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Review Article

Artificial Intelligence in Recruitment: A Multivocal Review of Benefits, Challenges, and Strategies

Hugo Trovão [1, 2], Henrique S. Mamede [1, 3*], Paulo Trigo [4], Vitor Santos [5, 6]

[1] *INESC TEC—Institute for Systems and Computer Engineering, Technology and Science, 4200-465 Porto, Portugal.*

[2] *University of Trás-Os-Montes E Alto Douro, Vila Real, Portugal.*

[3] *Department of Science and Technology, Universidade Aberta, Rua da Escola Politécnica, no. 147, 1269-001 Lisbon, Portugal.*

[4] *GuIAA; DEETC, Instituto Superior de Engenharia de Lisboa, Lisbon, Portugal.*

[5] *MagIC - Information Management Research Center, Lisboa, Portugal.*

[6] *NOVA Information Management School, Campus de Campolide, Lisboa 1070-312, Portugal.*

Abstract

This study investigates the role of artificial intelligence (AI) in recruitment, with a specific emphasis on small and medium enterprises (SMEs) and cultural diversity, two dimensions frequently underrepresented in existing research. The objective is to evaluate the benefits, challenges, and strategies for the responsible adoption of AI in recruitment. To achieve this, a Multivocal Literature Review (MLR) was conducted, systematically synthesising peer-reviewed studies and grey literature published from 2018 onwards. Following Kitchenham's systematic review guidelines and Garousi's multivocal extensions, academic and practitioner perspectives were analysed to capture both theoretical insights and real-world practices. The findings indicate that AI can streamline recruitment processes, improve decision-making accuracy, and enhance candidate experience through tools such as résumé screening, predictive analytics, and generative AI applications. However, issues of algorithmic bias, limited transparency, data quality, regulatory compliance, and workforce scepticism persist, particularly in SMEs that face resource constraints. Although much of the available evidence reflects Western contexts, this review broadens the scope by integrating global perspectives and highlighting how cultural and regional factors influence AI acceptance. The novelty of this study lies in combining academic and industry evidence to propose actionable strategies—such as bias audits, explainable AI frameworks, and human-in-the-loop approaches—for more inclusive, sustainable, and globally relevant adoption of AI in recruitment.

Keywords:

Artificial Intelligence;
Generative AI;
Large Language Models;
Human Resource Management;
Recruitment;
AI Ethics;
SMEs.

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1- Introduction

In today's data-driven environment, organisations and Human Resource (HR) departments are increasingly adopting artificial intelligence (AI) to enhance recruitment efficiency, accuracy, and scalability [1-3]. Applications range from résumé screening and predictive analytics to generative AI (GenAI) and large language models (LLMs), which enable automated job posting generation, tailored candidate feedback, and advanced candidate matching [4-7].

A growing body of academic and industry research highlights both the promises and risks of AI-enabled recruitment. Prior reviews consistently emphasise efficiency gains and cost reduction, while also pointing to challenges of algorithmic

* **CONTACT**: jose.mamede@uab.pt

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bias, lack of transparency, and ethical compliance [8-11]. For example, Chen [6] and Hangartner et al. (2022) [7] demonstrate how AI can mitigate certain human prejudices but may simultaneously introduce automation bias if not properly governed. Similarly, Hofeditz et al. [5] and Soleimani et al. [9] stress the importance of explainability and fairness frameworks to ensure candidate trust. These studies provide important foundations but remain primarily enterprise-centric and Western-focused.

Two significant gaps remain underexplored. First, small and medium enterprises (SMEs) - which constitute about 90% of global businesses - face unique barriers to AI adoption, such as budget constraints, limited technical expertise, and scepticism toward automation [12, 13]. Despite their economic relevance, SMEs are rarely the focus of existing systematic or narrative reviews. Second, cultural and regional diversity has been insufficiently addressed, even though frameworks such as Hofstede's cultural dimensions suggest that cultural norms strongly influence perceptions of fairness, trust, and the legitimacy of AI-based hiring systems [14]. The lack of attention to these dimensions risks over-generalisation of findings from large, Western organisations to diverse global contexts.

Against this backdrop, the present study provides a Multivocal Literature Review (MLR) of AI adoption in recruitment, systematically synthesising both peer-reviewed studies and grey literature, including industry white papers, consulting reports, and technical blogs. Building on Kitchenham's systematic review guidelines [15] and Garousi et al.'s multivocal extensions [16], this review bridges academic theory and industry practice to capture the latest technological developments and real-world challenges. Specifically, it addresses three research questions: (1) the benefits of AI in recruitment, (2) the challenges and ethical concerns it raises, and (3) strategies for responsible and inclusive adoption. By explicitly focusing on SMEs and cultural diversity - two dimensions neglected in prior reviews - this study makes a novel contribution, offering actionable recommendations for policymakers, practitioners, and researchers seeking to harness AI's potential in recruitment responsibly.

The rest of the paper proceeds as follows: Section 2 provides a conceptual background on the evolution of AI in Human Resource Management (HRM); Section 3 outlines the SLR methodology; Section 4 presents the core findings regarding AI's benefits, challenges, and mitigation strategies; and Section 5 concludes with recommendations for future work.

1-1- Related Reviews

Numerous academic and industry reports discuss AI-supported recruitment, often focusing on algorithmic bias mitigation, ethical frameworks, and transparency [5-9]. These works show how AI tools can automate processes such as résumé parsing and initial interviews while pinpointing concerns about fairness and accountability [10, 11]. Similarly, Gaebler et al. [4] investigate auditing frameworks for LLMs to ensure systematic checks for bias in AI-based recruitment decisions. Table 1 illustrates this review's different contributions to the existing knowledge.

Table 1. Reviews on AI-supported recruitment processes

Authors	Year	Bias Mitigation	Transparency	Collaboration	Fairness	Ethics	Focus on SMEs	Cultural and Global Diversity	Use of LLMs & Generative AI
Chen [5]	2023	✓		✓	✓				
Delecraz et al. [12]	2022	✓	✓		✓	✓			
Hofeditz et al. [5]	2022	✓	✓		✓				
Lee & Cha [8]	2023	✓	✓			✓			
Soleimani et al. [9]	2021	✓	✓	✓					
This review	2025	✓	✓	✓	✓	✓	✓	✓	✓

While most of these reviews highlight the promises of AI-driven hiring - such as efficiency gains and cost reductions - they consistently call for addressing persistent issues around data bias, trustworthiness, and compliance with various legal frameworks [13].

While most of these reviews highlight the promises of AI-driven hiring - such as efficiency gains and cost reductions - they consistently call for addressing persistent issues around data bias, trustworthiness, and compliance with various legal frameworks [13]. However, existing survey papers still emphasise larger enterprises, which benefit from robust infrastructures and specialised AI teams [14, 15]. SMEs - roughly 90% of global businesses - often lack such resources [16] and thus remain relatively underrepresented in these reviews. Similarly, there is limited coverage of how cultural or regional factors affect AI acceptance. Attitudes toward AI and automation can differ significantly by country or cultural context [17], even though these aspects can profoundly shape adoption strategies.

Moreover, as Gen AI and LLMs evolve, the functionality of AI-driven hiring tools expands to include natural-language chat-based communications, real-time feedback, and advanced language analytics [2, 18]. While some recent works explore these capabilities [1], many remain theoretical, and large-scale empirical data on widespread adoption are still needed. These gaps underscore a need to broaden the discussion beyond major enterprises and single-region contexts, reflecting the real-world diversity of organisational settings.

1-2- Study Contribution and Focus

This review aims to bridge these research voids by adopting two primary lenses:

- **Focus on SMEs:** We emphasise the unique needs of smaller firms, which often grapple with limited budgets, automation scepticism, and narrower applicant pools.
- **Recognition of Cultural and Global Diversity:** We extend beyond large-enterprise, Western-centric perspectives to consider how local regulations, data-privacy concerns, and cultural norms affect user trust and the readiness to adopt AI in recruitment [14, 17].

This MLR expands the AI recruitment discourse by integrating academic and grey literature to present a global, context-sensitive viewpoint. The review incorporates the latest research on generative AI and large language models, examining benefits and emerging challenges, particularly for SMEs and diverse cultural contexts. Practical frameworks for responsible AI adoption are provided, consistent with insights from industry sources such as the World Economic Forum and PwC (2024) [3].

2- Background and Context

Artificial intelligence (AI) integration into recruitment has accelerated significantly in recent years, driven by advancements in data analytics, shifting dynamics in talent markets, and increasing regulatory and ethical scrutiny [1, 2]. Understanding AI's evolving role in recruitment requires a brief examination of the historical progression of HR technologies, followed by a discussion of specific AI developments that underpin modern hiring practices.

HR technology has undergone several key transformations, initially focused on digital systems for payroll processing, personnel data tracking, and record-keeping [19]. Over time, organisations adopted more sophisticated Human Resource Information Systems (HRIS), enabling centralised management of geographically dispersed workforces and streamlining administrative tasks [19]. Subsequent developments introduced web-based electronic HR solutions, automating performance appraisals, training registration, and employee communications, marking a critical step toward HR digitalisation and process efficiency.

With the advent of Industry 4.0, characterised by big data analytics and powerful AI-driven tools, HR functions witnessed a transformative leap [14, 20]. Recruitment processes increasingly adopt machine learning (ML) algorithms to enhance decision-making and operational efficiency. AI-supported recruitment tasks commonly include résumé screening, candidate-job matching, and initial interviews through automated chatbots [21]. By leveraging ML capabilities, these systems significantly reduce manual workloads and increase consistency in identifying suitable candidates based on extensive applicant data.

The evolution toward deep learning (DL) - an advanced subset of ML employing multilayer neural networks - further expanded AI capabilities, allowing detailed analysis of less structured candidate data such as cover letters, social media activity, or conversational interactions. DL's strengths in pattern recognition and natural language processing made it particularly effective for tasks like sentiment analysis and candidate evaluation regarding personality fit or organisational culture alignment [22]. More recently, the emergence of Gen AI and LLMs has dramatically transformed AI applications in recruitment. Zheng et al. [23] proposed GIRL (GeneratIve job Recommendation based on Large language models), generating personalised job descriptions directly from a candidate's CV using reinforcement learning. This approach moves beyond traditional, opaque recommender systems, offering greater transparency and explainability to job seekers and recruiters.

Sun et al. [2] introduced MockLLM, an innovative role-playing AI framework where LLMs simulate realistic interview scenarios. This approach facilitates a comprehensive two-sided evaluation process, significantly enriching traditional resume-and-job-description-based assessments. By enabling agents to adapt dynamically based on previous successful interactions, MockLLM enhances both recruiter insight and candidate preparedness.

Despite clear benefits, integrating AI into recruitment poses several challenges. Algorithmic bias remains a critical issue, where historical patterns embedded in training datasets perpetuate discrimination against certain applicant groups [10, 11]. Real-world instances, such as Amazon's discontinued AI recruitment tool, highlight biased algorithms' severe reputational and ethical risks [22]. Transparency is also a significant concern, as advanced AI systems often function as "black boxes," complicating the explanation and justification of AI-driven hiring decisions [24, 25]. Consequently, Explainable AI (XAI) frameworks have become essential for fostering trust and compliance within HR practices.

Regulatory compliance further complicates AI deployment. Regional privacy regulations, notably Europe's General Data Protection Regulation (GDPR), significantly influence how AI tools handle candidate data, perform background checks, and maintain transparent decision-making processes [14, 17].

To address resource constraints, Gan et al. [1] introduced a framework that uses LLM agents explicitly designed for automated résumé screening. These AI agents classify résumé content, generate concise summaries, and assign evaluative grades, accelerating screening processes significantly faster than manual methods. This approach reduces privacy risks and enhances decision-making accuracy, highlighting the transformative potential of LLM-driven automation within HR processes.

In summary, contemporary AI recruitment solutions promise substantial efficiency, accuracy, and enhancements to inclusiveness. Realising this potential requires comprehensive, proactive management of associated ethical, operational, and acceptance-related challenges, particularly within smaller organisations and diverse cultural contexts. As AI advances in sophistication, organisations must navigate the interplay of efficiency, fairness, and accountability to create sustainable and equitable recruitment outcomes.

2-1- Theoretical Approach

The present review is grounded in a systematic evidence synthesis framework, combining principles of systematic literature reviews [26] with multivocal literature review (MLR) extensions designed to integrate both academic and grey literature [27]. This methodological foundation is complemented by three theoretical perspectives that inform how we interpret the role of AI in recruitment.

AI Ethics and Responsible Innovation. Concepts of fairness, accountability, transparency, and explainability (FATE) serve as the ethical lens for evaluating AI-enabled recruitment. These principles are central to discussions of algorithmic bias, governance, and candidate trust, and they provide a normative framework for assessing both risks and mitigation strategies [6, 7, 9].

Organizational Behaviour and Innovation Adoption. The review also draws upon organizational theories, including diffusion of innovations and resource-based views, to explain how firm size and resource availability shape adoption trajectories. This is particularly relevant for SMEs, which face constraints in financial, technical, and human resources that influence both readiness and capacity for AI adoption [14, 28].

Cross-Cultural Management. Finally, the review incorporates insights from cross-cultural management, notably Hofstede's cultural dimensions [29], to analyze how cultural and regional factors shape perceptions of legitimacy, fairness, and trust in AI-based recruitment. This perspective is essential for extending the predominantly Western evidence base toward a more global understanding of adoption challenges and opportunities.

By combining these perspectives, our theoretical approach moves beyond a descriptive synthesis of the literature. It situates the findings within a broader conceptual framework that bridges ethical, organizational, and cultural dimensions, thereby offering a more holistic understanding of how AI reshapes recruitment in diverse contexts.

3- Literature Review

A Multivocal Literature Review (MLR) systematically identifies, evaluates, and synthesises relevant research from both academic and industry sources [27]. Unlike traditional reviews, an MLR integrates formally published academic studies and grey literature, such as technical reports, white papers, and practitioner blogs [26]. By incorporating diverse perspectives, an MLR comprehensively understands current knowledge, combining rigorous scholarly insights with practical industry experiences [27].

3-1- Methodology

This study employs a structured MLR methodology adapted from widely recognised systematic review guidelines, enriched by protocols specifically designed for handling grey literature. We selected the protocol developed by Barbara Kitchenham due to its thoroughness in clearly addressing systematic review processes - planning, conducting, and reporting - while adopting Garousi et al.'s [27] multivocal extensions to integrate grey literature effectively, essential for capturing rapidly evolving industry practices, as summarised in Figure 1.

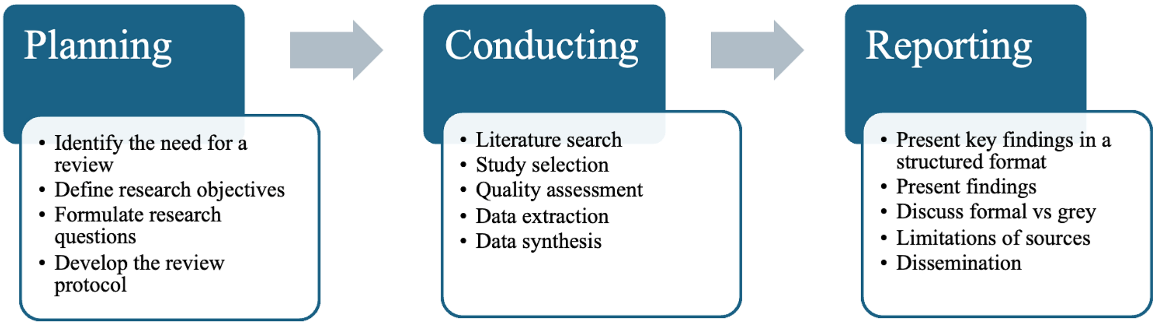

Figure 1. Summary of the review process phases and tasks

To ensure consistency and quality, explicit inclusion and exclusion criteria were established and applied uniformly across academic and grey literature. Sources were included if published in English from 2018 onward, provided full-text access, and explicitly addressed AI-supported recruitment. Works focused solely on technical AI algorithms without HR application, or those limited to single-country or single-sector case studies, were excluded. Academic publications were appraised using criteria adapted from the guidelines for systematic reviews [26]. Grey literature was assessed based on credibility, relevance, and utility using the multivocal approach proposed by Garousi et al. [27].

Planning

- **Identify the need for an MLR:** Our preliminary review revealed that traditional academic sources often fail to capture real-time developments, especially regarding emerging technologies like Gen AI and LLMs. Therefore, we opted for an MLR to bridge the gap between scholarly research and contemporary industry practices [27].
- **Define Scope (PICOC)**: Before formulating research questions, we clearly defined the boundaries of our review using the PICOC framework (Population, Intervention, Comparison, Outcome, Context) [26], as shown in Table 2.

Table 2. PICOC (Population, Intervention, Comparison, Outcome, Context)

Topic	Description
Population	Organisations in any activity sector
Intervention	AI applications for Recruitment Processes
Comparison	Recruitment processes with and without the usage of AI approaches
Outcome	Influence of AI on process duration, costs, and results
Context	HR departments and HR managers

- **Research Questions**: Our research questions (RQs) explicitly invite academic and practitioner perspectives, ensuring the relevance and applicability of our findings [27]. These questions, presented in Table 3, explore key opportunities and challenges associated with integrating AI into recruitment.

Table 3. Research Questions and Motivation

Research Question	Motivation
RQ1: What are the benefits of using AI in recruitment processes?	To understand how AI improves recruitment efficiency, accuracy, and scalability by automating repetitive tasks, enhancing decision-making, and offering data-driven insights into candidate selection.
RQ2: What are the challenges of using AI in recruitment processes?	To identify the risks AI brings, such as bias in algorithms, lack of transparency, and potential dehumanisation of recruitment, which could undermine its effectiveness.
RQ3: How can organisations mitigate the challenges of using AI in recruitment processes?	To explore strategies like XAI, continuous monitoring, and maintaining human oversight to ensure fairness, transparency, and effectiveness in AI-driven recruitment.

Conducting

- **Search Strategy**: To ensure consistency and quality, explicit inclusion and exclusion criteria were established and applied uniformly across academic and grey literature. Sources were included if published in English from 2018 onward, provided full-text access, and explicitly addressed AI-supported recruitment. Works focused solely on technical AI algorithms without HR application, or those limited to single-country or single-sector case studies, were excluded. Academic publications were appraised using criteria adapted from the guidelines for systematic reviews [26]. Grey literature was assessed based on credibility, relevance, and utility using the multivocal approach proposed by Garousi et al. [27].
- **Quality Assessment**: Both academic and grey literature underwent rigorous quality assessments. Academic sources were evaluated using established scientific criteria, while grey literature credibility was assessed through tailored criteria such as author expertise, publication venue, and industry relevance [27].

Reporting

- **Data Synthesis and Reporting**: Findings from academic and grey literature were integrated and differentiated, highlighting corroborative and conflicting insights.
- **Discussion of Limitations**: Potential biases or limitations inherent in academic and grey literature were openly addressed.
- **Recommendations**: Actionable insights for researchers and practitioners were provided, emphasising real-world applicability.

Using this framework, the review aims to provide a comprehensive overview of existing research, identify knowledge gaps, and guide future studies.

3-2- Planning

This section details the process of extracting data from the selected studies and synthesising the findings to answer the research questions. This overview establishes the systematic approach used to integrate evidence from both academic and industry sources.

3-2-1- Identifying the Need for an MLR

According to Kitchenham [26], a review should begin by explaining its motivation and objectives. In parallel, Garousi et al. [27] stress the importance of clarifying why a multivocal approach is needed - i.e., an approach that systematically integrates academic and grey literature.

This MLR aims to systematically collect and synthesise research relevant to our core research questions on AI in recruitment processes. While peer-reviewed journals and conference proceedings offer rigorous, theory-driven insights, many practitioner perspectives - especially around GenAI and LLMs - appear first in grey literature (e.g., industry reports, white papers, technical blogs, and consultancies). These emergent AI innovations are evolving too quickly for traditional publication cycles to capture comprehensively. By aligning with them, Garousi et al. (2019) [27], we ensure the real-world relevance of our findings, bridging the gap between established academic studies and fast-moving industry practices.

3-2-2- Defining the Research Questions

The second significant step in Kitchenham's protocol is formulating clear Research Questions (RQs). Following Garousi et al. for MLR, each question explicitly invites academic and non-academic voices.

Our MLR is structured around the three pivotal research questions in Table 3, which explore the opportunities and challenges of AI-integrated recruitment.

These questions collectively investigate the opportunities and pitfalls of AI-based recruitment, including the impact of GenAI and LLMs on efficiency, bias, and transparency. They also address mitigation strategies to ensure organisations can adopt AI while upholding fairness and effectiveness in talent acquisition.

RQ1: Benefits

RQ1 examines the benefits of using AI in recruitment processes. Research suggests that AI notably boosts efficiency, accuracy, and decision-making by automating tasks such as résumé screening and candidate matching [30]. Recent advancements, including LLMs and other Gen AI tools, streamline the identification and preliminary evaluation of top candidates. These findings echo industry data indicating that AI enhances hiring quality by minimising human error and infusing data-driven insights into talent acquisition [28]. Crucially, while AI accelerates the speed and scalability of recruitment, its real value lies in analysing large volumes of data to uncover candidate potential that might otherwise remain overlooked [31, 32]. By leveraging advanced analytics and generative models, organisations can more effectively shortlist applicants for further human review. This enables HR professionals to concentrate on final interviews and negotiations [1, 2]. However, several studies caution that automation can depersonalise the recruitment process. Research by [33, 31] shows that candidates prefer human interaction during later stages of the recruitment process. Transparent chatbot communication, feedback loops, and opportunities for human contact at decision points can help preserve candidate trust and engagement.

RQ2: Challenges

RQ2 explores the challenges AI poses in recruitment. Although AI offers numerous advantages, it can also introduce significant hurdles. Studies highlight concerns regarding algorithmic bias, transparency issues, and the potential dehumanisation of recruitment [28]. For instance, AI systems may perpetuate bias if trained on flawed datasets; moreover, the opacity of specific algorithms can leave hiring managers uncertain about the rationale behind AI-driven decisions [34, 35]. Excessive reliance on automation can also diminish the personal touch that candidates value, aligning with industry insights indicating that many job seekers prefer a more human-centred approach [5, 31]. Furthermore, ensuring compliance and validating AI-driven screening becomes increasingly challenging when job requirements and skill definitions are in flux [18]. Consequently, robust quality controls and responsible AI management remain urgent priorities.

Gaebler et al. [4] specifically investigate how advanced LLMs can still display demographic discrimination unless subjected to careful “correspondence experiments,” underscoring the importance of robust auditing frameworks.

RQ3: Mitigation

RQ3 investigates strategies for mitigating these challenges. Research suggests that tackling AI’s pitfalls requires a holistic approach. One essential measure involves reducing algorithmic bias through diversified training datasets and ongoing monitoring of AI decisions [28]. Increasing transparency through XAI further allows recruiters to understand, evaluate, and trust AI-generated outcomes [18]. Balancing automation with meaningful human interaction ensures that AI complements - rather than replaces - the personal element in recruitment [5]. That underscores the importance of embedding human oversight, such as assigning routine or repetitive queries to chatbots while reserving deeper conversations for human recruiters. Similarly, LinkedIn (2023) [31] highlights the effectiveness of "human-in-the-loop" governance, which combines algorithmic recommendations with a final human judgement. Companies can harness AI's efficiency benefits by implementing technical safeguards and clear organisational policies while upholding fair, candidate-centric hiring practices.

These RQs provide a unified lens for examining scholarly evidence and real-world practitioner insights in grey literature.

3-2-3- Protocol and Scope Definition

As shown in Table 2, the PICOC framework was applied to determine the boundaries of this MLR, following another key step outlined by Kitchenham.

3-2-4- Search Strategy

A systematic search protocol was developed to ensure comprehensive coverage of AI-supported recruitment across academic and grey literature. This protocol defines **(a)** the keywords and associated synonyms and **(b)** the precise Boolean queries used to locate relevant studies.

Keywords and Synonyms

Drawing on preliminary scoping, core terms related to artificial intelligence, HRM, and recruitment were identified. Table 4 provides an overview of these keywords and their associated synonyms, ensuring relevant studies are captured.

Table 4. Keywords, Associated, and Synonyms

Keywords	Associated and Synonyms
artificial intelligence	ai, machine learning, deep learning, generative AI, LLM
human resource management	hrm
benefit	advantage, positive impact, gain, value, improvement

We included synonyms for “artificial intelligence” (AI), such as “machine learning”, “deep learning”, “generative AI”, and “LLM,” along with general HRM-related phrases and possible outcome terms (like “benefit”, “challenge”, and “advantage”). This broad approach aims to capture both the positive and negative aspects of AI in hiring, providing a balanced dataset for our subsequent analysis.

Search Strings

Next, we combined these keywords and synonyms into inclusive Boolean expressions (capturing new developments) and precise (focusing on recruitment tasks within HRM). Table 5 shows the queries used to identify relevant publications.

Table 5. Search strings

Research Question	Search String
RQ1	("artificial intelligence" OR ai OR "machine learning" OR “deep learning” OR “generative ai” OR “llm”) AND ("human resource management" OR hrm) AND recruitment
RQ2	("artificial intelligence" OR ai OR "machine learning" OR “deep learning” OR “generative ai” OR “llm”) AND ("human resource management" OR hrm) AND recruitment AND challenge*
RQ3	("artificial intelligence" OR ai OR "machine learning" OR “deep learning” OR “generative ai” OR “llm”) AND ("human resource management" OR hrm) AND recruitment AND challenge* AND (mitigate OR mitigation)

By employing Boolean operators (e.g., AND, OR) and wildcard variations (e.g., challenge*), the search strategy ensured retrieval of literature discussing both the benefits (e.g., efficiency, bias reduction) and challenges (e.g., fairness issues, ethical concerns) of AI-driven recruitment. Terms such as “human resource management” or “HRM” were also included to anchor the search within people-focused organisational contexts.

Search strings were designed based on the research questions to ensure comprehensive coverage of relevant studies. The search string for RQ1 is broader, reducing the risk of missing key papers that address the topic without explicitly using the term “benefit.” This search string also encompasses results relevant to RQ2 and RQ3, enabling its use as a foundation for the entire search process.

3-2-5- Inclusion and Exclusion Criteria

Explicit inclusion and exclusion criteria were established. To narrow the focus on AI-supported recruitment, the inclusion and exclusion criteria shown in Table 6 were applied.

Table 6. Inclusion and exclusion criteria

Selection	Criteria
Include	Available in full-text Final and peer-reviewed Published from 2018 onwards
Exclude	Non-English publications Unavailable in full text Not specific to AI-supported recruitment processes Specific to AI algorithm Studies based on specific use cases, countries/regions, or sectors

By setting a publication range from 2018 onward, recent trends in AI-driven recruitment are captured. Limiting sources to English ensures accessibility and consistency in analysis, while the domain focus ensures that included studies directly relate to recruitment tasks within the broader HRM field.

3-2-6- Quality Assessment

Kitchenham [26] stresses the importance of systematically appraising primary studies. To score each source in formal academic literature, we adapted checklists from Ali et al. [36] and Sadoughi et al. (2020) [38]. Table 7 illustrates our quality assessment criteria for formal academic literature.

Table 7. Scientific Literature Quality Assessment (QA)

Question	Answer and score		
	Yes	Partially	No
Does a scientific methodology support the work?	1	0,5	0
Are the research objectives or questions clearly stated?	1	0,5	0
Are the research results presented comprehensively?	1	0,5	0
Is the discussion on the research objectives satisfactory?	1	0,5	0

Each scientific publication's final quality assessment score is the sum of the scores of the four answers. Publications with scores higher than two were included in the review.

Grey literature requires a distinct quality assessment approach compared to formal academic literature, as outlined by Garousi et al. [27]. This distinction arises due to the diverse nature of GL sources, which often lack traditional peer review but may still provide valuable practitioner insights. Consequently, assessing GL's credibility, relevance, and reliability demands tailored criteria for authorship, publication venue, and practical impact, as outlined in Table 8.

Table 8. Grey Literature Quality Assessment (QA)

Question	Answer and score	
	Yes	No
Is the subject "complex" and not solvable by considering only the formal literature?	1	0
Is there a lack of volume, quality of evidence, or a lack of consensus on outcome measurement in the formal literature?	1	0
Is the contextual information important to the subject under study?	1	0
Is it the goal to validate or corroborate scientific outcomes with practical experiences?	1	0
Is it the goal to challenge assumptions or falsify results from practice using academic research or vice versa?	1	0
Would synthesising insights and evidence from the industrial and academic communities benefit one or both communities?	1	0
Is there a large volume of practitioner sources indicating high practitioner interest in a topic?	1	0

Each grey literature publication's final quality assessment score is the sum of the scores of the seven answers. A score of one or higher suggests including the grey literature, meaning nine were included.

3-2-7- Motivating the Inclusion of Grey Literature

In alignment with Garousi et al. [27], we explicitly asked whether including grey literature was warranted. We considered:

1. **Rapidly Evolving Topic:** Gen AI and LLMs in recruitment are sometimes first reported in white papers, blogs, or industry surveys rather than peer-reviewed venues.
2. **Industry Significance:** Reports by Deloitte, Gartner, **McKinsey**, PwC, and LinkedIn often provide large-scale data or state-of-the-art practices not yet reflected in academic research.
3. **Contextual Insights:** Practitioners regularly share real-world barriers (e.g., policy constraints, budget limitations) that formal literature might overlook.

Given these factors, the search was expanded beyond academic databases to Google (effort-bound to the top 100 results) and targeted organisational websites (e.g., Gartner, McKinsey, Deloitte, LinkedIn). This approach ensured the inclusion of timely practitioner perspectives and cutting-edge AI use cases that traditional peer-reviewed channels may not yet document. By blending formal, peer-reviewed research with grey literature insights, Garousi et al.'s [27] guidelines were followed to develop a more comprehensive and practice-oriented understanding of AI-driven recruitment.

All signs pointed to the necessity of a multivocal approach to fully appreciate contemporary AI adoption in recruitment.

3-2-8- Moving Forward: From Planning to Conducting

Having established the need for, scope for, and rigour of this Multivocal Literature Review, the next step is the Conducting Phase. In this Phase, we implement the search protocol, screen identified sources, extract data, and **synthesise** the findings to address RQ1, RQ2, and RQ3.

3-3- Conducting

After defining the need for an MLR, clarifying the research questions, and detailing the scope, the study proceeded to the Conducting Phase. This phase implemented the planned search strategy, screening process, quality assessment, data extraction, and synthesis. Each step is outlined in detail below.

3-3-1- Search Strategy

Building on the Planning section, we executed comprehensive search queries across both formal and grey literature sources:

- **Academic Databases**: ACM Digital Library, IEEE Xplore, ScienceDirect, and Scopus.
- **Grey Literature**: Key consultancy reports, white papers, and technical blogs (e.g., Deloitte, LinkedIn, McKinsey, Gartner), using Google's top 100 search results for each query to identify non-academic references.

We used Boolean expressions (e.g. ((“human resource management” OR “HRM”) AND recruitment)) to capture a broad set of publications addressing AI-driven recruitment. Searches were constrained to English-language works published from 2018 onward, covering the evolving nature of AI and HRM.

3-3-2- Selection Process

We ran these queries from September 2024 to February 2025, obtaining an initial pool of 3409 records. As displayed in our planning tables, each record was subjected to a three-step filtering process**:**

1. **Duplication Removal:** We identified and removed 263 duplicates.
2. **Title and Abstract Screening:** We prioritised publications explicitly discussing HR, recruitment, and AI. Studies without an HR or recruitment context were excluded.
3. **Full-Text Review:** We retrieved the remaining texts for deeper evaluation. We excluded sources that did not meet our scope requirements or were irrelevant to at least one research question (benefits, challenges, mitigation strategies).

3-3-3- Inclusion and Exclusion Criteria

We consistently applied our established inclusion/exclusion criteria:

- **Inclusion**:
  - Studies/articles published from 2018 onward.
  - Full text available in English.
  - Direct relevance to AI in recruitment/HR (including but not limited to Gen AI or LLMs).
  - Peer-reviewed journal articles, conference papers, major industry reports, or credible technical blogs/white papers.
- **Exclusion**:
  - **Non-English** or non-full-text publications.
  - Studies have focused solely on algorithmic details without considering their HR applications.
  - Publications describing narrow single-sector or single-region use cases that lacked broader insights into AI-based recruitment.

Table 9 presents the results of applying our exclusion criteria to the selected publications.

Table 9. Exclusion criteria

Selection	Criteria	Excluded publications
Exclude	Non-English publications	1
	Unavailable in full text	20
	Not specific to AI-supported recruitment processes	1216
	Specific to AI algorithm	79
	Studies based on specific use cases, countries/regions, or sectors	16

Applying these criteria removed studies outside the intersection of AI and recruitment, significantly reducing the initial set. Publications were further filtered if they lacked robust methodology or explicit discussion of AI's benefits, challenges, or mitigation strategies in the hiring process.

3-3-4- Quality Assessment

A structured quality assessment was conducted to ensure the selected sources' reliability and validity. We adapted established checklists from Ali et al. [36, 37] and Sadoughi et al. [38]. Given that our review encompasses formal academic publications and grey literature (industry reports and white papers), two distinct checklists were employed to reflect their different characteristics and evaluation criteria better.

Academic studies were evaluated based on methodological rigour, relevance, and clarity using the questions from Table 7 and the evaluation criteria described in Section 3-2-6.

We used adapted evaluation criteria for grey literature sources reflecting their practical orientation and industry relevance, using the questions from Table 8 and the evaluation criteria described in Section 3-2-6.

3-3-5- Data Extraction and Synthesis

From the final pool of selected studies, we extracted the following:

- **Bibliographic Details**: Title, authors, year, source type (journal, conference, white paper, etc.).
- **AI Focus**: Gen AI, LLMs, machine learning, deep learning, or other approaches.
- **HR Function**: Specific recruitment tasks addressed (screening, interviewing, matching, etc.).
- **Key Findings**: Benefits, challenges, empirical outcomes, or theoretical implications.
- **Proposed Mitigations**: Technical (e.g., debiasing) or organisational (e.g., policy, training) solutions.

Results were synthesised using the three research questions (benefits, challenges, mitigation) to identify trends across formal and grey literature. Areas of consensus and divergence between academic and practitioner sources were noted, and conflicting results were flagged for deeper analysis [27]. This multivocal integration captured both theoretical depth and cutting-edge, real-world innovations in AI-based hiring.

3-3-6- Review Outcomes

After rigorous filtering (Table 10 shows the breakdown by source), we arrived at a final selection of 29 publications, supplemented by relevant grey literature. These included peer-reviewed articles on algorithmic fairness, industry-led reports addressing AI-driven recruitment best practices, and preprint server articles focusing on Gen AI and LLMs.

Table 10. Review process

Source	Search	Selection criteria	Remove duplicated	Read the title and abstract	Quality assessment
ACM Digital Library	121	71	63	8	1
IEEE Digital Library	66	60	43	11	2
ScienceDirect	723	449	423	7	2
Scopus	2394	1456	1250	86	15
Google	100	36	30	9	4
Targeted organisational websites	5	5	5	5	5

Figure 2 illustrates this selection flow, showing how each step refined the total set from 3409 initial hits to the final corpus with 29.

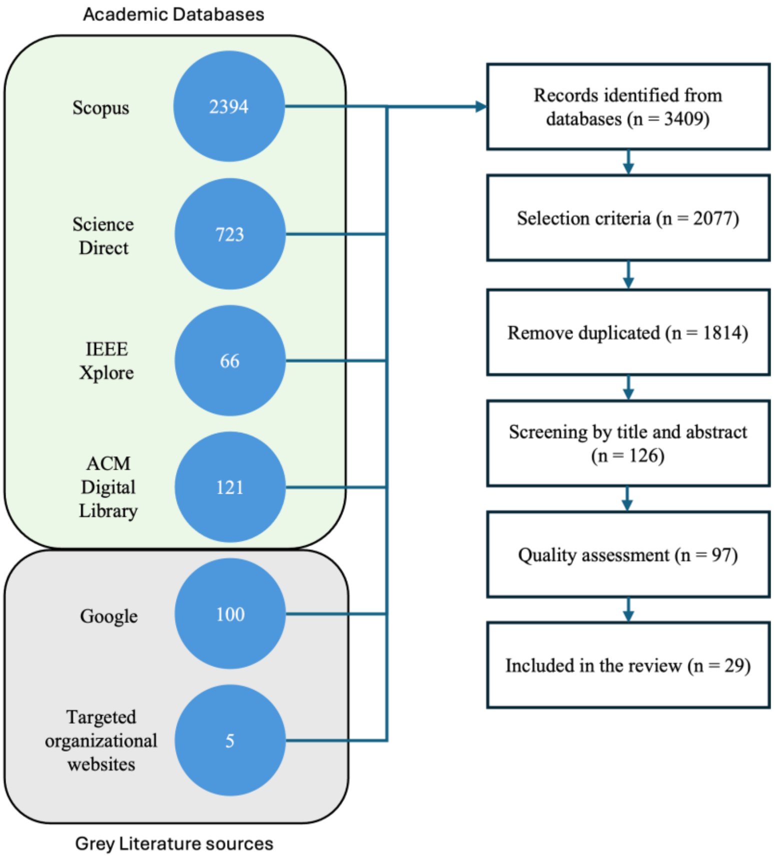

Figure 2. Results obtained in each step

In the subsequent sections, we present our bibliometric analysis and findings in alignment with RQ1 (benefits)**,** RQ2 (challenges)**,** and RQ3 (mitigations). Together, these results inform a nuanced view of AI's evolving role in recruitment, highlighting best practices and remaining gaps for future study.

3-3-7- Bibliometric Analysis

Although this review includes 29 papers, the bibliometric analysis was limited to the 20 papers published in peer-reviewed venues. The nine remaining papers, authored by industry practitioners or not formally published through academic channels, were excluded from this analysis due to the absence of standardised authorship metadata and institutional affiliations. Nonetheless, their inclusion in the overall review reflects the significant role of industry contributions.

The bibliometric analysis provides a comprehensive overview of the research trends and critical developments in AI applied to recruitment processes. By leveraging tools such as VOSviewer, Scimago Graphica, and Microsoft Excel to create charts based on study data, the analysis enables a detailed examination of the evolution of publications, highlighting the significant increase in research output in recent years [39]. These tools facilitate the visualisation of co-authorship networks and citation patterns, allowing for a deeper understanding of how key topics have evolved in AI-enabled hiring systems [40].

In particular, the analysis of publication trends shows a marked increase in AI-related studies, especially after 2020, as organisations have increasingly turned to AI to optimise recruitment efficiency. Bibliometric methods, such as citation analysis, help identify the most influential studies and authors contributing to the discourse on AI in recruitment [40]. For example, the works of critical researchers in AI ethics and decision-making frameworks are frequently cited, reflecting the growing concern over bias in AI recruitment tools [41].

Furthermore, mapping the data sources reveals that most AI research in recruitment is published in high-impact journals in fields such as computer science, HRM, and ethics. This interdisciplinary nature of AI research in recruitment highlights the importance of cross-domain knowledge exchange, as evidenced by the co-citation of works from technical and managerial domains [42].

Publication Trends

Since 2018, the number of publications on AI in recruitment processes has consistently increased, reflecting the growing interest in and implementation of AI technologies in HR practices (see Figures 3 and 4).

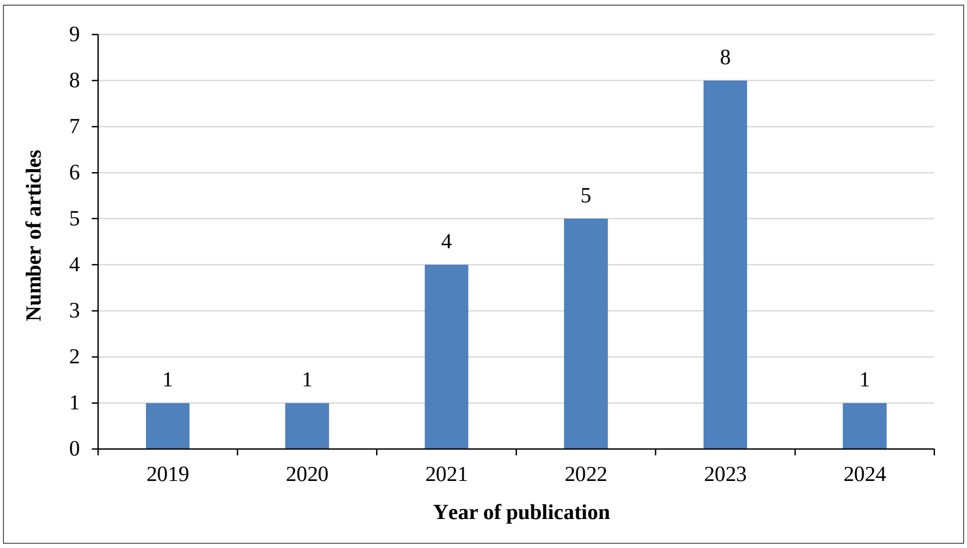

Figure 3. **Number of publications per year**

The spike in research activity aligns with advancements in artificial intelligence, which are increasingly used to streamline hiring processes and address biases.

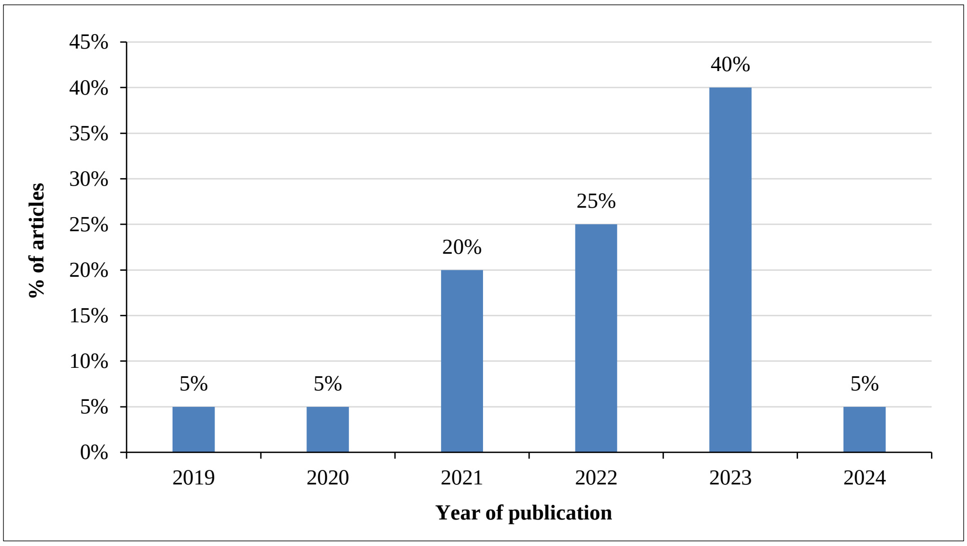

Figure 4. **Percentage of articles per year of publication**

This publication surge highlights the expanding recognition of AI's potential to transform traditional recruitment methods and enhance organisational decision-making.

Source Analysis

Looking at Tables 11 and 12, we can see that most publications are concentrated in high-impact journals, such as the European Management Journal and Human Resource Management Review, which consistently publish research on AI in HR. High-ranking journals in this domain underscore the interdisciplinary importance of AI recruitment studies and the focus on AI applications' technological and ethical dimensions in HR.

Table 11. Selected Journals

Journal	SJR (2022)	H-Index	Quartile
Electronic Markets	1.671	57	Q1
European Management Journal	1.785	124	Q1
Human Resource Management Review	3.302	121	Q1
International Journal of Human Resource Management	2.078	139	Q1
International Journal of Human-Computer Studies	1.435	145	Q1
Cognition, Technology & Work	0.629	52	Q2
Frontiers in Psychology	0.8	184	Q2
International Journal of Knowledge Management	0.37	30	Q2
Journal of Responsible Technology	N/A	8	Q2
IAES International Journal of Artificial Intelligence	0.365	22	Q3
Interacting with Computers	0.4	94	Q3
Grenze International Journal of Engineering & Technology	N/A	N/A	N/A

Of the 29 papers included in this study, 9 (31%) were authored solely by industry practitioners and were not published through peer-reviewed journals or conference proceedings. The remaining 20 papers (69%) were published in selected academic conferences and proceedings. Among the peer-reviewed venues, the proportion of industry-authored contributions varied, with some conferences including collaborative works between academia and industry, while others featured exclusively academic papers. The inclusion of non-peer-reviewed industry papers reflects the practical relevance of the topic. It highlights the industry's role in contributing to the discourse, even outside formal academic publication channels.

Table 12. Selected conferences and proceedings

Conference and Proceedings	SJR (2022)	H-Index	Quartile
Talent Acquisition: Artificial Intelligence to Manage Recruitment	0.182	39	N/A
Algorithmic Hiring in Practice: Recruiter and HR Professionals' Perspectives on AI Use in Hiring	0.453	38	N/A
Mitigating Age Biases in Résumé Screening AI Models	0.196	16	N/A
Performance Predicting in Hiring Process and Performance Appraisals Using Machine Learning	N/A	11	N/A
Artificial Intelligence (AI): Bringing a New Revolution in Human Resource Management (HRM)	N/A	N/A	N/A
The Role of Artificial Intelligence in Recruitment Process Decision-Making	N/A	N/A	N/A
AI Recruitment: Explaining job seekers' acceptance of automation in human resource management	N/A	N/A	N/A
Towards Automating the Human Resource Recruiting Process	N/A	N/A	N/A

Journal quartiles, determined by impact metrics like the SJR and H-Index, categorise journals into four quality tiers (Q1 to Q4). Q1 represents the highest quality, and Q4 represents the lowest. Journals in Q1 and Q2 are generally more reputable and influential within academic fields.

Figures 5 and 6 also show that most AI recruitment research is concentrated in top-quartile journals (Q1 and Q2), suggesting that this field is well-represented in high-impact, influential publications.

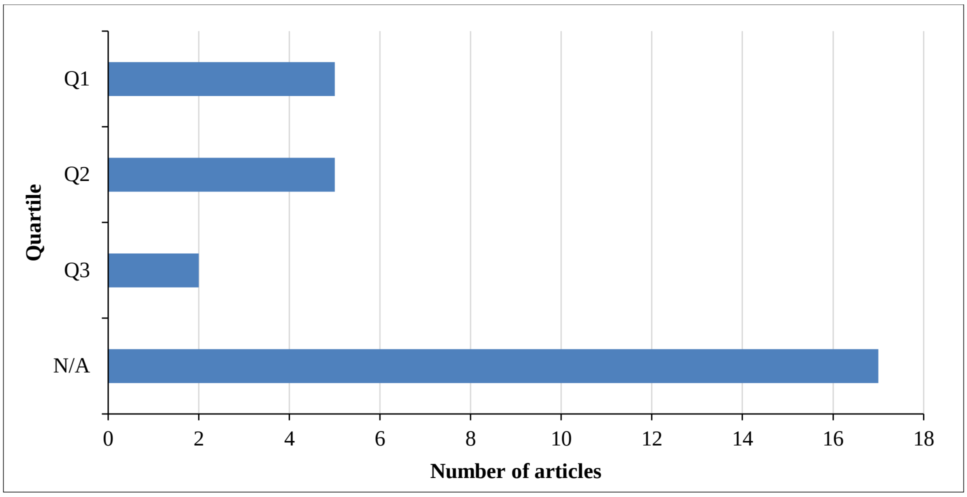

Figure 5. Count of publications per quartile

This concentration highlights the importance of AI in recruitment as a high-priority research area.

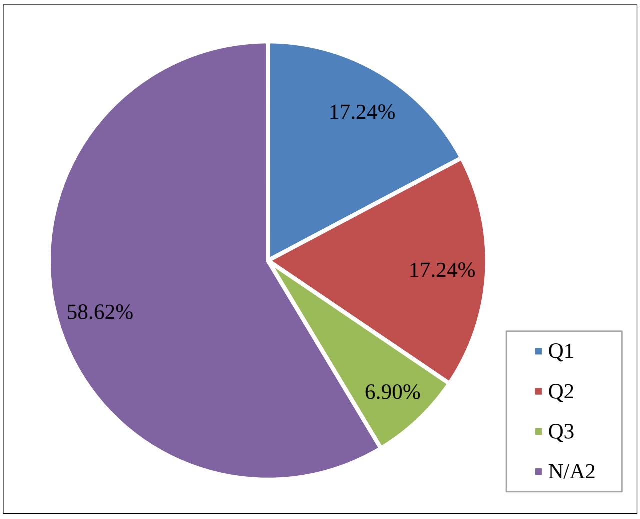

Figure 6. Percentage of publications per quartile

The citation flow diagram in Figure 7 highlights the impact and distribution of citations between journals across different quartiles. High-impact journals, such as the European Management Journal and Human Resource Management Review, often cite and are cited by other top-quartile journals, underscoring their central role in disseminating research on AI in recruitment. This flow illustrates the interdependencies between journals of varying quality rankings, showcasing how knowledge spreads and influences academic platforms.

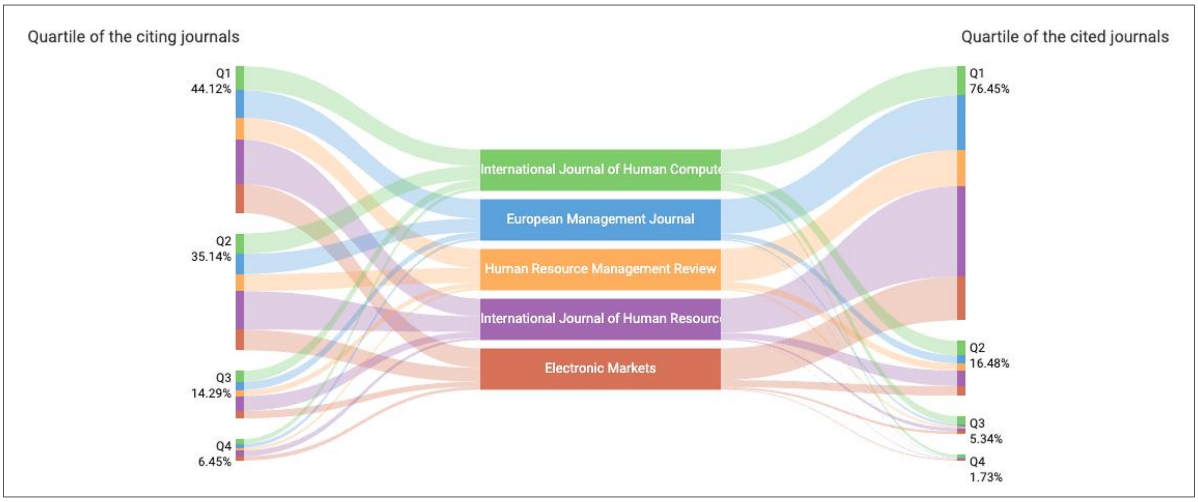

Figure 7. Citation Flow Between Quartiles of Journals

Strong citation flows among Q1 journals reveal a concentration of influential research, while flows between quartiles demonstrate broader knowledge dissemination and engagement across journals of varying quality. High-impact journals are critical nodes in this exchange, reinforcing their pivotal role in advancing AI recruitment research.

Additionally, Figure 8 shows the correlation plot between SJR, H-Index, and quartile rankings, which provides insights into journal quality indicators. Higher SJR scores and H-Index values are predominantly associated with Q1 journals, reflecting a concentration of impactful research in a select few. This analysis aids researchers in identifying the most influential journals for high-quality studies in AI recruitment, ensuring access to reputable sources.

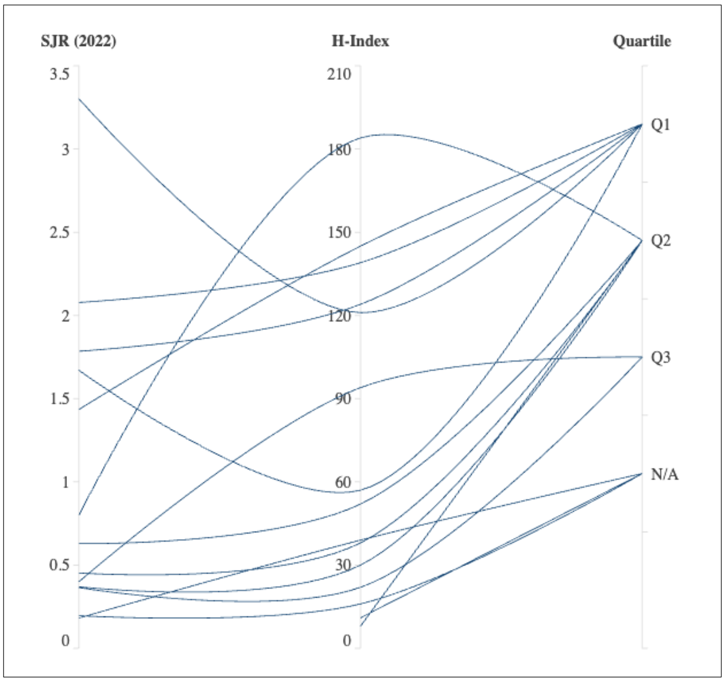

Figure 8. **Correlation of SJR, H-Index, and Quartile Rankings of Sources**

The citation network diagram in Figure 9 illustrates the interconnections of prominent journals in AI-supported recruitment research. Significant journals, such as the European Management Journal and Human Resource Management Review, appear as central nodes in the network, signifying their importance and influence within the field. This network reveals clusters of journals that frequently cite each other, reflecting thematic areas and the interdisciplinary nature of AI research in HRM.

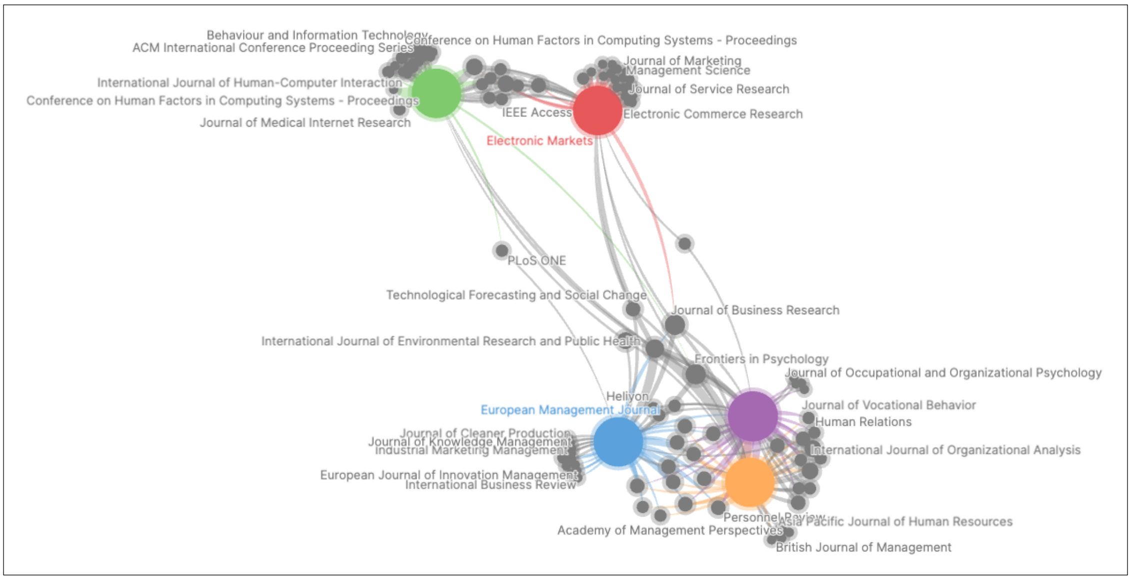

Figure 9. **Citation Network Diagram**

This citation network reveals clusters of closely linked journals, indicating AI recruitment research's collaborative and interconnected nature. Major journals like the European Management Journal and Human Resource Management Review are central hubs, showing their prominent role in shaping the field.

Co-Occurrence of Keywords

The keyword analysis shown in Figure 10 reveals a significant emphasis on “algorithmic bias”, “fairness”, and “ethics”, indicating a strong research focus on addressing ethical challenges in AI-driven recruitment. This alignment with growing concerns about the social implications of algorithmic decision-making in hiring underscores the critical importance of ethical considerations in this field.

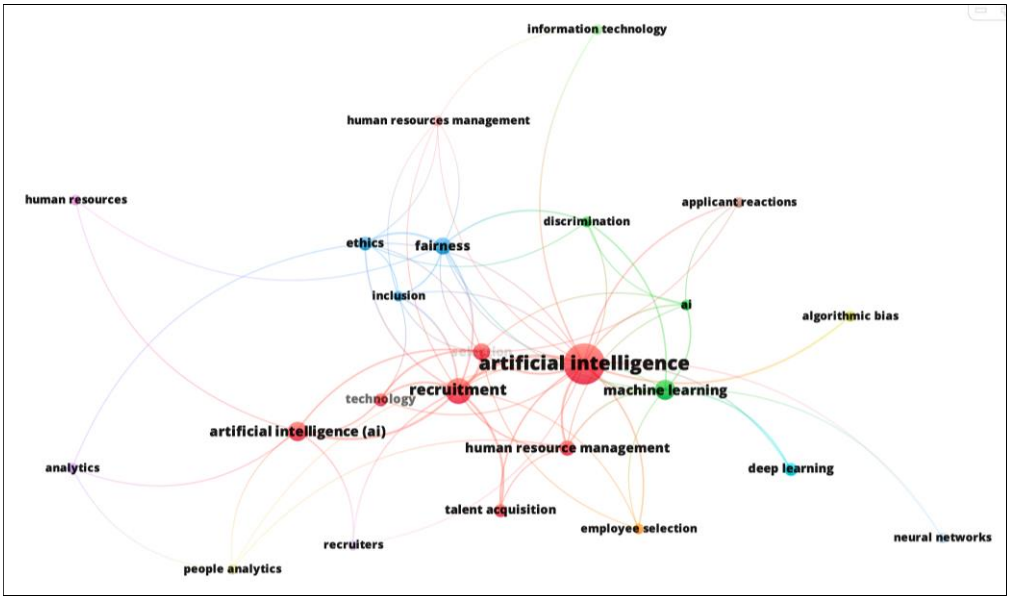

Figure 10. Keywords co-occurrence network visualisation based on the occurrences

The keywords co-occurrence network highlights the dominant research themes, including algorithmic bias, fairness, and ethics. These themes underscore the ethical focus within AI recruitment research, reflecting an ongoing concern for responsible and fair AI practices.

Co-Authorship and Collaboration Analysis

The co-authorship network illustrates key researchers and collaborative clusters within AI-supported recruitment. Distinct clusters represent various interdisciplinary and international collaborations, underscoring the field's highly cooperative nature, as shown in Figure 11.

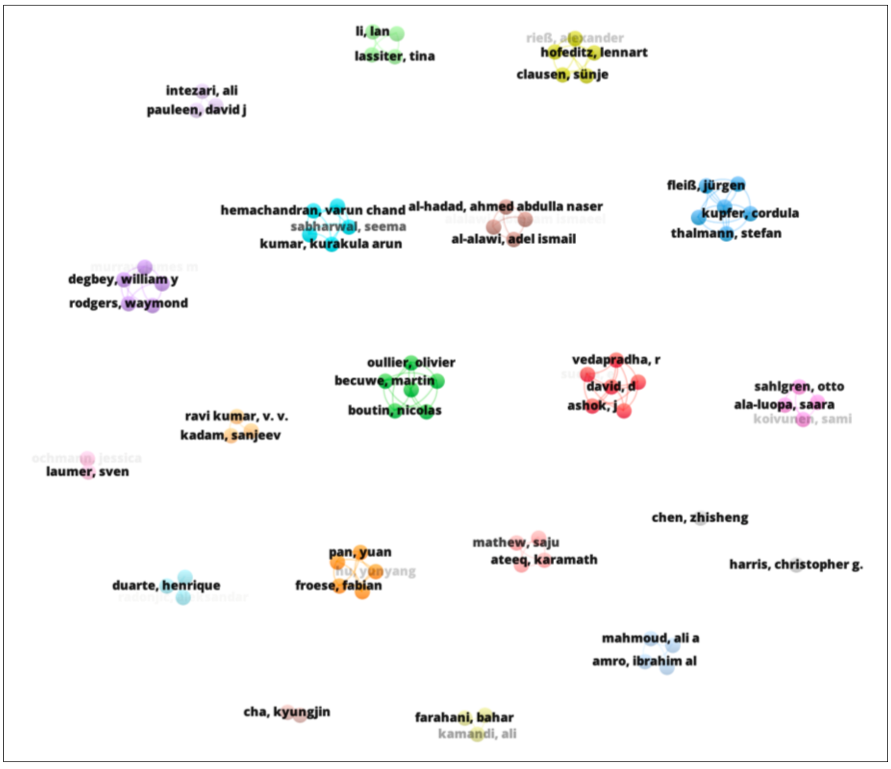

Figure 11. Co-Authorship Network

This network reveals how researchers from diverse backgrounds and regions converge to advance AI applications in HR and recruitment, highlighting the importance of collective expertise in addressing complex issues like algorithmic bias, ethics, and fairness in recruitment practices.

Geographical Distribution of Research

The geographical analysis illustrated in Figure 12 reveals that most research publications originate from the United States, the United Kingdom, and select European countries. This distribution suggests that interest in AI applications for recruitment is predominantly concentrated in North America and Europe, where technological advancements and AI adoption in human resources are more pronounced. Countries with fewer publications indicate emerging interest or limited resources for AI in HR research.

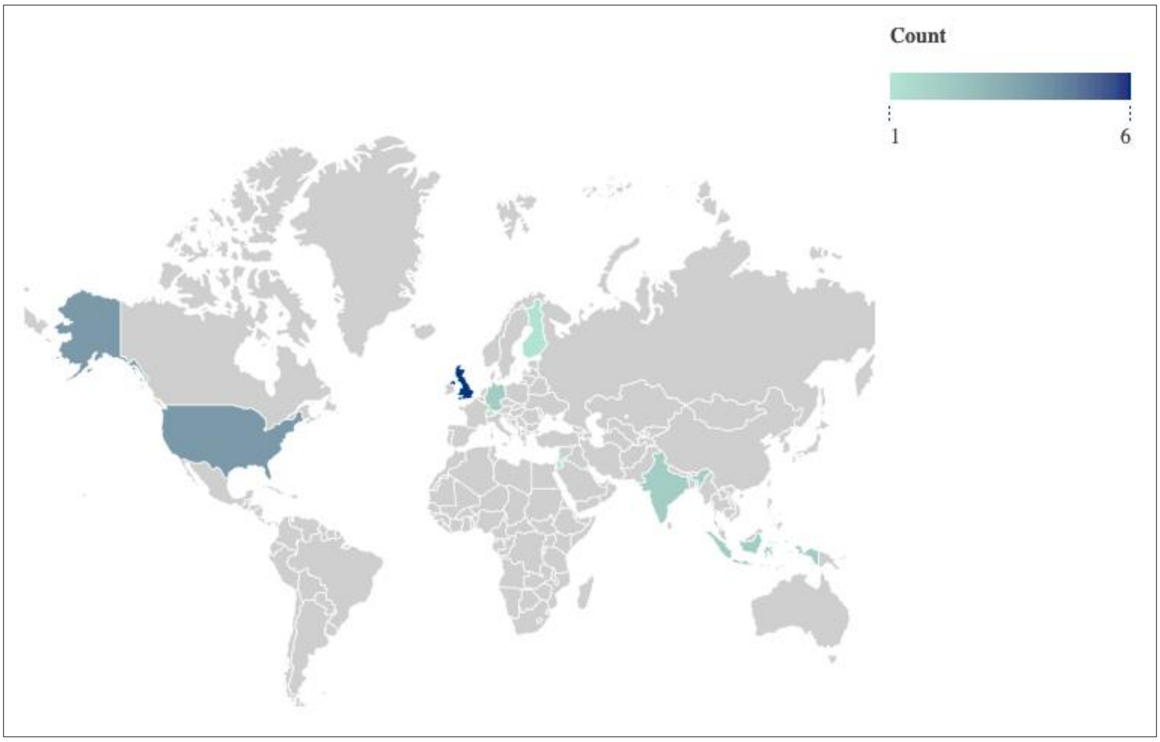

Figure 12. **Publication Count by Country**

Future research could explore the influence of regional regulations, such as GDPR in the EU, on AI recruitment research trends. Additionally, examining cultural attitudes toward AI across different countries may provide a more nuanced understanding of AI adoption in recruitment on a global scale.

Conclusion

This bibliometric analysis underscores the rapid evolution of AI in recruitment, mainly focusing on ethics and efficiency. However, gaps in geographical representation and longitudinal analysis highlight opportunities for future research.

3-4- Reporting

In the Reporting phase, we organise and present the findings of our Multivocal Literature Review (MLR). Specifically, this section elaborates on how the final set of studies answered our research questions and contextualises these findings with bibliometric analysis, thematic synthesis, and reflections on the broader implications of AI in recruitment.

3-5- Overview of Final Selection

Upon completion of the Conducting Phase, a final corpus of 29 studies was identified. The selected sources included peer-reviewed journals, conference proceedings, industry white papers, and targeted organisational websites listed in Table 13.

Table 13. List of selected publications

Author(s)	Year	Title	Type	Published
Gaebler et al. [4]	2024	Auditing the Use of Language Models to Guide Hiring Decisions	Grey literature	arXiv
Gan et al. [1]	2024	Application of LLM Agents in Recruitment: A Novel Framework for Résumé Screening	Grey literature	arXiv
Hemachandran et al. [34]	2024	A study on the impact of artificial intelligence on talent sourcing	Journal	International Journal of Artificial Intelligence
Sun et al. [2]	2024	Facilitating Multi-Role and Multi-Behaviour Collaboration of Large Language Models for Online Job Seeking and Recruiting	Grey literature	arXiv
World Economic Forum and PwC [3]	2024	Leveraging Generative AI for Job Augmentation and Workforce Productivity	Grey literature	Website
Rodgers et al. [25]	2023	An artificial intelligence algorithmic approach to ethical decision-making in human resource management processes	Journal	Human Resource Management Review
Kupfer et al. [24]	2023	Check the box! How to deal with automation bias in AI-based personnel selection	Journal	Frontiers in Psychology
Chen [5]	2023	Collaboration among recruiters and artificial intelligence: removing human prejudices in employment	Journal	Cognition, Technology & Work
Lee et al. [8]	2023	FAT-CAT - Explainability and augmentation for an AI system: A case study on AI recruitment-system adoption	Journal	International Journal of Human-Computer Studies
Harris [43]	2023	Mitigating Age Biases in Résumé Screening AI Models	Conf.	FLAIRS Conference
Koivunen et al. [17]	2023	Pitfalls and Tensions in Digitalising Talent Acquisition: An Analysis of HRM Professionals' Considerations Related to Digital Ethics	Journal	Interacting with Computers
McKinsey & Company [32]	2023	Generative AI and the future of HR	Grey literature	Website
Gartner [18]	2023	What Generative AI Means for Your Talent Strategy	Grey literature	Website
Deloitte [44]	2023	Generative AI and the Future of Work	Grey literature	Website
LinkedIn [31]	2023	Future of Work Report AI at Work	Grey literature	Website
Sen et al. [45]	2023	Role of Artificial Intelligence-Enabled Recruitment Processes in Sourcing Talent	Conf.	Int. Conf. on Intelligent Systems and Computing
Vedapradha et al. [30]	2023	Talent acquisition-artificial intelligence to manage recruitment	Conf.	E3S Web of Conferences
Zhen et al. [23]	2023	Generative Job Recommendations with Large Language Model	Grey literature	arXiv
Hofeditz et al. [5]	2022	Applying XAI to an AI-based system for candidate management to mitigate bias and discrimination in hiring	Journal	Electronic Markets
Radonjić et al. [46]	2022	Artificial intelligence and HRM: HR managers' perspective on decisiveness and challenges	Journal	European Management Journal
Soleimani et al. [9]	2022	Mitigating cognitive biases in developing AI-assisted recruitment systems: A knowledge-sharing approach	Journal	International Journal of Knowledge Management
Delecraz et al. [47]	2022	Responsible Artificial Intelligence in Human Resources Technology: An innovative inclusive, and fair by design matching algorithm for job recruitment purposes	Journal	Journal of Responsible Technology
Pan et al. [14]	2022	The adoption of artificial intelligence in employee recruitment: The influence of contextual factors	Journal	Int. Journal of Human Resource Management
Li et al. [48]	2021	Algorithmic Hiring in Practice: Recruiter and HR Professionals' Perspectives on AI Use in Hiring	Conf.	AAAI/ACM Conference on AI, Ethics, and Society
Mathew et al. [49]	2021	Artificial Intelligence (AI): Bringing a new revolution in Human Resource Management (HRM)	Journal	Grenze International Journal of Engineering & Technology
Al-Alawi et al. [50]	2021	The Role of Artificial Intelligence in Recruitment Process Decision-Making	Conf.	Int. Conference on Decision Aid Sciences and Application
Rafiei et al. [28]	2021	Towards Automating the Human Resource Recruiting Process	Conf.	National Conf. on Advances in Enterprise Architecture
Ochmann et al. [33]	2020	AI recruitment: Explaining job seekers' acceptance of automation in human resource management	Conf.	International Conference on Wirtschaftsinformatik
Mahmoud et al. [51]	2019	Performance Predicting in Hiring Process and Performance Appraisals Using Machine Learning	Conf.	Int. Conf. on Information and Communication Systems

This curated set reflects current trends in AI-driven recruitment, including:

- **Traditional AI** approaches (résumé parsing, ATS ranking, candidate matching).
- **Gen AI & LLM** innovations (automated job postings, chatbot-based candidate interactions).
- **Fairness, Ethics, and Governance** frameworks.
- **SME-centred** perspectives on resource constraints and scale.

We used a standardised data-extraction form to record each study's publication details, methods, focus areas, and key takeaways.

3-6- Academic vs. Grey Literature Insights

A hallmark of multivocal reviews is weaving together formal academic research with real-world**,** practice-driven commentary**.** In our review:

- **Academic Publications:** Offer rigorous, theory-based discussions on algorithmic bias, interpretability, and methodological frameworks.
- **Industry/Practitioner Reports:** These provide immediate, large-scale data insights (e.g., adoption rates, cost analyses), case studies, and emergent best practices, especially regarding Gen AI/LLMs.

Notably, both sources converge on the importance of human oversight, robust data governance, and an evolving regulatory landscape. However, academic work often delves deeper into longer-term social impacts and fairness metrics, whereas industry sources emphasise pragmatic ROI and short-term deployment challenges.

3-7- Threats to Validity

We considered the following potential threats:

1. **Selection Bias:** Although our search was broad, limiting the language to English and focusing on 2018–present might exclude some earlier or non-English perspectives.
2. **Quality Variability:** Integrating grey literature means sources vary in rigour and peer review. We mitigated this using credibility checks by Garousi et al. [27].
3. **Rapid Technological Shifts:** As AI, particularly generative models**,** evolve rapidly, newer tools or frameworks may emerge that supersede existing findings.

These threats underscore the importance of periodically updating the review, especially in fast-moving fields like AI.

3-8- Limitations

In addition to validity considerations, several broader limitations influence how these findings should be interpreted:

- **Context Specificity:** Most included studies focus on Western, enterprise contexts, SMEs, or culturally diverse settings that may face unique challenges.
- **Evolving Ethical/Regulatory Frameworks:** By publication, new laws or guidelines (e.g., the EU AI Act) may shift best practices.
- **MLR Scope:** We restricted our scope to recruitment tasks within HRM, potentially excluding interesting AI use cases (e.g., performance management, employee retention) that relate to but do not directly involve hiring.

3-9- Conclusion of the Reporting Phase

The Reporting phase synthesizes how AI transforms recruitment, balancing efficiency gains against unresolved ethical risks - particularly bias and explainability. By combining academic insights with practitioner evidence, we capture a holistic view of where AI-based recruitment stands today. These findings set the stage for our discussion and conclusion chapters, where we propose actionable recommendations for adopting AI responsibly and highlight targeted areas for future research.

Next, the pool was filtered according to the exclusion criteria in Table 6. The most frequent reasons for exclusion included insufficient specificity to AI-supported recruitment (n = 1216) and the unavailability of full text (n = 20). Additionally, studies focusing purely on technical details of AI algorithms (n = 79) without an HR or recruitment context were excluded, reflecting the MLR emphasis on combining academic and practice-oriented perspectives to address real-world hiring processes [5, 28].

At this stage, title and abstract reviews proved sufficient to remove documents outside our scope, including those missing references to AI-driven recruitment or HR.

This process involved systematically extracting relevant information from each study, followed by careful monitoring to ensure consistency and accuracy. Finally, we synthesised the extracted data to identify common themes, patterns, and insights that directly contribute to answering the research questions.

4- Findings

The synthesised results of the Multivocal Literature Review (MLR) are presented below, with each subsection aligned to a research question (RQ) from Section 1. This structure highlights (1) the benefits of AI for recruitment (RQ1), (2) key adoption challenges (RQ2), and (3) viable mitigation strategies (RQ3). Insights from both academic and grey literature relevant to SMEs and cultural contexts are also highlighted.

4-1- Benefits of AI in Recruitment (RQ1)

AI-driven recruitment technologies consistently demonstrate measurable efficiency improvements by automating résumé screening, candidate-job matching, and interview scheduling [13, 34]. These benefits go beyond reducing administrative workload: they allow HR staff to reallocate time toward more strategic tasks, such as diversity initiatives, employee engagement, or long-term workforce planning. For large enterprises, this contributes to stronger employer branding and a more personalised candidate experience, while for SMEs, it can compensate for small HR teams that often operate with limited resources [5, 28].

Newer tools based on Gen AI and LLMs routinely draft personalised interview questions, generate job descriptions, and deliver tailored feedback to applicants [2, 18, 31]. This significantly enhances the candidate experience through timely and personalised interactions, contributing positively to employer branding and satisfaction.

Table 14 summarises these benefits, highlighting core advantages such as improved matching and potential bias reduction when appropriate safeguards are in place.

Table 14. Benefits of using AI in recruitment processes

Benefits	References
Increased Efficiency and Time Savings	[1, 2, 28, 30, 31, 34, 44, 46]
Improved Accuracy and Quality of Hires	[3, 14, 18, 23, 46, 52]
Reduction of Bias in Hiring	[2, 4, 6, 24, 34, 46]
Cost Reduction	[12, 34, 44, 46]
Enhanced Decision-Making	[1, 2, 6, 52]
Scalability and Handling Large Volumes of Applications	[3, 7, 23, 28]
Improved Candidate Experience	[6, 18, 30, 31, 32, 44]

Another significant benefit is improved accuracy and quality of hires. By processing vast datasets, AI systems can identify patterns that may remain hidden to human recruiters, thereby improving person–job matching [14, 52]. However, this improvement hinges on data quality; when implemented thoughtfully with robust datasets, AI reduces the likelihood of poor hiring decisions, which in turn lowers turnover costs and improves team cohesion. For SMEs, where a single mis-hire can have disproportionate effects, this enhanced precision is particularly valuable.

AI can also contribute to bias reduction when equipped with “blind recruitment” features that anonymise personal identifiers [24]. Studies indicate that, under appropriate safeguards, such systems reduce the influence of unconscious human bias in early-stage screening [6, 7]. Yet this outcome is not automatic; without active auditing and fairness checks, algorithms may perpetuate existing inequities. Thus, AI’s role is better understood as offering bias management tools rather than guaranteed bias elimination.

Finally, AI significantly enhances the candidate experience by providing timely, personalised, and interactive communication. Chatbots and GenAI-driven systems can keep applicants informed, answer routine questions instantly, and deliver feedback throughout the recruitment process [31, 44]. This responsiveness is increasingly valued in competitive talent markets and can improve employer reputation. Importantly, these tools allow even SMEs with small HR departments to provide an applicant experience comparable to larger firms.

Building on the benefits explored in RQ1, this section delves into the challenges and risks organisations face when implementing AI-driven recruitment.

4-2- Challenges (RQ2)

The literature also reveals serious concerns associated with AI adoption in hiring. These include algorithmic bias, ethical and legal complexities, and workforce scepticism, especially in resource-constrained SMEs [5, 28]. The authors specifically investigate how advanced LLMs can still display demographic discrimination unless subjected to careful "correspondence experiments," underscoring the importance of robust auditing frameworks. These concerns and issues of transparency and workforce scepticism appear prominently in the literature and are highlighted in Table 15.

Table 15. Challenges of using AI in recruitment processes

Challenges	References
Algorithmic Bias and Discrimination	[1, 2, 4, 7, 24, 43]
Lack of Transparency and Explainability	[1, 7, 9, 25, 53]
Data Quality and Availability Issues	[5, 7, 9, 14, 28]
Regulatory and Legal Compliance Risks	[4, 7, 14, 28]
Resistance to Automation and Workforce Scepticism	[5, 9, 28]
Resource Constraints, Particularly in SMEs	[5, 14, 28]
Cost and Resource Requirements	[1, 5, 9, 28]

Despite the advantages, several critical challenges remain. The most cited concern is algorithmic bias, which can reproduce or amplify discrimination when historical datasets encode unequal treatment [24, 43]. High-profile examples, such as Amazon's discontinued AI recruitment system, underscore the reputational, legal, and ethical risks of unmonitored bias [22]. For SMEs, this challenge is compounded by smaller applicant pools, where limited data diversity makes it harder to train unbiased models [14].

Another persistent issue is the opacity of advanced AI systems. Many recruitment tools function as "black boxes," producing recommendations without transparent reasoning [7, 25]. Recruiters and candidates alike may perceive these outcomes as unfair or arbitrary, which erodes trust. This lack of explainability is particularly problematic under regulatory regimes such as GDPR, which emphasise the right to explanation [17].

Data quality and availability further constrain effective adoption. Incomplete or inconsistent candidate data can undermine algorithmic reliability [5]. For SMEs with limited applicant tracking systems, collecting structured data remains a significant barrier [28]. This creates a paradox: organisations most in need of efficiency gains often lack the clean, large-scale data that AI requires to function optimally.

Regulatory and compliance risks also loom large. The evolving legal landscape - including the forthcoming EU AI Act - introduces uncertainty about acceptable practices [13]. Organisations must balance innovation with compliance, but SMEs may lack the legal expertise to navigate complex requirements, heightening their vulnerability.

Finally, workforce scepticism and resistance to automation reflect concerns that AI dehumanises recruitment. Candidates often prefer human contact in the final decision stages, while HR professionals fear a loss of control or accountability [5, 14]. Without careful change management and hybrid approaches, these attitudes can hinder adoption.

A frequent criticism is that AI can perpetuate or amplify existing biases against underrepresented groups [24, 43]. LLM-based tools carry the same risk if they learn from skewed corpora or stereotypical text [1, 2]. Another well-cited challenge is the opacity of advanced AI models [7, 25]. HR professionals and applicants alike want transparent reasoning behind candidate rankings or rejections. Without user-friendly explainability tools, scepticism can undermine trust [8].

Data quality issues - biased, incomplete, or unrepresentative datasets inevitably erode model accuracy [7]. SME-specific data challenges, including smaller applicant pools and inconsistent data collection practices, can compound this problem [14]. Low-volume or narrowly sampled training data makes it harder to achieve robust results, especially in multi-regional or multicultural hiring contexts [17]. From a compliance standpoint, AI in recruitment must comply with anti-discrimination laws**,** data privacy standards**,** and emerging AI regulations [13]. Non-adherence can invite legal action, reputational damage, and ethical backlash [6, 17]. Furthermore, new or pending policies like the European Union's AI Act add complexity to compliance, creating uncertainty about how best to structure AI governance.

Organisations often lack the technical expertise to deploy and manage AI solutions confidently [5, 31]. Resistance to automation typically arises from fears regarding fairness, transparency, or job security [14]. These fears might be most potent in smaller enterprises, where employees handle multiple roles and have limited capacity to manage new technology adoption [28]. Costs pose another notable barrier, as advanced AI platforms or robust vendor support can be prohibitively expensive, particularly for SMEs with limited investment capabilities [5, 9].

4-3- Mitigating strategies (RQ3)

Addressing these challenges requires a combination of technical safeguards and organisational practices.

First, bias audits and fairness monitoring are widely recommended. Regular evaluations of model outputs using fairness metrics, coupled with diverse training datasets, can mitigate risks of discrimination [2, 7, 24]. Open-source tools such as Fairlearn or AIF360 offer cost-effective entry points, particularly for SMEs unable to fund enterprise-scale auditing [14].

Second, explainable AI (XAI) frameworks provide transparency. Techniques such as LIME, SHAP, or rule-based dashboards can clarify why a candidate was shortlisted or rejected [9, 25]. This transparency not only builds trust among recruiters but also supports compliance with regulations demanding accountability [17].

Third, data quality management is essential. Standardising data collection processes, integrating applicant tracking systems, and, where feasible, pooling anonymised data across SME consortia can enhance model robustness [14]. Cloud-based, low-code recruitment platforms also offer practical solutions for organisations without extensive IT departments [51].

Fourth, ethical governance structures such as internal AI ethics committees or accountability officers - ensure continuous oversight [3, 44]. Embedding human oversight into critical decision points (e.g., final hiring stages) preserves empathy and fairness while leveraging AI efficiency [33]. This human-in-the-loop model is especially effective at addressing candidate scepticism.

Finally, training and change management are crucial. HR professionals must be equipped to understand AI's capabilities and limitations, ensuring that algorithms complement - rather than replace - human judgement [12, 31]. This cultural adaptation fosters greater acceptance internally and externally. Having examined both the benefits (RQ1) and challenges (RQ2), this section now investigates how organisations can mitigate risks and enhance the responsible use of AI in recruitment.

The literature proposes technical and organisational strategies to mitigate these challenges, including algorithmic debiasing, policy frameworks, training, and stakeholder engagement. Deloitte (2023) [44] further recommends internal AI ethics committees and human-in-the-loop oversight mechanisms to enhance trust. A phased approach pairing risk management with continuous workforce training can foster more effective and trusted AI deployment [3].

While strategies such as bias audits, explainable AI, and workforce training are valuable, their implementation can be challenging for SMEs operating with limited budgets and technical expertise. For such organizations, cost-effective alternatives include using open-source AI fairness tools, focusing audits on the highest-risk decision points, incorporating human oversight at final selection stages, and engaging in collaborations or consortia to share resources. These pragmatic steps provide SMEs with feasible entry points to adopt responsible AI practices without the prohibitive costs often associated with enterprise-scale solutions.

Table 16 consolidates these mitigation strategies into key themes, ranging from data-quality interventions to human oversight and training recommendations.

Table 16. Mitigation of the challenges of using AI in recruitment processes

Mitigation of challenges	References
Implementing Bias Mitigation Techniques	[2, 7, 8, 9, 17, 24, 31, 43, 51]
Ensuring Transparency and Explainability	[6, 8, 9, 18, 23, 25, 33]
Enhancing Data Quality and Diversity	[1, 5, 7, 14, 32]
Addressing Ethical and Legal Concerns	[6, 17, 18, 50]
Training and Educating HR Professionals	[8, 9, 14, 31]
Balancing Automation with Human Oversight	[8, 9, 17, 32, 43]

Researchers and practitioners propose debiasing methods, XAI frameworks, and robust governance guidelines in response to these challenges. Proactive bias detection (via periodic audits, fairness metrics, and third-party evaluations) and diverse training datasets emerge as some of the most recommended approaches [4, 7, 24]. Tools tailored to LLMs have emerged, seeking to identify and reduce biased or harmful text generation [23].

XAI frameworks - like rule-based models, interactive dashboards, or local interpretable model-agnostic explanations (LIME) - clarify how decisions are made [8, 25]. In HR, XAI can foster trust among candidates, recruiters, and legal oversight bodies, ensuring transparent decision rationales [4, 9, 33, 44].

Since AI effectiveness hinges on robust training data, best practices call for standardised data collection, ongoing curation, and cross-company data sharing [5, 14]. SMEs, in particular, may benefit from vendor partnerships or consortia data pools to offset small sample sizes [1, 18, 28, 32].

Ethical governance frameworks - encompassing data-protection standards (e.g., GDPR), bias audits, and transparency mandates - ***aid*** organisations in tracking compliance [3, 4]. Several grey sources (e.g., [18, 32] also highlight the importance of an AI ethics committee or an internal "Accountability Officer" who oversees fairness metrics, interpretability, and candidate feedback systems. Such roles are especially critical in global contexts with varied legal constraints [17]. Ongoing professional development ensures that recruiters and HR staff understand AI's limitations and can interpret its outputs critically [8, 9, 31]. This can be done through specialised training sessions or cross-functional "AI working groups", enabling close collaboration between data scientists and recruiters to sustain trust and oversight [3, 14].

Many studies emphasise that automation should complement - not replace - human judgement [21, 33]. Hybrid models, in which AI handles the initial stages, and humans make final decisions, combine algorithmic efficiency with empathy and accountability [3, 17, 44].

4-4- Comparison with Previous Studies

The results of this review broadly corroborate prior studies that emphasize efficiency gains, enhanced candidate matching, and time savings as the primary benefits of AI in recruitment [5, 18, 22, 26]. Consistent with earlier findings, concerns regarding fairness, explainability, and candidate acceptance remain persistent challenges in practice [11, 12, 20].

At the same time, this review extends prior work in several important ways. Earlier studies focused predominantly on large enterprises and Western contexts, while our multivocal approach incorporates both peer-reviewed and grey literature to highlight underexplored dimensions. In particular, we identify the unique barriers faced by small and medium enterprises (SMEs), including limited budgets, lack of in-house expertise, and scepticism toward automation. These constraints are rarely addressed in prior systematic reviews, despite SMEs constituting the majority of global businesses [27].

A further contribution of this review is its explicit attention to cultural and regional diversity. Previous studies have largely overlooked how cultural norms and local regulations influence perceptions of trust, fairness, and legitimacy in AI-based hiring [15, 28]. By framing cultural diversity as a decisive factor in AI acceptance, this review challenges the generalisability of enterprise-centric findings. Finally, through the inclusion of grey literature, this study captures recent generative AI (GenAI) and large language model (LLM) applications - such as automated job description generation and real-time candidate feedback - that are not yet widely represented in academic publishing [3, 4, 7].

In sum, the findings of this study are consistent with earlier work in acknowledging efficiency gains and ethical risks, but they extend prior analyses by systematically addressing SMEs, cultural variation, and emerging GenAI practices. These contributions underscore the necessity of context-sensitive and inclusive strategies for sustainable AI adoption in recruitment.

4-5- Summary of Findings

In summary, academic and grey literature converge on three key insights. First, AI in recruitment delivers tangible benefits in efficiency, accuracy, and candidate experience, particularly through advanced tools such as LLMs and generative AI. Second, significant challenges remain, especially algorithmic bias, lack of transparency, data quality issues, regulatory compliance, and workforce scepticism. These challenges are amplified in SMEs, which face acute resource constraints, and are further complicated by cultural diversity, an underexplored dimension shaping trust and acceptance. Third, the literature highlights the need for multi-dimensional governance strategies that integrate technical safeguards (bias audits, explainable AI) with organisational practices (human oversight, training, ethical governance). Future research should focus on long-term impacts on workforce diversity, SME-specific adoption frameworks, and cross-cultural validation to bridge the gap between theoretical promise and practical implementation [27].

5- Conclusions and Future Work

This multivocal literature review examined the adoption of artificial intelligence (AI) in recruitment by synthesising insights from both peer-reviewed and grey literature. The findings indicate that AI offers tangible benefits in terms of efficiency, candidate matching, and scalability, consistent with prior studies [5, 18, 22]. At the same time, significant challenges persist, particularly regarding fairness, transparency, data quality, and candidate acceptance [11, 12, 20]. While earlier reviews have largely focused on large enterprises and Western contexts, this study contributes by explicitly highlighting two underexplored dimensions: the constraints faced by small and medium enterprises (SMEs) and the influence of cultural and regional diversity on AI adoption. SMEs frequently encounter budget limitations, lack of in-house expertise, and scepticism toward automation, factors that can impede adoption [27]. Furthermore, cultural values and local regulations significantly shape perceptions of fairness and trust in AI-enabled hiring [15, 28]. By also incorporating grey literature, this review captures the most recent generative AI (GenAI) and large language model (LLM) applications, including automated job description generation and personalised candidate feedback [3, 4, 7], which remain under-represented in academic publishing.

The implications of these findings are twofold. For practitioners and policymakers, the results underscore the importance of developing cost-effective, transparent, and culturally sensitive recruitment solutions that balance efficiency with fairness and accountability. For researchers, this review highlights the need to extend investigations beyond enterprise-centric contexts, integrating SMEs and cross-cultural perspectives into future analyses. Addressing these gaps is essential to avoid overgeneralising conclusions from limited contexts and to ensure that AI-driven recruitment practices are both globally relevant and socially responsible. While this review provides a comprehensive synthesis, its reliance on currently available literature means that future research should continuously revisit these themes as technology evolves and regulatory frameworks mature. Overall, this study advances the discourse by offering a more inclusive and practice-orientated understanding of AI in recruitment, bridging academic theory and industry practice, and paving the way for more sustainable adoption strategies.

This section revisits key insights, underscores theoretical and managerial implications, addresses review limitations, and suggests future research directions.

5-1- Key Insights

***Efficiency and Enhanced Matching*:** Our findings confirm that AI-driven solutions - including ML, D-, and LLM-based approaches - consistently expedite repetitive tasks and improve applicant matching accuracy [13, 52]. By automating large-scale screening, organisations free up HR resources for more strategic, relationship-centric activities.

***Persistent Challenges*:** Fairness and transparency issues remain significant despite these efficiency gains. Algorithmic bias is especially problematic, given historical patterns embedded in training data [25]. Smaller enterprises often lack the requisite budgets or expertise to deploy complex AI systems effectively [5, 28], and cultural differences in data usage and attitudes toward automation further complicate consistent adoption.

***Mitigation Strategies*:** Effective countermeasures include bias audits, diversified training sets, robust XAI frameworks supported by well-defined policies and ongoing staff training [9, 43]. Furthermore, many researchers recommend hybrid or "human-in-the-loop" approaches that combine algorithmic efficiency with human judgement [17].

5-2- Theoretical Implications

Our review highlights a theoretical gap at the intersection of organisational behaviour, AI ethics, and cross-cultural management. Existing studies rarely integrate these theoretical perspectives with practical deployment issues, leaving unanswered questions about how organisational or cultural contexts influence AI adoption in HR. Future research should explore how individual attitudes toward AI intersect with organisational and societal values, especially within SMEs and culturally diverse settings. Gen AI and LLMs introduce critical dimensions - such as interpretability, content quality, and user trust - that require deeper interdisciplinary investigation [1, 2].

While SMEs face unique challenges in adopting AI due to limited budgets and technical expertise, practical solutions are available. Open-source platforms such as TensorFlow, Scikit-learn, or Fairlearn can be used to implement basic analytics and fairness audits without licensing costs. SMEs may also benefit from affordable applicant tracking systems, such as Zoho Recruit or Recruitee, which integrate simple AI features. In contexts where cultural diversity is a key concern, SMEs can draw on open-source bias detection tools to monitor recruitment outcomes across demographic groups. These concrete measures provide SMEs with realistic starting points for AI adoption, complementing the broader call for SME-specific frameworks and cross-cultural validation.

5-3- Managerial Implications

- **Responsible Adoption:** We advise HR leaders to treat AI as an augmenting tool, leveraging its computational speed and scalability while preserving human judgement for nuanced or sensitive decisions [33].
- **Data Governance:** Enterprises, including SMEs, should prioritise robust data governance frameworks to ensure consistent data quality and compliance, particularly if they rely on third-party AI vendors or have limited in-house data science capabilities [14].
- **Bias Awareness and Training:** Ongoing staff development - from bias detection courses to advanced AI literacy - can encourage responsible AI usage, enhance interpretability, and foster trust among internal and external stakeholders [17].
- **Localisation and Cultural Sensitivity:** Global or cross-border enterprises must align AI-based hiring tools with local regulations, cultural norms, and candidate expectations. Failure to tailor language usage, privacy standards, or fairness definitions to local contexts may dilute AI's potential benefits [13].

5-4- Limitations of the Review

Despite synthesising extensive literature, some caveats remain:

- **Publication Window**: Focusing on works published post-2018 emphasises the latest AI developments but may omit earlier seminal contributions.
- **Language Bias**: Prioritising English-language peer-reviewed literature can overlook critical insights from other languages or non-traditional publication channels.
- **Evolving AI Landscape**: Because AI evolves so quickly - especially in LLM-based solutions - new techniques may supersede our findings, requiring periodic updates to remain relevant.
- **Contextual Variations**: While SMEs and cultural factors are highlighted, the enormous diversity of global hiring contexts cannot be fully captured, nor can region-specific legislation be accounted for beyond broad overviews.

Much of the grey literature, particularly industry reports, presents optimistic narratives about AI adoption that may not fully reflect the lived experiences of SMEs, especially those operating with resource constraints. In addition, the evidence base is dominated by studies from Western contexts, which raises the risk of overgeneralizing when drawing "global" implications. This highlights the importance of culturally diverse and locally grounded research to capture the full spectrum of adoption challenges and opportunities.

Although this review identifies general trends in AI adoption for recruitment, the evidence base is geographically skewed, with most studies originating in North America and Europe. This imbalance has important implications for global adoption, as factors such as regulatory frameworks, data protection regimes, labor market structures, and cultural attitudes toward technology vary considerably across regions. For example, jurisdictions with weaker data privacy protections may face different risks, while collectivist cultures may emphasize fairness and transparency differently than individualist ones. These variations suggest that conclusions derived largely from Western settings cannot be assumed to apply universally, underscoring the need for region-specific studies that explore how adoption trajectories and ethical concerns manifest in diverse contexts.

5-5- Future Research Directions

Several promising directions emerge from our analysis:

- **Longitudinal Diversity Outcomes:** Long-term evaluations are necessary to validate whether AI-centric hiring fosters sustained workforce diversity beyond initial bias reductions [14, 52].
- **Deeper Exploration of Gen AI and LLMs:** Ongoing research should compare generative and non-generative approaches across user trust, bias, and recruitment outcomes to understand how advanced text generation (LLMs) might reshape HR dynamics [1, 23].
- **SME-Specific Implementation Frameworks:** Because SMEs operate with limited resources, future studies might develop specialised frameworks or cloud-based AI "pay-as-you-go" options that respect smaller budgets and data limitations [28]. Future frameworks could emphasise scalable, low-code or no-code AI platforms to support SMEs better, enabling non-technical users to implement and maintain recruitment tools [54]. SME networks could collaborate on shared talent databases, lowering the cost of AI training data acquisition. For example, SMEs could begin with accessible tools such as Microsoft Copilot or Zoho Recruit, which offer low-code automation features and pre-trained AI models tailored for HR tasks.
- **Cross-Cultural Validation:** Investigations across multiple regions and industries can clarify how cultural attitudes - toward privacy, fairness, or automation - shape AI acceptance in HR, guiding more culturally adaptive frameworks [14, 17].
- **XAI in HR Settings:** Empirical, case-based evaluations of XAI solutions in real-world HR contexts remain limited. Detailed evidence of how XAI dashboards or interactive explanations impact HR adoption, candidate satisfaction, and fairness would strengthen the field's practical foundation [8].

5-6- Final Reflections

In conclusion, AI in recruitment is moving beyond Gen AI and LLMs. While the efficiency dividends are indisputable, implementing AI responsibly demands ongoing oversight, robust ethics protocols, and clarity in model interpretability. Crucially, there is no one-size-fits-all solution - SMEs and culturally diverse markets each present unique challenges and opportunities for AI-based hiring. As new AI methods emerge, it will be vital for practitioners and scholars to adapt, evaluate, and refine these approaches for equitable and effective recruitment worldwide.

6- Declarations

6-1- Author Contributions

Conceptualization, H.T. and H.S.M.; methodology, H.T.; software, H.T.; validation, H.T., H.S.M., P.T., and V.S.; formal analysis, H.T.; investigation, H.T.; resources, H.S.M., P.T., and V.S.; data curation, H.T.; writing—original draft preparation, H.T.; writing—review and editing, H.T., H.S.M., P.T., and V.S.; visualization, H.T.; supervision, H.S.M.; project administration, H.S.M.; funding acquisition, H.S.M. All authors have read and agreed to the published version of the manuscript.

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Data sharing is not applicable to this article.

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6-4- Institutional Review Board Statement

Not applicable.

6-5- Informed Consent Statement

Not applicable.

6-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

7- References

[1] Gan, C., Zhang, Q., & Mori, T. (2024). Application of LLM Agents in Recruitment: A Novel Framework for Automated Resume Screening. Journal of Information Processing, 32, 881–893. doi:10.2197/ipsjjip.32.881.

[2] Sun, H., Lin, H., Yan, H., Song, Y., Gao, X., & Yan, R. (2025). MockLLM: A Multi-Agent Behavior Collaboration Framework for Online Job Seeking and Recruiting. Proceedings of the 31st ACM SIGKDD Conference on Knowledge Discovery and Data Mining, 2714-2724. doi:10.48550/arXiv.2405.18113.

[3] World Economic Forum, & PwC. (2025). Leveraging generative AI for job augmentation and workforce productivity. World Economic Forum, Cologny, Switzerland. Available online: https://www.weforum.org/publications/leveraging-generative-ai-for-job-augmentation-and-workforce-productivity/ (accessed on November 2025).

[4] Gaebler, J. D., Goel, S., Huq, A., & Tambe, P. (2024). Auditing the use of language models to guide hiring decisions. arXiv Preprint, arXiv:2404.03086. doi:10.48550/arXiv.2404.03086.

[5] Hofeditz, L., Clausen, S., Rieß, A., Mirbabaie, M., & Stieglitz, S. (2022). Applying XAI to an AI-based system for candidate management to mitigate bias and discrimination in hiring. Electronic Markets, 32(4), 2207–2233. doi:10.1007/s12525-022-00600-9.

[6] Chen, Z. (2023). Collaboration among recruiters and artificial intelligence: removing human prejudices in employment. Cognition, Technology and Work, 25(1), 135–149. doi:10.1007/s10111-022-00716-0.

[7] Hangartner, D., Kopp, D., & Siegenthaler, M. (2021). Monitoring hiring discrimination through online recruitment platforms. Nature, 589(7843), 572-576. doi:10.1038/s41586-020-03136-0.

[8] Lee, C. H., & Cha, K. J. (2023). FAT-CAT—Explainability and augmentation for an AI system: A case study on AI recruitment-system adoption. International Journal of Human Computer Studies, 171, 102976. doi:10.1016/j.ijhcs.2022.102976.

[9] Soleimani, M., Intezari, A., & Pauleen, D. J. (2022). Mitigating cognitive biases in developing AI-assisted recruitment systems: A knowledge-sharing approach. International Journal of Knowledge Management, 18(1), 1–18. doi:10.4018/IJKM.290022.

[10] Binns, R. (2020). On the apparent conflict between individual and group fairness. FAT* 2020 - Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency, 514–524. doi:10.1145/3351095.3372864.

[11] Mehta, M., Derasari, R., Patel, S., Kakadiya, A., Gandhi, R., Chaudhary, S., & Goswami, R. (2019). A service-oriented human capital management recommendation platform. 13th Annual IEEE International Systems Conference, Proceedings (SysCon 2019), 1-8. doi:10.1109/SYSCON.2019.8836842.

[12] Delecraz, S., Eltarr, L., Becuwe, M., Bouxin, H., Boutin, N., & Oullier, O. (2022). Responsible Artificial Intelligence in Human Resources Technology: An innovative inclusive and fair by design matching algorithm for job recruitment purposes. Journal of Responsible Technology, 11, 100041. doi:10.1016/j.jrt.2022.100041.

[13] Köchling, A., Wehner, M. C., & Warkocz, J. (2023). Can I show my skills? Affective responses to artificial intelligence in the recruitment process. Review of Managerial Science, 17(6), 2109–2138. doi:10.1007/s11846-021-00514-4.

[14] Pan, Y., Froese, F., Liu, N., Hu, Y., & Ye, M. (2022). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. International Journal of Human Resource Management, 33(6), 1125–1147. doi:10.1080/09585192.2021.1879206.

[15] Van Esch, P., Black, J. S., & Ferolie, J. (2019). Marketing AI recruitment: The next phase in job application and selection. Computers in Human Behavior, 90, 215–222. doi:10.1016/j.chb.2018.09.009.

[16] World Bank. (2023). SME Finance: Development News, Research, Data. World Bank, Washington, D.C., United States. Available online: https://www.worldbank.org/en/topic/smefinance (accessed on November 2025).

[17] Koivunen, S., Sahlgren, O., Ala-Luopa, S., & Olsson, T. (2023). Pitfalls and Tensions in Digitalizing Talent Acquisition: An Analysis of HRM Professionals' Considerations Related to Digital Ethics. Interacting with Computers, 35(3), 435–451. doi:10.1093/iwc/iwad018.

[18] Gartner. (2023). What generative AI means for your talent strategy. Gartner, Connecticut, United States. Available online: https://www.gartner.com/en/insights/generative-ai-for-business (accessed on November 2025).

[19] Hmoud, B. I., & Várallyai, L. (2020). Artificial Intelligence in Human Resources Information Systems: Investigating its Trust and Adoption Determinants. International Journal of Engineering and Management Sciences, 5(1), 749–765. doi:10.21791/ijems.2020.1.65.

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

[21] Hunkenschroer, A. L., & Luetge, C. (2022). Ethics of AI-Enabled Recruiting and Selection: A Review and Research Agenda. Journal of Business Ethics, 178(4), 977–1007. doi:10.1007/s10551-022-05049-6.

[22] Meechang, K., Leelawat, N., Tang, J., Kodaka, A., & Chintanapakdee, C. (2020). The acceptance of using information technology for disaster risk management: A systematic review. Engineering Journal, 24(4), 111–132. doi:10.4186/ej.2020.24.4.111.

[23] Zheng, Z., Qiu, Z., Hu, X., Wu, L., Zhu, H., & Xiong, H. (2023). Generative job recommendations with large language model. arXiv Preprint, arXiv:2307.02157. doi:10.48550/arXiv.2307.02157.

[24] Kupfer, C., Prassl, R., Fleiß, J., Malin, C., Thalmann, S., & Kubicek, B. (2023). Check the box! How to deal with automation bias in AI-based personnel selection. Frontiers in Psychology, 14. doi:10.3389/fpsyg.2023.1118723.

[25] Rodgers, W., Murray, J. M., Stefanidis, A., Degbey, W. Y., & Tarba, S. Y. (2023). An artificial intelligence algorithmic approach to ethical decision-making in human resource management processes. Human Resource Management Review, 33(1), 100925. doi:10.1016/j.hrmr.2022.100925.

[26] Keele, S. (2007). Guidelines for performing systematic literature reviews in software engineering. Technical report, Ver. 2.3 EBSE Technical Report. EBSE Technical Report, EBSE-2007-01.

[27] Garousi, V., Felderer, M., & Mäntylä, M. V. (2019). Guidelines for including grey literature and conducting multivocal literature reviews in software engineering. Information and Software Technology, 106, 101–121. doi:10.1016/j.infsof.2018.09.006.

[28] Rafiei, G., Farahani, B., & Kamandi, A. (2021). Towards Automating the Human Resource Recruiting Process. Proceedings of 5th National Conference on Advances in Enterprise Architecture, 43–47. doi:10.1109/NCAEA54556.2021.9690504.

[29] Hoftede, G., Hofstede, G. J., & Minkov, M. (2010). Cultures and organizations: software of the mind: intercultural cooperation and its importance for survival. McGraw-Hill, New York, United States.

[30] Vedapradha, R., Hariharan, R., David Winster Praveenraj, D., Sudha, E., & Ashok, J. (2023). Talent acquisition-artificial intelligence to manage recruitment. E3S Web of Conferences, 376, 5001. doi:10.1051/e3sconf/202337605001.

[31] LinkedIn. (2023). Future of Work Report: AI at Work. LinkedIn, California, United States. Available online: https://economicgraph.linkedin.com/research/future-of-work-report-ai (accessed on November 2025).

[32] Wilmers, N. (2024). Generative AI and the Future of Inequality: An MIT Exploration of Generative AI. McKinsey & Company, Illinois, United States. doi:10.21428/e4baedd9.777b7123.

[33] Ochmann, J., & Laumer, S. (2020). AI Recruitment: Explaining job seekers' acceptance of automation in human resource management. WI2020 Zentrale Tracks, 1633–1648. doi:10.30844/wi_2020_q1-ochmann.

[34] Hemachandran, V. C., Kumar, K. A., Sikandar, S. A., Sabharwal, S., & Kumar, S. A. (2024). A study on the impact of artificial intelligence on talent sourcing. IAES International Journal of Artificial Intelligence, 13(1), 1–8. doi:10.11591/ijai.v13.i1.pp1-8.

[35] An, H., Acquaye, C., Wang, C., Li, Z., & Rudinger, R. (2024). Do Large Language Models Discriminate in Hiring Decisions on the Basis of Race, Ethnicity, and Gender?. arXiv Preprint, arXiv:2406.10486. doi:10.48550/arXiv.2406.10486.

[36] Ali, O., Shrestha, A., Soar, J., & Wamba, S. F. (2018). Cloud computing-enabled healthcare opportunities, issues, and applications: A systematic review. International Journal of Information Management, 43, 146–158. doi:10.1016/j.ijinfomgt.2018.07.009.

[37] Ali, O., Jaradat, A., Kulakli, A., & Abuhalimeh, A. (2021). A Comparative Study: Blockchain Technology Utilization Benefits, Challenges and Functionalities. IEEE Access, 9, 12730–12749. doi:10.1109/ACCESS.2021.3050241.

[38] Sadoughi, F., Ali, O., & Erfannia, L. (2020). Evaluating the factors that influence cloud technology adoption—comparative case analysis of health and non-health sectors: A systematic review. Health Informatics Journal, 26(2), 1363–1391. doi:10.1177/1460458219879340.

[39] Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. Journal of Business Research, 133, 285–296. doi:10.1016/j.jbusres.2021.04.070.

[40] Mingers, J., & Leydesdorff, L. (2015). A review of theory and practice in scientometrics. European Journal of Operational Research, 246(1), 1–19. doi:10.1016/j.ejor.2015.04.002.

[41] Zupic, I., & Čater, T. (2015). Bibliometric Methods in Management and Organization. Organizational Research Methods, 18(3), 429–472. doi:10.1177/1094428114562629.

[42] Chen, C., Ibekwe-SanJuan, F., & Hou, J. (2010). The structure and dynamics of cocitation clusters: A multiple-perspective cocitation analysis. Journal of the American Society for Information Science and Technology, 61(7), 1386–1409. doi:10.1002/asi.21309.

[43] Harris, C. G. (2023). Mitigating Age Biases in Resume Screening AI Models. Proceedings of the International Florida Artificial Intelligence Research Society Conference, FLAIRS, 36. doi:10.32473/flairs.36.133236.

[44] Scoble-Williams, N., Sinti, D., Vert, G., & Cantrell, S. (2024). Generative AI and the future of work. Deloitte. Available online: https://www.deloitte.com/global/en/services/consulting/research/generative-ai-and-the-future-of-work.html (accessed on July 2025).

[45] Sen, S., Kadam, S., & Ravi Kumar, V. V. (2023). Role of Artificial Intelligence-Enabled Recruitment Processes in Sourcing Talent. 6th International Conference on Information Systems and Computer Networks, ISCON 2023, 10112009. doi:10.1109/ISCON57294.2023.10112009.

[46] Radonjić, A., Duarte, H., & Pereira, N. (2024). Artificial intelligence and HRM: HR managers' perspective on decisiveness and challenges. European Management Journal, 42(1), 57–66. doi:10.1016/j.emj.2022.07.001.

[47] Delecraz, S., Eltarr, L., Becuwe, M., Bouxin, H., Boutin, N., & Oullier, O. (2022). Making Recruitment More Inclusive: Unfairness Monitoring With a Job Matching Machine-Learning Algorithm. Proceedings - International Workshop on Equitable Data and Technology, FairWare 2022, 34–41. doi:10.1145/3524491.3527309.

[48] Li, L., Lassiter, T., Oh, J., & Lee, M. K. (2021). Algorithmic Hiring in Practice: Recruiter and HR Professional's Perspectives on AI Use in Hiring. AIES 2021 - Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society, 166–176. doi:10.1145/3461702.3462531.

[49] Mathew, S., Oswal, N., & Ateeq, K. (2021). Artificial Intelligence (AI): Bringing a new revolution in Human Resource Management (HRM). 12th International Conference on Advances in Computing, Control, and Telecommunication Technologies, ACT 2021, 2021-August, 211–218.

[50] Al-Alawi, A. I., Naureen, M., Alalawi, E. I., & Naser Al-Hadad, A. A. (2021). The Role of Artificial Intelligence in Recruitment Process Decision-Making. 2021 International Conference on Decision Aid Sciences and Application, DASA 2021, 197–203. doi:10.1109/DASA53625.2021.9682320.

[51] Mahmoud, A. A., Al Shawabkeh, T., Salameh, W. A., & Al Amro, I. (2019). Performance Predicting in Hiring Process and Performance Appraisals Using Machine Learning. 2019 10th International Conference on Information and Communication Systems, ICICS 2019, 110–115. doi:10.1109/IACS.2019.8809154.

[52] Syrigou, A., & Williams, S. (2023). Professionalism and professionalization in human resources (HR): HR practitioners as professionals and the organizational professional project. Journal of Professions and Organization, 10(2), 151-164. doi:10.1093/jpo/joad008.

[53] Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. Big Data and Society, 5(1), 2053951718756684. doi:10.1177/2053951718756684.

[54] Domański, R., Wojciechowski, H., Lewandowicz, J., & Hadaś, Ł. (2023). Digitalization of Management Processes in Small and Medium-Sized Enterprises—An Overview of Low-Code and No-Code Platforms. Applied Sciences (Switzerland), 13(24), 13078. doi:10.3390/app132413078.