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Artificial Intelligence Recruitment—A Literature Review Based on Equity and Efficiency Perspectives

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Abstract: As organizations increasingly adopt Artificial Intelligence (AI) technologies in their hiring processes, the issues of fairness and efficiency have gained significant attention. The potential risks of bias and discrimination may disproportionately affect vulnerable groups. Clearly defining fairness and efficiency is crucial, as it provides measurable criteria for assessing and mitigating bias. This ensures that AI recruitment systems do not worsen existing inequalities, but instead foster equal opportunities for all job candidates, while enhancing recruitment efficiency. This paper categorizes and examines AI recruitment use cases from the perspectives of fairness and efficiency across four dimensions. As AI technology in recruitment is still in its early stages, the topic remains a frontier area in academic research. To provide valuable references for future research and strengthen the theoretical foundation, this paper offers a comprehensive review of the available literature.

1. Introduction

As technology advances, Artificial Intelligence (AI) has permeated various business sectors and workplace settings. Notably, AI is transforming staffing and selection processes in organizations[1]. Compared to traditional screening and assessment methods[7], AI-driven selection tools are highly attractive to organizations because of their efficiency advantages. This paper identifies two key shortcomings in AI recruitment research: first, the literature offers limited theoretical grounding for the concepts of fairness and efficiency, leading to numerous discussions that lack strong support. Second, the current approaches to mitigating fairness risks are overly broad and lack detailed guidelines for implementation in specific areas of the hiring process. Focusing on specific areas is essential, as generalized normative guidance often fails to be practically useful due to its lack of depth.

2. Research Method

This paper adopts the systematic literature review framework proposed by Snyder (2019) to provide a comprehensive assessment of the current literature on AI recruitment. The systematic review involves the comprehensive collection and analysis of literature, focusing on the issues of equity and efficiency in AI recruitment, which are examined in three phases: First, in order to reveal how existing studies measure the equity and efficiency of AI recruitment, we screened the selected literature based on the four dimensions of high efficiency and high equity, high efficiency and low equity, low efficiency and high equity, and low efficiency and low equity. The literature was categorized and summarized. Second, we reviewed the specific applications of AI in recruitment. Finally, we summarize strategies and methods proposed to promote fairness and improve recruitment efficiency. Figure 1 illustrates the research design and flow of this paper.

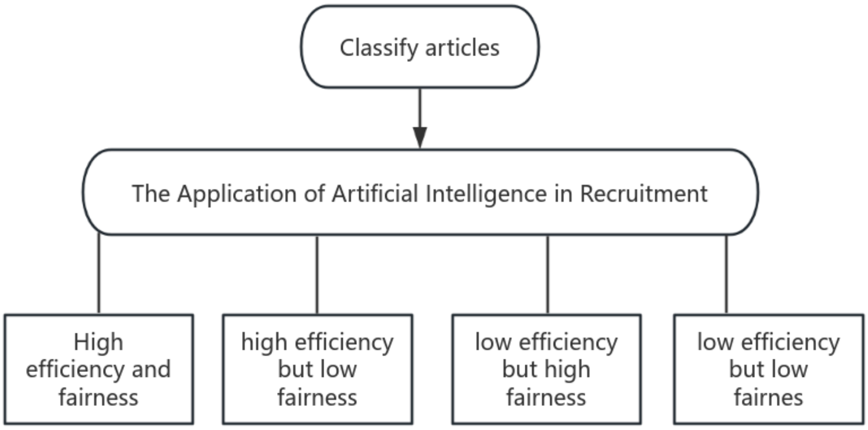

Figure 1: Research design

3. Criteria for Selection, Inclusion, and Exclusion

In the context of management and technology fields, ABI, SCOPUS, and Web of Science—three widely recognized databases in business academia—were chosen to offer a comprehensive overview of relevant research. Given the innovative and interdisciplinary nature of AI recruitment research, this study employs a broad literature search strategy combining the terms “recruitment,” “fairness,” “efficiency,” and “AI.” To ensure quality, only Q1 and Q2 articles were included, with no time restrictions, focusing on English-language literature. After reviewing titles, abstracts, and full texts, 33 articles closely related to the research topic were selected.

To ensure comprehensive coverage, this study followed Webster and Watson’s (2002) recommendation by first tracing relevant citations in the initially screened articles to uncover additional references, which were then used to further identify pertinent literature. Additionally, this study rigorously screened papers published in high-ranking journals, such as those listed in ABDC (Australia) and CABS (UK), ultimately identifying 257 articles most relevant to the research focus. Figure 2 summarizes the criteria for data collection and selection.

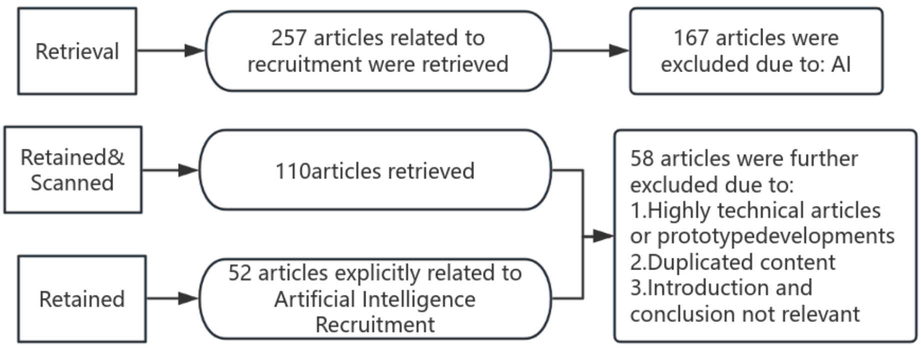

Figure 2: Articles selection and retention process.

4. Structural Analysis of the Literature and Categorization

The time span of the selected literature underscores the novelty and significance of this research, with the earliest publication dating to 2019. The 47 papers cover diverse research areas, including law, management, organizational psychology, robotics, and computer science, and are published in 37 different academic journals. Figure 3 presents the distribution of these papers by year.

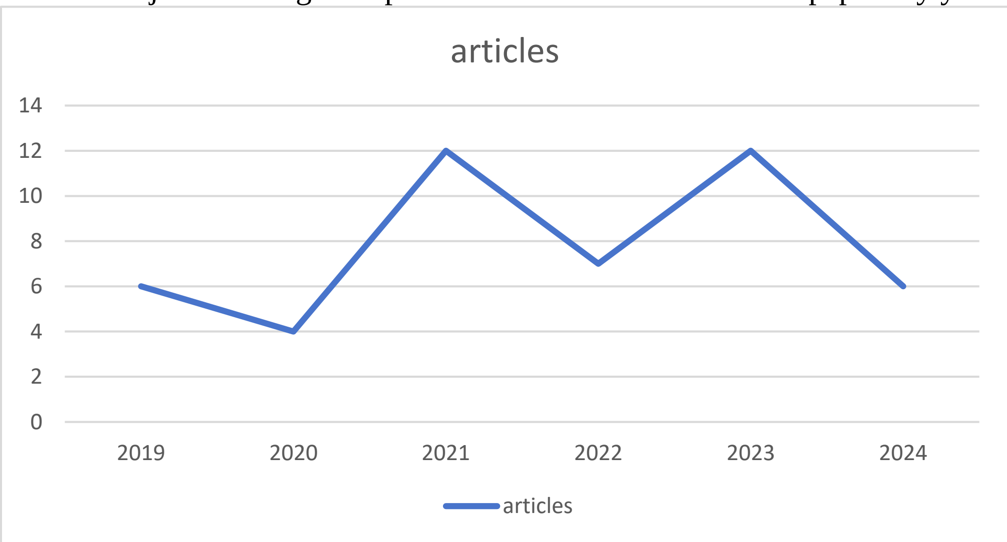

Figure 3: Distribution of articles per year

5. Context analysis

Work motivation is influenced not only by the actual compensation received but also by employees’ perceptions of the fairness of its distribution. Employees often unconsciously compare their input and compensation to those of others, evaluating fairness based on these comparisons. This sense of fairness directly influences employees’ motivation and performance. Recruitment efficiency refers to the degree to which an employer achieves an optimal match between a candidate, a target position, and the organization, given constraints such as time and cost. It is mainly reflected in the following four aspects: first, to be able to achieve the recruitment goals within the specified time; second, to be able to meet the needs of the employer's specific positions; third, to pursue the minimization of recruitment costs; and fourth, to ensure that the staff to maintain a low turnover rate.

A comprehensive assessment of recruitment efficiency includes key dimensions such as: the scientific and rational setting of recruitment targets, the control of recruitment costs, and the optimization of time and financial investments. Additional indicators include alignment between recruits and job requirements, employee compliance with leadership, teamwork cohesion, and turnover rates. These are essential indicators of recruitment efficiency. To examine the relationship between equity and efficiency, this study classifies the cases in the literature into four categories: high efficiency and high equity, high efficiency and low equity, low efficiency and high equity, and low efficiency and low equity. Figure 4 categorizes the relevant cases.

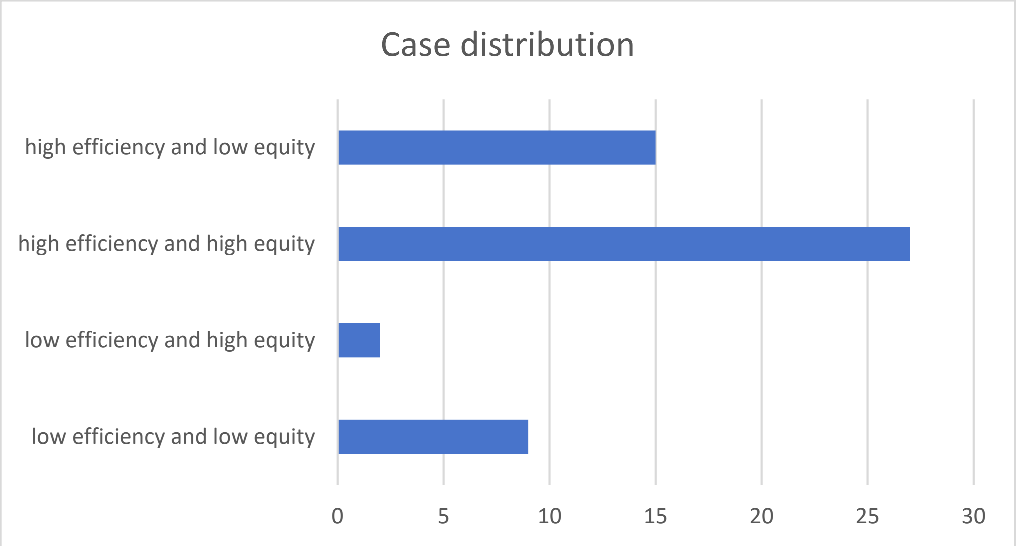

Figure 4: Case classification

5.1 High Efficiency and Fairness in AI Recruitment

5.1.1 The Efficiency and Equity of Talent Access and Cost-Effectiveness

Traditionally, organizations have relied on executive search firms to access passive candidates, which limits their scope to proprietary networks and databases, making the process costly. As a result, few organizations adopt this method, leaving competition for passive candidates minimal. AI recruitment tools overcome these limitations, allowing firms to bypass search agencies and their fees, thereby providing cost-effective access to millions of passive candidates through platforms such as Facebook and LinkedIn[6]. This approach expands the talent pool, providing more candidates with the opportunity to compete, thereby promoting fairness. Additionally, companies can access a broader and more diverse talent pool, increasing the likelihood of finding the right candidates and improving recruitment efficiency.

5.1.2 High Efficiency and Fairness through Selection Process Optimization

AI-powered selection tools enhance employers' cost and time efficiency in the hiring process[8]. AI allows employers to rapidly shortlist high-potential candidates and streamline the selection process. For example, AI can process hundreds of applications in a short time, significantly shortening the recruitment cycle and improving efficiency. It screens based on objective criteria, reducing human bias and ensuring fairness in selection. AI-driven video interviews enhance efficiency by reducing both the selection process duration and the time and distance candidates must travel. This not only saves time and costs for both parties but also simplifies and enhances the hiring process, enabling candidates from diverse geographic regions to participate more equitably, regardless of location, thereby reflecting fairness.

5.2 High Efficiency, Low Fairness in Artificial Intelligence Recruitment

5.2.1 High Efficiency and Low Fairness Due to Model and Data Bias

Artificial intelligence-based selection tools with poorly designed statistical models—such as flawed model architecture and inaccurate parameter settings—can undermine the fairness of recruitment. Although AI can efficiently perform tasks like resume screening and interview analysis, the underlying model may fail to accurately assess candidates' abilities or job fit due to its flaws. As a result, some qualified candidates may be unjustly rejected, while others who are poorly suited for the role may be selected, undermining fairness. An unbalanced training dataset that overrepresents certain groups or minorities can introduce various biases. For example, historical bias can reinforce past inequalities, perpetuating discrimination against specific groups in the hiring process. Aggregation bias, in contrast, makes it challenging for a single model to represent diverse groups adequately, putting certain groups at a disadvantage in the selection process. For example, a sourcing algorithm trained on data indicating that men predominantly occupy technical or engineering roles may fail to identify women as potential candidates for these positions[3]. Despite AI's potential to expedite the hiring process, this gender bias, stemming from data imbalance, violates fairness principles and results in discriminatory treatment of female candidates.

5.2.2 High Efficiency and Low Fairness Due to Barriers Faced by Special Groups

Although AI recruitment tools can efficiently process applications for large numbers of standard candidates, they often fail to ensure fair participation for underrepresented groups, revealing a significant fairness gap. Even if AI recruitment demonstrates high efficiency in areas like resume screening and interview analysis, it remains unfair due to its failure to provide disabled applicants with equal opportunities to participate. For example, screen readers used by visually impaired applicants may have difficulty converting videos or images into text, while blind applicants may encounter challenges when interacting with Chatbots. Additionally, deaf or hard-of-hearing applicants may struggle with audio-dependent recruitment processes, even if captions are provided. As a result, disabled applicants face disadvantages in the recruitment process.

5.3 Inefficiency and Inequity in Artificial Intelligence Recruitment

5.3.1 Inefficiency and Inequity Due to Algorithmic Decision Errors

Some scenarios, such as when algorithms autonomously determine benefit payments and make inaccurate calculations under human supervision[4], or when AI evaluates employee performance and results in inappropriate decisions[5], illustrate fairness issues. These scenarios exemplify unfairness, as inaccurate calculations and improper decisions can directly impact the rights and interests of those involved. For example, employees may be unfairly treated due to unjustified benefit payments or performance appraisals. From an efficiency standpoint, once incorrect decisions are made, significant time and resources are required for subsequent corrections, such as re-calculating benefits or re-evaluating performance. For example, the Amazon recruitment algorithm exhibits bias against female candidates in test mode due to its training data predominantly representing male attributes, which leads to lower scores for female resumes[8]. This algorithmic discrimination clearly violates the principle of fairness, putting female candidates at a disadvantage and depriving them of an equal opportunity to compete. From an efficiency perspective, by wrongly screening out potentially suitable female candidates, the algorithm may prevent the organization from effectively selecting the right talent.

5.3.2 Inefficiency and Inequity Due to the Limited Functionality of Adaptive Devices

Applicants using adaptive devices or features, such as AI-generated captions, often find them less reliable than professional live captioning[2]. This unreliability can cause significant issues for deaf or hard-of-hearing applicants, who may misinterpret interview questions due to incorrect captions, particularly when specialized vocabulary or acronyms are involved. Once applicants recognize that the captions are incorrect, it not only harms their interview performance but also undermines their trust in the AI-generated captions. Doubts about the accuracy may prevent full participation in subsequent interviews, further affecting performance. From an efficiency perspective, applicants may repeatedly misinterpret or underperform due to captioning errors, potentially leading to repeated interviews or requiring additional evaluation time, thereby slowing the hiring process and reducing overall efficiency.

5.4 Inefficiency and Equity in Artificial Intelligence Recruitment

5.4.1 Algorithmic Screening Limitations Lead to Inefficiency and Inequity

While algorithms can efficiently recommend the best job openings for candidates based on initial screening, some algorithms have significant flaws. Some algorithms rely solely on keywords, fail to identify suitable candidates, and overlook difficult-to-quantify qualities. As a result, high-quality applicants may be overlooked, and companies must spend additional time revisiting misjudged candidates or expanding the screening process to find truly suitable talent. For example, after the initial screening, the algorithm identified seemingly suitable candidates but missed key traits because they were not matched by keywords. As a result, the company had to recheck other applicants, increasing the complexity and time costs of the recruitment process and significantly reducing efficiency.

5.4.2 Negative Emotions and Time-Consuming Decision-Making Lead to Inefficiency and Inequity

Algorithmic decisions alone can trigger negative emotions in applicants or employees, potentially leading to anger[8]. To maintain acceptance, a balanced approach between algorithmic and human decision-making is adopted, where the algorithm provides recommendations and humans verify and make the final decision[1]. While this approach ensures fairness, it introduces human intervention, reducing the efficiency of fully automated decision-making. Humans must verify and finalize the algorithm's suggestions, which inevitably consumes more time and resources, slowing the hiring process and reducing efficiency. For example, while the algorithm can quickly generate hiring recommendations, manual verification and final decisions for each candidate slow the process.

6. Conclusion

Artificial Intelligence (AI) tools have become a crucial component of modern recruitment and selection practices. This paper provides a comprehensive review of the literature on fairness and efficiency in AI recruitment and systematically organizes existing studies in this emerging field. This paper provides a comprehensive assessment of fairness and efficiency across various cases, clearly presenting the current state of the literature and offering valuable guidance for future research in AI recruitment.

First, future research on artificial intelligence in human resources management is crucial for reducing information asymmetry. This can be achieved by increasing transparency between organizations and individuals, while also ensuring proper protection of sensitive data. This research direction could improve AI applications in HRM at both individual and organizational levels. At the individual level, the benefits include improved perceptions of fairness, greater respect for rights, and better optimization of benefits in the HRM process. At the organizational level, the benefits include optimizing overall outcomes, enhancing perceptions of justice, and ensuring strict compliance with legal requirements, promoting responsible and ethical decision-making.

Second, existing research on fairness shows an uneven focus, with some aspects receiving considerable attention, while others remain underexplored. Most studies primarily address bias in both humans and algorithms. However, key issues, such as accountability in AI-based recruitment practices, remain underexplored in most of the reviewed papers. This gap hinders clear and in-depth discussions on organizing accountability for AI in recruitment. Current solutions to mitigate fairness risks in AI are broad and generic, lacking specificity for the recruitment context. These solutions often mirror the generic recommendations found in existing AI fairness guidelines. Since generalized guidelines often lack practical relevance, future research should focus on specific domains (e.g., recruitment) to ensure applicability. Implementation guides should be sensitive to domain-specific details and align with relevant regulations.

Finally, this paper identifies key, contradictory topics in AI recruitment that must be addressed through future empirical research. First, future research should focus on understanding the accuracy and effectiveness of AI recruitment tools. Key questions in this context include: What is the standardized effectiveness of different AI forms in the recruitment process? Does AI recruitment offer advantages over traditional selection methods in specific situations? Second, answering these questions accurately requires more than establishing measurement equivalence with traditional methods. Specifically, for web-based assessment tools, research must validate AI tools using a tailored approach, rather than benchmarking them against traditional formats. To achieve this, quantitative research, such as performance-based measures, should focus on testing the predictive validity of AI tools.

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