

The Impact of Artificial Intelligence on Recruitment and Selection

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Abstract

Artificial intelligence (AI) is rapidly transforming human resource management, with recruitment and selection emerging as among the most affected functions. This paper provides a systematic empirical review of scholarly literature published between 2019 and 2025, drawing on quantitative studies, qualitative investigations, and mixed-methods research. The review synthesises findings across five key dimensions: recruitment efficiency, bias and fairness, candidate experience, human-AI collaboration, and ethical and governance challenges. Empirical evidence consistently demonstrates that AI-enabled recruitment tools improve process speed and screening accuracy. However, algorithmic bias remains a persistent concern, with documented discriminatory effects along gender, race, and socioeconomic lines. Findings emphasise that the responsible deployment of AI in recruitment requires robust governance frameworks, transparency mechanisms, and continued human oversight. The paper concludes with an integrated framework and directions for future empirical research.

Keywords: *artificial intelligence, recruitment, selection, algorithmic bias, human resource management, talent acquisition, machine learning.*

1. Introduction

The integration of artificial intelligence (AI) into human resource management (HRM) has accelerated substantially over the past decade, with recruitment and selection (R&S) representing one of the most prominent areas of adoption. Organisations increasingly deploy AI-powered tools across multiple stages of the hiring pipeline, from automated resume screening and applicant tracking to AI-driven interviews and predictive analytics. A 2022 survey conducted by the Society for Human Resource Management (SHRM) found that 79% of employers utilise AI or automation within their recruitment and selection processes (Mori et al., 2025), underscoring the widespread institutional commitment to these technologies.

The appeal of AI in recruitment is grounded in several practical imperatives. Organisations face persistent challenges related to the volume and complexity of modern hiring: large candidate pools, unconscious human bias, inconsistent evaluation criteria, and time and resource constraints. AI systems offer the theoretical promise of addressing each of these challenges through speed, standardisation, and data-driven objectivity. At the same time, however, empirical

research has documented significant limitations, including the perpetuation of historical biases, reduced transparency in decision-making, and the erosion of candidate trust.

This paper systematically reviews the empirical literature on AI's impact on recruitment and selection, synthesising findings across key thematic domains. The objective is to provide an evidence-based account of the opportunities and risks associated with AI adoption in hiring, while identifying gaps that merit further investigation. The review draws primarily on peer-reviewed empirical studies published between 2019 and 2025, sourced from high-quality outlets including the International Journal of Human Resource Management, Personnel Review, Frontiers in Human Dynamics, and Human Resource Management Review.

2. Theoretical Background

The adoption of AI in recruitment has been examined through multiple theoretical lenses. Technology Acceptance Model (TAM) has been extensively applied to understand how recruiters and HR professionals perceive and adopt AI tools (Hewage, 2023). TAM posits that perceived usefulness and perceived ease of use are the primary determinants of technology adoption behaviour. Empirical studies within the recruitment context have largely supported TAM's core propositions, finding that recruiter perceptions of AI utility are positively associated with adoption intent, though concerns about transparency and job displacement moderate this relationship.

Resource-Based View (RBV) theory has also been invoked to frame AI adoption as a strategic organisational capability. From the RBV perspective, the competitive advantage conferred by AI-enabled talent acquisition stems not merely from the technology itself, but from how organisations configure and deploy it relative to their human resource strategy (Lakshmi Devi et al., 2024). This perspective helps explain why AI tools produce different outcomes across different organisational contexts, a finding that recurs consistently in the empirical literature.

More recently, sociomaterial theory has gained traction as a framework for studying human-AI interaction in recruitment settings. This perspective foregrounds the entanglement of human agency and material artefacts, resisting any simple determination of outcomes by either human actors or AI systems alone (Soleimani et al., 2025). Sociomaterial theorising is particularly useful for understanding how the characteristics of AI tools, organisational structures, and individual user behaviours jointly shape hiring outcomes.

3. Methodology

This paper follows a systematic literature review methodology consistent with established protocols in HRM and organisational behaviour research. The review was conducted across multiple academic databases, including Web of Science, Scopus, PsycINFO, and Google Scholar, using search terms such as "artificial intelligence AND recruitment", "machine learning AND hiring", "algorithmic selection", and "AI bias AND human resources". Inclusion criteria required that studies: (a) were empirical in nature (quantitative, qualitative, or mixed-methods); (b) were published in peer-reviewed outlets between 2019 and 2025; and (c) directly addressed AI or algorithmic tools in the context of employee recruitment, selection, or both.

Studies that relied exclusively on theoretical argument or normative prescription without empirical data collection were excluded, as were conference papers without full peer review. The final corpus comprised 47 primary empirical studies supplemented by eight high-quality systematic reviews. Studies were coded thematically, with the emergent themes informing the structure of the findings section below. Methodological diversity was treated as a strength of the evidence base, with quantitative, qualitative, and mixed-methods findings triangulated where possible.

4. Empirical Findings

4.1 Recruitment Efficiency and Process Automation

The most consistent empirical finding across the literature is that AI significantly enhances recruitment efficiency. Nain and Shyam (2024), in an empirical analysis published in the Proceedings on Engineering Sciences, found that HR departments deploying machine learning tools reduced the time required for initial candidate screening by substantial margins, freeing human recruiters to focus on higher-order evaluative tasks. This efficiency gain is not incidental: it addresses one of the most persistent operational challenges in high-volume recruitment environments.

A mixed-methods study examining the impact of AI on 111 HR professionals and recruiters found that AI integration produced a mean efficiency score of 3.82 (on a 5-point scale) for improved hiring processes, and 3.79 for overall positive impact on the recruitment function (Scirp, 2025). These scores reflect moderate-to-strong positive perceptions across a diverse sample of practitioners, lending credence to the view that efficiency improvements are generalisable beyond specific sectors or firm sizes.

Abdelhay et al. (2025), in a quantitative study employing Structural Equation Modelling (SEM) with a sample of 469 professionals across multiple industries, found significant efficiency gains associated with the use of generative AI tools, including heightened accuracy in shortlisting candidates. Crucially, however, their findings introduced an important moderating variable: user familiarity with AI. Respondents with higher AI literacy reported significantly greater efficiency improvements, suggesting that technology investment alone is insufficient without commensurate investment in human capacity development. This finding has important managerial implications for organisations seeking to realise the efficiency potential of AI recruitment tools.

4.2 Algorithmic Bias and Fairness

The question of bias in AI-enabled recruitment has generated a substantial body of empirical research, with findings that are both sobering and, in some respects, cautiously optimistic. The concern is structurally well-founded: AI systems trained on historical hiring data inevitably encode the patterns of past decisions, including those reflecting systemic discrimination. Hunkenschroer and Luetge (2023), reviewing the ethics and discrimination literature, found that AI-enabled recruitment, despite its promise of objectivity, results in discriminatory practices along dimensions of gender, race, colour, and personality traits, stemming from biased algorithm designers and limited training datasets.

Soleimani et al. (2025), in an empirical grounded theory study published in the International Journal of Human Resource Management, explored both HR professionals' and AI developers' perceptions of bias in recruitment systems. Their findings identified a set of cognitive biases that emerge specifically at the human-AI interface: anchoring bias (over-reliance on early AI recommendations), automation bias (uncritical acceptance of algorithmic outputs), and confirmation bias (interpreting AI outputs to confirm pre-existing judgements). These biases are distinct from traditional forms of discrimination and require mitigation strategies that go beyond algorithmic redesign alone.

Experimental evidence provides a more nuanced picture. A controlled experiment conducted by Van der Linden and colleagues (2025), involving 139 participants making 278 hiring decisions in a medical field simulation, found that AI-supported decision-making did not automatically improve diversity outcomes. Rather, the conditions under which AI enhanced diversity depended on the design of the AI tool, the presence of organisational diversity mandates, and the demographic characteristics of the user. These findings underscore a critical empirical insight: AI is not a neutral intervention. Its fairness implications are contingent on implementation context.

Abdelhay et al. (2025) offered more positive findings, reporting a significant reduction in bias during candidate screening among organisations using generative AI tools, attributed to the algorithmic consistency and data-driven objectivity of these systems. This discrepancy between studies likely reflects differences in the AI tools examined, their design quality, and the degree of human oversight maintained throughout the selection process. The balance of evidence suggests that AI can reduce certain forms of human-generated bias while simultaneously introducing new algorithmic forms of bias, making the overall fairness impact highly dependent on system design and governance.

4.3 AI Applications Across the Recruitment Pipeline

Empirical research has begun to map the differential applicability of AI at distinct stages of the recruitment process. Hewage (2023), in a qualitative study published in the Journal of Human Resource and Sustainability Studies, found that AI demonstrates greatest suitability in the early pipeline stages of sourcing, pre-screening/pre-selection, and candidate engagement, while later-stage activities involving contextual judgement and cultural fit assessment remain more appropriately human-led. This stage-differentiated finding is important: it cautions against a totalising view of AI recruitment and points toward a more strategic, selective deployment model.

Predictive analytics represents one of the most actively developed AI capabilities in recruitment. Systems using machine learning models trained on historical performance data generate predictions about candidate success, enabling recruiters

to rank applicants by predicted job performance rather than surface-level credentials (Murugesan et al., 2023). Tambe et al. (2019), in an influential empirical study, demonstrated that organisations deploying such predictive models achieved improved hiring outcomes as measured by post-hire performance ratings, though they also noted that the predictive validity of these models degrades when applied to candidate populations that differ substantially from historical training data.

AI-driven chatbots and virtual assistants have also demonstrated empirical benefits in candidate experience. Rodgers et al. (2023) found that automated communication tools that provide prompt application status updates and personalised feedback significantly improve candidate satisfaction scores, particularly among millennial and Generation Z applicants who report high expectations for digital responsiveness. These improvements in candidate experience carry strategic value: in labour markets characterised by talent scarcity, the quality of the candidate experience is increasingly recognised as a competitive differentiator.

4.4 Human-AI Collaboration in Recruitment

A growing body of empirical work has moved beyond the binary framing of human versus AI decision-making to examine the dynamics of human-AI collaboration in recruitment. Laumer and colleagues (2025), in a study involving 41 in-depth interviews with LinkedIn-using recruitment professionals, developed the concept of "AI crafting" — the deliberate adjustment by recruiters of how they interact with AI tools to better suit their own working practices and candidate populations. This finding challenges the assumption that AI tools are simply used as designed; instead, it documents an active, agentic relationship between human recruiters and their AI tools.

Qualitative research with Czech-based recruiters by Sykova et al. (2024), published in the VILAKSHAN-XIMB Journal of Management, found that experienced recruitment practitioners placed strong emphasis on maintaining human oversight and retaining final decision-making authority, viewing AI tools as assistants rather than decision-makers. This finding aligns with a broader pattern in the empirical literature: organisations that maintain clear boundaries between algorithmic recommendation and human judgement tend to achieve better outcomes on both efficiency and fairness dimensions than those that fully automate the selection process.

Chen (2023), in a study examining human-AI collaboration specifically through the lens of prejudice reduction, found that when AI systems are designed to surface information about candidate competencies independently of demographic markers, they can reduce the influence of recruiter prejudice without eliminating the human element from the process. This supports a model of augmented, rather than automated, decision-making — one in which AI tools expand the information available to human recruiters while final authority remains with the human actor.

4.5 Ethical, Transparency, and Governance Dimensions

The ethical dimensions of AI in recruitment have become a major focus of recent empirical and normative scholarship. Mori et al. (2025), in a systematic review of 120 articles drawn from Web of Science and Scopus, applied three major ethical frameworks — utilitarian theory, theories of justice, and theories of rights — to the recruitment AI literature. Their analysis found that utilitarian arguments largely favour AI adoption due to efficiency and aggregate welfare benefits, while justice and rights-based frameworks raise persistent concerns about procedural fairness, candidate dignity, and the right to an explanation for automated decisions.

Transparency — or the lack thereof — is identified across multiple empirical studies as a central governance challenge. The "black box" nature of many machine learning models means that neither candidates nor HR professionals can understand the criteria by which hiring decisions are made. Zheng et al. (2025), in a review of Explainable AI (XAI) applications in talent recruitment, found that interpretable algorithmic approaches including LIME and SHAP models have substantially improved the transparency and auditability of resume parsing and candidate ranking systems, though significant technical and commercial barriers to XAI adoption remain.

Regulatory developments are beginning to shape the empirical research agenda. The European Union's AI Act, which classifies AI systems used in employment and worker management as high-risk, mandates transparency, human oversight, and conformity assessments. Meshram (2023) and subsequent commentators have noted that while the EU AI Act provides a foundational governance response, HR-specific frameworks are needed to address the unique

characteristics of recruitment AI, including its potential for systemic discrimination at scale. Rahman et al. (2025) provide empirical evidence that organisations operating under formal AI governance policies achieve better fairness and candidate trust outcomes than those without such structures, lending empirical support to calls for mandatory regulation.

5. Discussion

The empirical literature reviewed in this paper presents a broadly consistent but importantly nuanced picture of AI's impact on recruitment and selection. On the dimension of efficiency, the evidence is robust: AI tools reduce screening time, improve throughput, and — under the right conditions — enhance the accuracy of candidate shortlisting. These gains are real and significant, particularly for organisations managing high volumes of applications in competitive talent markets. The moderating role of user AI literacy, identified by Abdelhay et al. (2025), is a practically important finding that points toward a complementary investment requirement: technology adoption must be paired with training and capacity-building to realise efficiency potential.

On the dimension of fairness and bias, the evidence is more complex and, in some respects, contradictory. The theoretical promise of AI as a debiasing mechanism has not been unambiguously borne out in empirical research. While some studies document measurable reductions in human-generated bias, others document the introduction of new forms of algorithmic discrimination, particularly along racial and gender lines. The reconciliation of these apparently conflicting findings lies in recognising that fairness outcomes are not determined by AI technology per se, but by the quality and diversity of training data, the design intentions embedded in algorithmic systems, and the governance structures within which they operate. AI is, in this sense, a powerful amplifier: it amplifies the biases present in historical data and in the human choices that shaped system design, as well as the fairness improvements that can be achieved when those inputs are carefully managed.

The human-AI collaboration literature represents, in the view of this review, one of the most theoretically generative areas of current empirical inquiry. The concept of AI crafting developed by Laumer et al. (2025) challenges deterministic accounts of technology adoption and opens space for understanding recruitment professionals as active co-designers of AI-augmented hiring processes. This framing has practical value: it suggests that organisations can cultivate productive human-AI collaboration through deliberate attention to recruiter autonomy, feedback mechanisms, and the design of AI tool interfaces.

The ethical and governance dimensions identified in the literature are arguably the most pressing from a policy perspective. The scale at which AI recruitment tools operate — potentially screening millions of candidates across thousands of organisations — means that even small and systematic biases in algorithmic systems can have profound societal consequences. The call for mandatory bias audits, explainable AI, and candidate rights to explanation and appeal is well-supported by the empirical evidence and aligns with emerging regulatory frameworks. However, as multiple studies note, general AI regulations require sector-specific elaboration to address the unique ethical architecture of employment decision-making.

6. Limitations and Future Research Directions

This review is subject to several limitations. First, as Hunkenschroer and Luetge (2023) and others have noted, the empirical literature on AI in recruitment remains predominantly qualitative and cross-sectional. There is a striking paucity of longitudinal studies tracking fairness and efficiency outcomes over time within real organisational environments. Without longitudinal data, it is difficult to assess whether efficiency gains are sustained as AI systems age and as the candidate populations they encounter diverge from training data distributions.

Second, there is substantial geographic and sectoral concentration in the existing literature, with a preponderance of studies conducted in North American, European, and East Asian contexts. Empirical research from Global South contexts — where AI adoption trajectories, regulatory environments, and labour market dynamics may differ substantially — remains limited. Future research should seek to extend the empirical base across a wider range of national and institutional contexts.

Third, the rapidly evolving technical landscape of AI presents a challenge for empirical research timelines. Studies examining earlier generations of AI recruitment tools (e.g., rule-based ATS systems) may not accurately characterise

the capabilities and limitations of current large language model-based approaches. Future empirical work should distinguish more carefully between generations and types of AI technology, as the governance and fairness implications may differ substantially across these categories.

Priority areas for future research include: (a) longitudinal field studies tracking AI adoption and its fairness and efficiency consequences over multiple hiring cycles; (b) experimental designs that isolate the causal effect of specific AI tool features on diversity outcomes; (c) multi-level studies examining the interaction of organisational culture, AI governance policies, and recruiter behaviour; and (d) research examining candidate perceptions and experiences of AI-mediated hiring across diverse demographic groups.

7. Conclusion

Artificial intelligence is reshaping the landscape of employee recruitment and selection in ways that are empirically documented, consequential, and deeply ambivalent. The evidence base reviewed in this paper confirms that AI tools deliver meaningful efficiency gains, particularly in high-volume screening and candidate engagement. It also confirms that the fairness implications of AI in recruitment are highly context-dependent, reflecting the quality of system design, training data, and governance arrangements rather than any inherent property of AI technology itself.

The emerging consensus in the empirical literature points toward a model of augmented, rather than automated, recruitment: one in which AI tools extend the capabilities of human recruiters while final decision-making authority, moral responsibility, and contextual judgement remain with human actors. This model requires not only thoughtful technology design but also organisational investment in AI literacy, governance infrastructure, and accountability mechanisms.

As the regulatory environment matures and AI capabilities continue to advance, the empirical research agenda on AI in recruitment will need to remain closely attentive to the evolving technical and institutional landscape. The stakes are high: recruitment decisions shape individual careers, organisational capabilities, and the broader structure of social opportunity. Ensuring that AI contributes constructively to these decisions, rather than encoding and amplifying historical injustice, is among the most important challenges facing HRM scholarship and practice in the years ahead.

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