are progressively attracting attention within the recruitment community. These approaches aim to bridge the gap between document understanding and semantic reasoning by jointly processing visual and textual information, thereby enabling more robust representations of candidate profiles.

Despite the remarkable progress achieved in resume understanding and information extraction, several challenges remain unresolved. Existing approaches frequently suffer from domain dependency, lack of explainability, limited benchmarking datasets, and difficulties in capturing implicit human competencies such as leadership, adaptability, and interpersonal skills. Moreover, variations in resume formats and the dynamic evolution of labor market requirements continue to hinder the development of universally applicable systems. These limitations have encouraged researchers to move beyond information extraction toward semantic candidate-job matching approaches, where contextual representations and large language models are leveraged to estimate the compatibility between candidate profiles and organizational requirements. The next section therefore examines recent advances in semantic job-candidate matching and the transition from conventional similarity measures to transformer-based and Generative AI-driven matching frameworks.

V. SEMANTIC JOB-CANDIDATE MATCHING

Semantic job-candidate matching has emerged as one of the most active research areas in AI-driven Human Resource Management. Unlike traditional Applicant Tracking Systems (ATS), which primarily rely on keyword matching and manually defined rules, modern matching systems aim to understand the contextual relationships between candidate profiles

and job requirements. Conventional approaches often fail to identify implicit competencies, transferable skills, and semantic similarities among heterogeneous descriptions, leading to inaccurate candidate rankings and the exclusion of potentially suitable candidates [5], [3]. The increasing complexity of labor markets and the rapid evolution of required skills have therefore motivated the transition from syntactic matching toward semantic and context-aware recommendation systems.

Early matching systems were mainly based on statistical techniques such as TF-IDF, cosine similarity, and vector space models [5]. Although these approaches provided computational efficiency and straightforward implementation, they were limited by their inability to capture semantic meanings and contextual dependencies. To overcome these shortcomings, researchers progressively adopted distributed word representations such as Word2Vec and Doc2Vec [36], which enabled the construction of continuous vector spaces capable of modeling semantic relationships between terms. However, these methods still suffered from the lack of contextual awareness and struggled with polysemy and domain-specific terminology.

Recent advances in transformer architectures have profoundly transformed semantic matching systems. Contextual embedding models, particularly BERT [34] and Sentence-BERT (SBERT) [35], have demonstrated superior capabilities in representing both resumes and job descriptions within a common semantic space. The included studies report that such similarity measures outperform conventional keyword-based approaches by capturing latent relationships between skills, experiences, and qualifications [8], [16], [5]. The study in [8] illustrates this evolution by integrating semantic embeddings with fuzzy matching mechanisms to provide more accurate candidate ranking. Such systems improve robustness by considering contextual similarities rather than relying solely on lexical overlap.

The emergence of Large Language Models has further accelerated this transformation. Recent works published in arXiv, OpenReview, and ResearchGate demonstrate that LLM-based matching frameworks provide richer semantic representations and superior adaptability across multiple domains. In particular, the study in [19] highlights the capacity of LLMs to capture implicit competencies and improve matching performance across heterogeneous occupational contexts. These models are capable of understanding complex descriptions, extracting latent skills, and reasoning beyond explicit textual correspondences, thereby enabling more personalized and context-aware recruitment processes.

Another important development concerns ranking optimization techniques. Recent studies such as [20] introduce preference optimization mechanisms that leverage human feedback and ranking objectives to refine candidate recommendation processes. Unlike traditional similarity-based approaches, these methods attempt to align ranking outputs with recruiter preferences and organizational requirements. Such approaches represent an important step toward more adaptive and human-centered recruitment systems capable of continuously learning from interactions and feedback.

Retrieval-Augmented Generation (RAG) architectures have also emerged as promising solutions for semantic candidate-job matching. Recent studies combining vector databases,

semantic retrieval mechanisms, and generative models demonstrate that RAG-based frameworks can provide more explainable and reliable recommendations. By augmenting language models with external knowledge sources, these architectures improve contextual understanding and mitigate hallucination phenomena frequently associated with standalone LLMs. Recent work in [21] illustrates how semantic retrieval combined with generative reasoning enhances both candidate evaluation and recommendation transparency.

In parallel, researchers have explored hybrid approaches combining Natural Language Processing with blockchain technologies and semantic similarity algorithms to improve security, traceability, and authenticity in recruitment systems [25]. These frameworks aim to address issues related to resume fraud and credential verification while maintaining efficient semantic matching capabilities. Other studies have investigated graph-based representations and context-aware models to incorporate relationships between skills, occupations, and career trajectories, thus enabling more comprehensive modeling of candidate suitability [27].

Despite these remarkable advances, several limitations remain. Most existing studies rely on relatively small datasets and domain-specific benchmarks, making it difficult to assess the generalizability of proposed approaches. Moreover, evaluation metrics vary significantly across studies, which complicates objective comparisons between methods. Bias inherited from training data, explainability issues, privacy concerns, and computational costs associated with large language models also constitute major challenges. In addition, current systems primarily focus on static candidate-job compatibility and often neglect temporal aspects such as career evolution, skill acquisition, and organizational dynamics.

These limitations have motivated the emergence of a new generation of intelligent recruitment systems based on Generative Artificial Intelligence and Large Language Models. Rather than acting solely as semantic similarity engines, these systems aim to perform reasoning, personalized recommendation, conversational interaction, and decision support throughout the recruitment lifecycle. Consequently, recent research increasingly focuses on Generative AI, agentic architectures, and human-AI collaboration frameworks, which are discussed in the following section.

VI. GENERATIVE AI AND LLMs IN HR

The emergence of Generative Artificial Intelligence (GenAI) and Large Language Models (LLMs) represents one of the most significant technological disruptions currently reshaping Human Resource Management. While traditional machine learning approaches have primarily focused on automating isolated tasks such as resume parsing and candidate ranking, recent advances in foundation models have enabled the development of intelligent systems capable of reasoning, generating content, interacting with users, and supporting decision-making throughout the recruitment lifecycle [2]. The transition from predictive AI to generative and conversational AI is gradually transforming recruitment processes from static matching mechanisms into adaptive ecosystems.

Recent studies indicate that LLMs provide substantial improvements in understanding complex candidate profiles

and job descriptions by leveraging contextual representations and reasoning capabilities [19]. Unlike conventional semantic similarity models, large language models are capable of interpreting implicit competencies, inferring transferable skills, and generating comprehensive explanations for candidate recommendations. Studies published in arXiv and OpenReview have demonstrated that transformer-based architectures significantly enhance candidate-job compatibility analysis and improve adaptability across different professional domains. Similarly, the work [19] highlights the superior ability of LLMs to model contextual relationships between experience, qualifications, and occupational requirements while maintaining robust performance across heterogeneous positions.

Beyond semantic matching, Generative AI has introduced new paradigms for recruiter-candidate interaction. Recent studies on AI-driven recruitment demonstrate that conversational systems based on large language models can automate candidate screening, answer frequently asked questions, provide personalized recommendations, and assist recruiters in evaluating candidate profiles. The study [2] emphasizes that Generative AI is not merely a tool for automation but rather a catalyst for transforming recruitment processes into more responsive and personalized experiences. These intelligent assistants contribute to reducing administrative workload while improving candidate engagement and decision-making efficiency.

Another major development concerns the integration of Retrieval-Augmented Generation (RAG) architectures into recruitment systems. Unlike standalone language models, RAG frameworks combine semantic retrieval mechanisms with generative reasoning capabilities to enhance factual accuracy and contextual relevance. Recent studies in [21] demonstrate that external knowledge sources and vector databases significantly improve the reliability and explainability of recommendations. By grounding responses in retrieved information, these systems mitigate hallucination phenomena and provide more transparent candidate assessments. Consequently, RAG-based architectures are increasingly viewed as promising solutions for developing trustworthy recruitment assistants and intelligent decision-support systems.

Recent research has also explored optimization strategies designed to align language models with recruiter expectations and organizational requirements. Preference optimization methods, including [20] and reinforcement learning approaches, aim to refine ranking mechanisms by incorporating human feedback into the learning process. Such techniques enable recruitment systems to adapt dynamically to organizational preferences and evolving labor market conditions. This shift from static similarity measures to preference-aware models represents an important step toward human-centered AI systems capable of continuous improvement and personalized recommendations.

Generative AI has further expanded its applications beyond recruitment into broader talent management activities. Several recent studies highlight the potential of LLMs in workforce analytics, career planning, employability prediction, and professional profile recommendation. AI-driven systems are increasingly used to identify skill gaps, recommend training opportunities, and support long-term career development. Research focusing on personalized career planning demonstrates how Generative AI can provide tailored guidance based on

candidate competencies, aspirations, and market trends. Similarly, predictive workforce analytics frameworks leverage AI to anticipate future talent requirements.

Despite their impressive capabilities, large language models present several limitations that currently hinder their widespread adoption in Human Resource Management. Hallucination phenomena [38], lack of explainability, privacy concerns, computational complexity, and dependency on proprietary models remain important challenges. Furthermore, bias inherited from training datasets may lead to unfair recommendations and discriminatory outcomes, raising ethical and regulatory concerns. Recent studies advocating human-centric AI emphasize that AI systems should augment rather than replace human expertise, preserving transparency, accountability, and trust throughout recruitment processes. The work [22] supports this perspective by demonstrating that human-AI collaboration can improve fairness while maintaining human oversight.

The evolution of Generative AI is also paving the way for more autonomous and collaborative architectures. Emerging concepts such as Agentic AI and Multi-Agent Systems suggest a future in which specialized AI agents cooperate to perform resume analysis, candidate ranking, interview preparation, workforce forecasting, and personalized career recommendation. These architectures move beyond conventional chatbot paradigms and aim to establish intelligent ecosystems capable of continuously learning and interacting with both recruiters and candidates. Although still in their early stages, agentic frameworks represent one of the most promising directions for next-generation Human Resource Management systems.

Overall, the literature published during January 2025 and May 2026 clearly indicates a transition from isolated machine learning applications toward integrated ecosystems powered by Large Language Models, Retrieval-Augmented Generation, and human-AI collaboration. However, the increasing complexity and autonomy of these systems have amplified concerns regarding fairness, transparency, explainability, and regulatory compliance. These issues have motivated the development of responsible and trustworthy AI frameworks, which constitute a crucial research direction and are examined in the following section.

VII. ETHICAL AND RESPONSIBLE AI

The rapid integration of Artificial Intelligence and Generative AI into Human Resource Management has generated considerable enthusiasm due to their ability to improve recruitment efficiency, automate repetitive tasks, and support decision-making processes. However, alongside these technological advances, concerns regarding fairness, transparency, explainability, privacy, and accountability have become increasingly prominent [9]. Since recruitment decisions directly affect individuals' professional opportunities and organizational diversity, the adoption of AI-driven systems raises critical ethical questions that extend beyond technical performance. Consequently, responsible AI has emerged as one of the most important research directions in intelligent Human Resource Management [10].

One of the primary concerns associated with AI-powered recruitment systems is algorithmic bias. Machine learning models are inherently dependent on historical data, which

may contain hidden prejudices [9] reflecting social inequalities, demographic imbalances, or discriminatory practices. Consequently, AI systems trained on biased datasets may unintentionally reproduce or amplify these inequalities, leading to unfair candidate evaluations and exclusion of underrepresented groups. Recent studies investigating ethical AI in recruitment suggest that fairness cannot be achieved solely through algorithmic optimization, but requires continuous monitoring, representative datasets, and human oversight [17]. The work in [22] emphasizes that collaboration between recruiters and intelligent systems can significantly improve decision consistency while mitigating cognitive biases.

Beyond fairness, explainability has become a central challenge for AI-driven Human Resource Management. Although deep learning models and Large Language Models offer remarkable predictive capabilities, their internal reasoning processes are often difficult to interpret. The lack of transparency associated with black-box models limits trust among recruiters and candidates [9] and complicates the justification of hiring decisions. Recent studies advocating fair and transparent AI for hiring highlight the importance of Explainable Artificial Intelligence (XAI) frameworks [9] capable of providing understandable explanations for recommendations and ranking decisions [5]. Such mechanisms are essential for increasing user confidence, facilitating auditing procedures, and ensuring accountability in high-stakes applications such as recruitment and talent management.

The increasing adoption of Generative AI and Large Language Models introduces additional challenges related to reliability and hallucination phenomena. Unlike traditional machine learning models, generative systems may produce inaccurate or fabricated information, potentially affecting candidate evaluations and recommendation quality. Retrieval-Augmented Generation architectures partially address these limitations by grounding responses in external knowledge sources, thereby improving factual consistency and transparency. Nevertheless, ensuring the reliability and traceability of AI-generated outputs remains an open research problem, particularly in contexts where recruitment decisions have legal.

Privacy and data protection also represent major concerns in AI-enabled Human Resource Management [18]. Recruitment systems typically process highly sensitive information, including personal identities, educational backgrounds, professional experiences, and behavioral data. The increasing use of Large Language Models and cloud-based infrastructures raises questions regarding data confidentiality, ownership, and regulatory compliance. Existing regulations, including the General Data Protection Regulation (GDPR) [40] and the EU Artificial Intelligence Act [41], require organizations to guarantee transparency, lawful processing, and the protection of personal information. Consequently, privacy-preserving machine learning techniques, anonymization strategies, and secure architectures are becoming increasingly important components of intelligent recruitment systems.

Recent research further emphasizes the importance of human-centric AI and organizational readiness in ensuring successful AI adoption. The study [23] argues that technological performance alone does not guarantee effective integration within organizations. Instead, trust, organizational culture, transparency, and employee acceptance play a crucial role

in the sustainable deployment of intelligent systems. Human-centric approaches advocate the design of AI systems that augment human capabilities rather than replace human expertise, thereby promoting collaboration and preserving human agency throughout decision-making processes.

Accountability constitutes another critical dimension of responsible AI. As intelligent recruitment systems become increasingly autonomous, determining responsibility for erroneous or discriminatory decisions becomes more challenging. Current research suggests that maintaining meaningful human control and establishing clear governance mechanisms are essential for ensuring ethical accountability [17]. Human-AI collaboration frameworks are therefore emerging as promising solutions capable of combining algorithmic efficiency with human expertise and ethical judgment. Rather than fully autonomous recruitment systems, the literature increasingly advocates hybrid approaches [17] in which AI supports human decision-makers while preserving transparency.

Despite significant progress, responsible AI in Human Resource Management remains an evolving field characterized by numerous unresolved challenges. Existing fairness metrics often fail to capture complex societal biases, explainability techniques remain limited for large language models, and regulatory frameworks are still under development [9]. Furthermore, balancing predictive performance with transparency, privacy, and fairness represents a major trade-off for future intelligent recruitment systems. These limitations indicate that the development of trustworthy AI requires multidisciplinary efforts combining artificial intelligence, ethics, law, organizational sciences, and human-centered design principles.

Overall, the literature published during January 2025 and May 2026 demonstrates that ethical and responsible AI has become a fundamental prerequisite rather than an optional requirement for intelligent Human Resource Management. While technological advances continue to enhance recruitment and talent management capabilities, ensuring fairness, explainability, transparency, and accountability will determine the long-term acceptance and sustainability of AI-driven systems. These unresolved issues, together with the rapid emergence of Agentic AI and multimodal architectures, motivate the identification of open challenges and future research directions, which are discussed in the next section.

VIII. OPEN CHALLENGES AND FUTURE DIRECTIONS

A. Open Challenges

Table I summarizes the major challenges identified throughout the reviewed studies and highlights potential research directions proposed by the literature. Although significant progress has been achieved in AI-driven Human Resource Management, unresolved issues related to explainability, fairness, privacy, and benchmark scarcity continue to limit the large-scale adoption of intelligent recruitment systems. These challenges motivate the development of more transparent, adaptive, and trustworthy architectures.

B. Taxonomy of AI and Generative AI Techniques in HRM

Fig. 2 presents a comprehensive taxonomy of Artificial Intelligence and Generative AI techniques employed in Human

TABLE I. OPEN CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Challenge	Current Limitations	Potential Solutions
Explainability	Black-box models	Explainable AI
Fairness	Algorithmic bias	Bias mitigation techniques
Hallucinations	Incorrect outputs	RAG architectures
Data Privacy	Sensitive HR data	Privacy-preserving AI
Data Scarcity	Lack of benchmarks	Public HR datasets
Dynamic Skills	Static representations	Continual Learning
End-to-End Recruitment	Fragmented systems	Agentic AI
Trust and Adoption	Human resistance	Human-AI collaboration
Regulatory Compliance	GDPR and AI Act constraints	Responsible AI frameworks

Resource Management. Based on the analysis of the selected studies, six major research domains emerge, namely AI-driven recruitment, resume understanding, semantic job-candidate matching, workforce analytics, Generative AI and LLM-based systems, and ethical and responsible AI. Furthermore, the taxonomy highlights the evolution of HR systems toward future paradigms based on Agentic AI and multi-agent architectures. Cross-cutting enablers such as data quality, vector databases, and human-AI collaboration constitute essential components supporting the development of intelligent HR ecosystems.

C. Comparative Analysis of Existing Studies

Table II provides a comparative overview of ten representative studies drawn from the corpus of 21 included studies. The analysis reveals a clear evolution from conventional machine learning approaches toward transformer-based and LLM-driven systems. While recent studies demonstrate remarkable improvements in semantic understanding and recommendation accuracy, most experiments remain limited by small datasets, domain dependency, and the lack of standardized evaluation protocols. Moreover, explainability and fairness remain insufficiently addressed in many existing frameworks.

D. Evolution of AI Paradigms

Table III illustrates the progressive evolution of AI paradigms in Human Resource Management. The literature reveals a transition from keyword-based ATS systems to more sophisticated architectures integrating deep learning, semantic matching, and Generative AI. More recently, RAG-based systems and Agentic AI architectures have emerged as promising directions capable of enabling autonomous and collaborative talent management ecosystems. However, these new paradigms also introduce additional challenges regarding governance, transparency, and accountability.

E. Future Research Directions

Based on the identified gaps and emerging trends, Fig. 3 outlines future research directions, emphasizing the growing convergence of Generative AI, Agentic AI, multimodal architectures, and human-centered frameworks. The next generation of intelligent Human Resource Management systems is likely to evolve from isolated recruitment tools toward autonomous and collaborative ecosystems capable of continuously learning, reasoning, and interacting with both recruiters and candidates.



Fig. 2. Taxonomy of artificial intelligence and generative AI techniques in human resource management.

TABLE II. COMPARATIVE ANALYSIS OF TEN REPRESENTATIVE STUDIES FROM THE INCLUDED CORPUS

Reference	Year	Application	Contribution	Limitations
[1]	2025	Workforce Analytics	Strategic talent forecasting	Limited focus on semantic matching
[2]	2026	Recruitment	Transformation of recruitment processes	Conceptual study
[6]	2025	Resume Parsing	Skill extraction and classification	Rule dependency
[8]	2025	Candidate Evaluation	Multi-stage scoring system	Small dataset
[16]	2025	Job Matching	Improved candidate-job matching	Domain dependence
[19]	2025	Matching	Context-aware recommendations	Computational cost
[20]	2025	Ranking Optimization	Human-aligned ranking	Limited HR benchmarks
[21]	2025	Resume Analysis	Explainable recommendations	Hallucination remains possible
[22]	2026	Ethical Recruitment	Reduced bias and improved fairness	Evidence limited to experimental settings
[23]	2026	AI Adoption	Organizational perspective	Non-technical approach

TABLE III. EVOLUTION OF AI PARADIGMS IN HUMAN RESOURCE MANAGEMENT

Generation	Technologies	Characteristics	Limitations
Traditional ATS	Keywords, Rules	Fast and simple filtering	Poor semantic understanding
Machine Learning-based HR Systems	Classification, Regression	Data-driven recruitment	Feature engineering required
Deep Learning Systems	BERT, Transformers	Contextual understanding	Limited explainability
Semantic Matching Systems	SBERT, Cross-Encoders	Better candidate-job similarity	Computational complexity
LLM-based Recruitment Systems	GPT, Llama, Gemini	Reasoning and contextual analysis	Hallucinations and bias
RAG-based HR Systems	LLM + Vector Databases	More reliable recommendations	Knowledge base dependency
Agentic AI Systems	Multi-Agent Systems	Autonomous collaboration	Governance and accountability challenges
Human-AI Collaborative Systems	Explainable AI + Human-in-the-loop	Trustworthy decision support	Increased system complexity

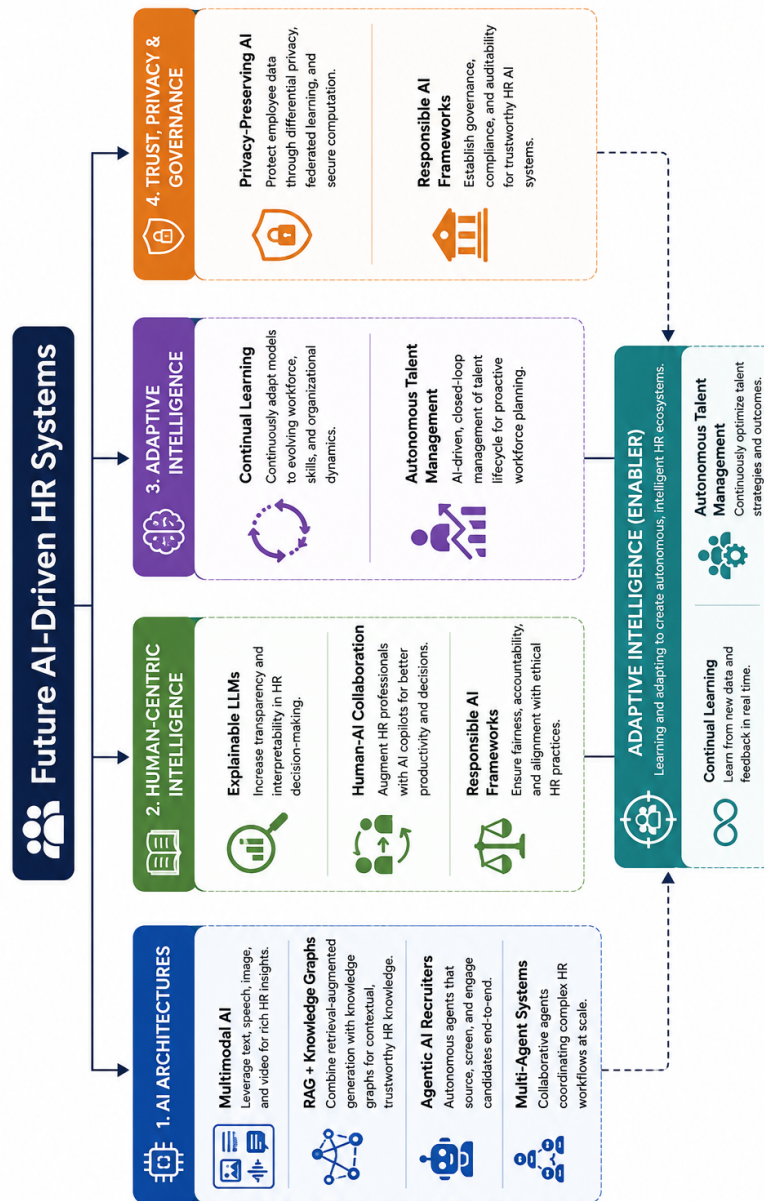


Fig. 3. Emerging directions toward future AI-Driven HR systems.

IX. CONCLUSION AND FUTURE PERSPECTIVES

This paper presented a PRISMA-based systematic literature review of recent advances in Artificial Intelligence and Generative Artificial Intelligence for Human Resource Management, focusing on studies published between January 2025 and May 2026. The review demonstrates a clear paradigm shift from traditional keyword-based recruitment systems toward intelligent ecosystems driven by transformer models, Large Language Models (LLMs), Retrieval-Augmented Generation (RAG), and emerging Agentic AI. Based on the analyzed literature, this work contributes a comprehensive taxonomy of AI-driven HR systems, a comparative synthesis of current approaches, and the identification of key research challenges.

Despite significant progress, current AI-driven HR systems remain constrained by issues related to explainability, fairness, privacy, evaluation standardization, and fragmented recruitment workflows. These limitations highlight that the next generation of intelligent HR systems should not only achieve higher predictive performance but also ensure transparency, trustworthiness, and effective human-AI collaboration.

Future research should move beyond isolated AI applications toward autonomous and collaborative HR ecosystems integrating multimodal AI, knowledge graphs, RAG, continual learning, and multi-agent architectures. Such systems have the potential to transform Human Resource Management from a recruitment automation tool into an intelligent decision-support ecosystem capable of continuously understanding, reasoning, and adapting to organizational and workforce dynamics. This evolution positions Agentic AI and human-centered intelligence as key enablers of the next generation of sustainable and trustworthy talent management systems.

REFERENCES

- SENGER, Elena, CAMPBELL, Yuri, VAN DER GOOT, Rob, et al. Toward more realistic career path prediction: evaluation and methods. *Frontiers in Big Data*, 2025, vol. 8, p. 1564521.
- BANH, Leonardo, REX, Alexander, STROBEL, Gero, et al. Hiring Tomorrow's Talents: How Generative Artificial Intelligence Transforms Human Resources Recruitment. 2026.
- Xue, Shengyi. "Employment Status Prediction and Job Matching via XGBoost and BERT-Based Mathematical Modeling." *Proceedings of the 2025 2nd International Conference on Big Data and Digital Management*. 2025.
- CHIHAB, Marouane, et al. "AI-Driven Professional Profile Categorization and Recommendation System." *International Journal of Advanced Computer Science & Applications* 16.11 (2025).
- Khelkhal, Kenza, and Dihia Lanasri. "Smart-Hiring: An Explainable end-to-end Pipeline for CV Information Extraction and Job Matching." *arXiv preprint arXiv:2511.02537* (2025).
- Karunamurthy, Dr. A. "AI-Powered Resume Analysis Using SpaCy for Skill Extraction and Job Matching." *International Scientific Journal of Engineering and Management* (2025): n. pag.
- Saouabe, Abdelkrim, et al. "Evolution of human resources management methods: From traditional approaches to generative artificial intelligence." *2024 International Conference on Decision Aid Sciences and Applications (DASA)*. IEEE, 2024.
- KUMAR, CHANDAN. Smart ATS: An AI-Driven Multi-Stage Resume Scoring and Recruitment Automation System. *Journal of Emerging Technology and Digital Transformation*, 2025, vol. 4, no 4, p. 19-23.
- Algamaty, Ragda Khaled. "Fair and Transparent AI for Hiring: Evaluating Resume-Job Matching, Bias Mitigation, and Human-in-the-Loop Auditing." *Libyan Open University Journal of Applied Sciences (LOU-JAS)* (2025): 01-10.
- Rajeswari, M., et al. "Design and Validation of an Explainable Artificial Intelligence-Based Decision Intelligence Model for Cyber Risk-Aware Quality Systems and Ethical Human Resource Management: Investigating the Moderating Influence of Corporate Social Responsibility in Digitally Transformed Organizations." *Quality-Access to Success* 27.210 (2026): 427.
- Arseneault, Rene, and Jialiang Yang. "Exploring the HR analyst position around the globe." *International Journal of Cross Cultural Management* 25.1 (2025): 183-206.
- Filatova, Vira, Andrii Zelenchuk, and Dmytro Filatov. "AI-Driven Decision-Making System for Hiring Process." *arXiv preprint arXiv:2512.20652* (2025).
- Kingsley, John. "FROM DATA LAKES TO TALENT PIPELINES: LEVERAGING BIG DATA AND AI FOR WORKFORCE FORECASTING." (2025).
- PAGE, Matthew J., MCKENZIE, Joanne E., BOSSUYT, Patrick M., et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ*, 2021, vol. 372, p. n71. <https://doi.org/10.1136/bmj.n71>
- Saouabe, Abdelkrim, Ahmed Boulahoual, and Hicham Oualla. "AI-Driven Recruitment: Enhancing Profile Recommendations in Digital-Age Management." *International Conference on the Leadership and Management of Projects in the Digital Age*. Cham: Springer Nature Switzerland, 2025.
- AJJAM, Mohammed-Hassan et AL-RAWESHIDY, Hamed S. AI-driven semantic similarity-based job matching framework for recruitment systems. *Information Sciences*, 2025, p. 122728.
- Sureshkumar, Prabhu. Investigation on how does the integration of AI in IT recruitment impact the efficiency and decision-making processes of recruiters in the IT industry. Diss. Dublin, National College of Ireland, 2025.
- Kulkarni, Neetta, and S. B. Sawant. "Artificial Intelligence for Sustainable and Smart Management: Ethical Concerns in AI-Enabled HR Decisions." *Artificial Intelligence* 4 (2026): 2.
- SUN, Jingran. Large Language Model-based Resume-Job Intelligent Matching Algorithm and Its Adaptability Case Study Across Different Positions in the Hotel Industry. *International Journal of Emerging Technologies and Advanced Applications*, 2025, vol. 2, no 7, p. 1-7.
- ZHANG, Yafei, WANG, Murray, WANG, Yu, et al. RankPO: Preference Optimization for Job-Talent Matching. *arXiv preprint arXiv:2503.10723*, 2025.
- PATIL, Pritesh, KHARDE, Ashish, DEOCHAKE, Sarthak, et al. Application of RAG (Retrieval-Augmented Generation) in AI-Driven Resume Analysis and Job Matching. *system*, 2025, vol. 5, no 4.
- LESZCZYŃSKI, Grzegorz, GACZEK, Piotr, et ŁAWRYNOWICZ, Maciej. The bright side of AI in hiring: Collaborating with algorithms supports ethical decision-making. *Journal of Business Research*, 2026, vol. 203, p. 115812.
- PURANAM, Phanish. The business case for human-centric organizing: Implications for artificial intelligence (AI) adoption1. *Strategic Organization*, 2026, vol. 24, no 2, p. 419-439.
- PEUTZ, Martin C., PETROVA, Silvia, LOZENETS, Sofia, et al. Innovative Recruitment Solutions: Integrating AI and Digital Communication to Improve Job Matching.
- GUDIVAKA, Raj Kumar, BASANI, Dinesh Kumar Reddy, GUDIVAKA, Rajya Lakshmi, et al. NLP and Semantic Matching Algorithms with Blockchain: Advancing AI-Powered Resume Classification for Enhanced Job Candidate Matching.
- Gupta, Akriti, et al. "Predicting employees' organizational citizenship behavior: A comparative study using artificial intelligence techniques." *Acta Psychologica* 262 (2026): 106032.
- Le, Ngoc Luyen, Marie-Hélène Abel, and Bertrand Laforge. "Vers un cadre ontologique pour la gestion des compétences: à des fins de formation, de recrutement, de métier, ou de recherches associées." *36es Journées francophones d'Ingénierie des Connaissances (IC 2025)@ Plate-Forme Intelligence Artificielle (PFIA 2025)*. Association Française pour l'Intelligence Artificielle, 2025.
- KITCHENHAM, Barbara et CHARTERS, Stuart. Guidelines for performing Systematic Literature Reviews in Software Engineering. EBSE

Technical Report EBSE-2007-01, Keele University and Durham University, 2007.

- [29] VRONTIS, Demetris, CHRISTOFI, Michael, PEREIRA, Vijay, et al. Artificial intelligence, robotics, advanced technologies and human resource management: a systematic review. *The International Journal of Human Resource Management*, 2022, vol. 33, no 6, p. 1237-1266. <https://doi.org/10.1080/09585192.2020.1871398>
- [30] VOTTO, Alexis M., VALECHA, Rohit, NAJAFIRAD, Peyman, et RAO, H. Raghav. Artificial Intelligence in Tactical Human Resource Management: A Systematic Literature Review. *International Journal of Information Management Data Insights*, 2021, vol. 1, no 2, p. 100047. <https://doi.org/10.1016/j.jjime.2021.100047>
- [31] PAN, Yuan et FROESE, Fabian J. An interdisciplinary review of AI and HRM: Challenges and future directions. *Human Resource Management Review*, 2023, vol. 33, no 1, p. 100924. <https://doi.org/10.1016/j.hrmr.2022.100924>
- [32] HUNKENSCHROER, Anna Lena et LUETGE, Christoph. Ethics of AI-Enabled Recruiting and Selection: A Review and Research Agenda. *Journal of Business Ethics*, 2022, vol. 178, no 4, p. 977-1007. <https://doi.org/10.1007/s10551-022-05049-6>
- [33] BUDHWAR, Pawan, CHOWDHURY, Soumyadeb, WOOD, Geoffrey, et al. Human resource management in the age of generative artificial intelligence: Perspectives and research directions on ChatGPT. *Human Resource Management Journal*, 2023, vol. 33, no 3, p. 606-659. <https://doi.org/10.1111/1748-8583.12524>
- [34] DEVLIN, Jacob, CHANG, Ming-Wei, LEE, Kenton, et TOUTANOVA, Kristina. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *Proceedings of NAACL-HLT 2019*, p. 4171-4186.
- [35] REIMERS, Nils et GUREVYCH, Iryna. Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks. *Proceedings of EMNLP-IJCNLP 2019*, p. 3982-3992.
- [36] MIKOLOV, Tomas, CHEN, Kai, CORRADO, Greg, et DEAN, Jeffrey. Efficient Estimation of Word Representations in Vector Space. *arXiv preprint arXiv:1301.3781*, 2013.
- [37] LEWIS, Patrick, PEREZ, Ethan, PIKTUS, Aleksandra, et al. Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks. *Advances in Neural Information Processing Systems 33 (NeurIPS 2020)*, p. 9459-9474.
- [38] JI, Ziwei, LEE, Nayeon, FRIESKE, Rita, et al. Survey of Hallucination in Natural Language Generation. *ACM Computing Surveys*, 2023, vol. 55, no 12, article 248, 38 p. <https://doi.org/10.1145/3571730>
- [39] XU, Yiheng, LI, Minghao, CUI, Lei, et al. LayoutLM: Pre-training of Text and Layout for Document Image Understanding. *Proceedings of KDD 2020*, p. 1192-1200.
- [40] European Parliament and Council. Regulation (EU) 2016/679 (General Data Protection Regulation). *Official Journal of the European Union*, L 119, 4 May 2016.
- [41] European Parliament and Council. Regulation (EU) 2024/1689 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). *Official Journal of the European Union*, L series, 12 July 2024.