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Original Paper

Evaluating the Use of Artificial Intelligence in Recruitment and Selection: A Four-Dimensional Framework

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Abstract

Artificial intelligence is increasingly used across recruitment and selection. Existing research has mainly examined its applications at different stages of recruitment and the trade-off between efficiency and fairness. However, a framework for assessing the appropriate boundaries of AI use across the recruitment process remains undeveloped. This paper develops a four-dimensional framework based on standardization, future-oriented judgment, opportunity visibility, and explainability. It applies the framework to the early, middle, and late stages of recruitment and selection. The analysis shows that AI should play different roles across stages. In the early stage, it can support job definition and attraction strategies. In the middle stage, AI may support sourcing and initial screening, but it also raises concerns about opportunity visibility and screening fairness, which require close attention. In the later stage, AI should not be used as a black-box tool to infer personality, potential, or future performance, nor should it make independent hiring decisions. The key issue in AI recruitment is therefore not efficiency alone, but its implications for candidate opportunity, procedural fairness, and accountability.

Keywords

artificial intelligence; recruitment and selection; algorithmic hiring; explainability; opportunity visibility

1. Introduction

Existing studies have examined the application of artificial intelligence in recruitment from multiple perspectives. On the one hand, a substantial body of research analyzes the main uses of AI across different stages of the recruitment process (Herold & Roedenbeck, 2025; Hunkenschroer & Luetge, 2022; Tursunbayeva et al., 2026). On the other hand, many studies focus on the potential consequences of AI-enabled recruitment. While highlighting its advantages, such as improved efficiency, reduced costs, and greater consistency in evaluation, this line of research also draws attention to risks, including algorithmic

bias, black-box decision-making, procedural injustice, and ambiguity in allocation of responsibility (Hunkenschroer & Luetge, 2022; Köchling & Wehner, 2020; Rigotti & Fosch-Villaronga, 2024) However, existing research still lacks an analytical framework that spans the different stages of recruitment and can be used to assess the boundaries of AI applicability.

Therefore, building on a review of existing literature, this paper identifies four key dimensions that shape the boundaries of AI roles in recruitment. The relevant studies span such issues as AI applications in recruitment, algorithmic fairness, future performance prediction, opportunity allocation, and system interpretability. On this basis, the paper develops a four-dimensional framework consisting of standardization, future-oriented judgment, opportunity visibility, and explainability. Using this framework, the paper analyzes the applicability of AI to different activities and assesses the early, middle, and later stages of recruitment. The aim is to show that, under different task conditions, AI should be positioned either as a supportive tool, a limited tool, or merely as an auxiliary reference (Fabris et al., 2025).

2. A Four-Dimensional Framework for Evaluating the Application of Artificial Intelligence in Recruitment

The applicability of artificial intelligence in recruitment cannot be assessed solely in terms of efficiency or accuracy. This is because recruitment is not merely a process of information processing, but also involves the evaluation of candidates, the inference of future performance, the allocation of opportunities, and the maintenance of procedural legitimacy. Even where a system demonstrates a high degree of technical consistency or predictive capability, it may still narrow candidates' visibility at the early stages of recruitment or reduce their ability to contest decisions and correct errors when outcomes are difficult to explain.

Therefore, the use of AI in recruitment and selection should not be judged by a single criterion but evaluated across multiple interrelated dimensions. Existing research has mainly focused on three core concerns: the tension between standardization and flexibility, the predictive validity of algorithmic assessments for future performance, and the conflict between fairness and explainability (Kassir et al., 2022; Kelan, 2023; Schumann et al., 2020). On this basis, this paper further introduces opportunity visibility as an additional, yet crucial dimension that has received relatively limited attention in prior research. It thereby constructs a four-dimensional analytical framework to comprehensively assess the boundaries of AI applicability and its organizational implications in recruitment.

2.1 Standardization

The degree of standardization refers to the extent to which a recruitment task can be clearly codified, structured, and proceduralized.

Artificial intelligence is generally better at achieving efficiency gains in tasks with clearly defined requirements, rule-based procedures, and relatively standardized evaluation criteria (Mazurova & Standaert, 2024). In contrast, in tasks that depend heavily on contextual understanding, holistic

assessment, and careful evaluation, excessive standardization may distort the object of evaluation (Lievens, Sackett, & Zhang, 2020). As a result, inherently complex forms of assessment may be reduced to overly simplistic rules.

2.2 Future-Oriented Judgment

Future-oriented judgment refers to the extent to which a recruitment task requires predictions about a candidate's future potential, job adaptability, and the possibility of environmental change.

Not all recruitment tasks involve the same type of judgment. Some tasks are primarily concerned with verifying existing facts, such as whether a candidate's educational background, work experience, qualifications, or application materials meet clearly specified requirements. Other tasks require inferring candidates' future performance, including whether they will be competent in the role, adapt to the organization, and continue to perform well over time. The former type of task focuses on confirming existing information and, therefore, allows a relatively high degree of AI applicability. The latter, by contrast, involves much higher uncertainty regarding future potential, adaptability, and performance. As a result, algorithmic outputs may replicate preexisting biases and inherit historical biases embedded in the input or training data (Köchling & Wehner, 2020).

Therefore, in tasks characterized by a high degree of future-oriented judgment, AI is more suitably positioned as an auxiliary reference rather than being treated as an independent basis for decision-making.

2.3 Opportunity Visibility

Opportunity visibility refers to whether, in an algorithm-mediated recruitment environment, candidates can be reached by job-related information and brought within the employer's visible range before entering the formal evaluation process. This dimension concerns the more upstream mechanisms through which opportunities are distributed. For example, some recruitment platforms may prioritize delivering high-paying technical positions to users based on historical click-through and conversion rates (Lambrecht & Tucker, 2019). By contrast, users with similar qualifications may receive systematically skewed ad delivery because the platform's algorithm optimizes for engagement and may be trained on biased data.

Therefore, opportunity visibility is distinct from conventional screening fairness. The latter focuses on comparing and ranking candidates after they have entered the screening process. In contrast, the former concerns who is seen and included in the comparison in the first place, rather than before formal screening begins.

2.4 Explainability

Explainability refers to the extent to which the basis of AI evaluation, scoring logic, and outputs can be understood, explained, and questioned by recruiters and candidates (Phillips et al., 2021). When explainability is low, it becomes more difficult for organizations to provide a full account of the basis for their decisions. At the same time, candidates have less scope to raise complaints and seek the correction of errors. As a result, the attribution of responsibility and the legitimacy of procedure become more ambiguous.

3. Analysis of Recruitment Stages under the Four-Dimensional Framework

To examine the boundaries of AI applicability in recruitment more concretely, this paper divides the recruitment process into three stages: job definition and candidate attraction, application sourcing and candidate screening, and final selection and hiring decision-making (Breaugh, 2008; Stone et al., 2013). Because stages differ in task characteristics, assessment objects, and decision-making risks, the significance of four dimensions—standardization, future-oriented judgment, opportunity visibility, and explainability—also varies accordingly. As these conditions change, the roles that artificial intelligence also changes across stages.

3.1 Early Stage: Job Definition and Candidate Attraction

Artificial intelligence applications in early-stage recruitment have considerable potential for standardization. Scattered historical records of recruitment, performance data, turnover information, employee feedback, and external reviews can be organized into structured analysis objects. From these materials, common characteristics associated with high performance, positive experience, or organizational attractiveness can be identified. These characteristics can then inform job definition and candidate attraction, rather than relying solely on managers' experience or impressions. This type of analysis provides a more traceable evidential basis for discussions of job requirements and employer value propositions. It also enables organizations to explain more systematically why particular skills, experiences, or organizational characteristics are regarded as important (Zhang et al., 2025).

However, this stage is not merely concerned with organizing existing facts. It also involves a clear element of future-oriented judgment. In relation to job definition, organizations must not only summarize which kinds of people performed well in the past, but also infer which kinds of people should be sought out and developed in the future. In relation to candidate attraction, organizations are not simply describing their current image; they are also predicting what kinds of information and conditions are likely to elicit responses from different groups of candidates. It is at this point that the core limitations of AI become visible. Success profiles derived from historical data are often better at reproducing the pathways that the organization has previously rewarded. However, such profiles may favor applicants with typical amounts of experience and avoid candidates with atypical experience, even when those candidates have strong potential (Wechtler et al., 2022). In addition, such forecasts are difficult to rely on as accurate accounts of the future. Point forecasts are of limited value unless they are very accurate. When uncertainty is high, relying on them too heavily may be misleading (Farmer & Lafond, 2016). This means that if model outputs are treated as definitive answers rather than as inputs for discussion, existing standards and biases may be reproduced. At the same time, strategic misjudgments may be amplified in highly uncertain environments.

At the same time, AI can help organizations identify the concerns of different groups by analyzing employee-generated and social media data across different groups and contexts. Such insights can inform strategies to refine the employee value proposition and strengthen employer branding (Mohammadi & Mohammadian, 2025). However, this type of analysis can easily compress complex experiences into

surface-level indicators. Such experiences are often inherently multi-layered, and in some cases, even low-frequency signals may still be important. Their compressed forms may include sentiment scores, topic rankings, or group preferences. As a result, organizations may find it easier to detect surface-level signals, while still struggling to achieve the contextual understanding needed to interpret their substantive meaning (Tan et al., 2023). This first raises a problem of explainability: system outputs may not genuinely capture or explain the substance of candidates' and employees' experiences. In addition, the issue also involves a bias in experiential visibility. Voices that can be more easily datafied, aggregated, and analyzed for patterns are more likely to enter organizational decision. By contrast, accounts that do not conform to dominant patterns are more likely to be overlooked or erased (Le, 2026). Consequently, attraction strategies developed with AI support may invisibly amplify already visible needs while weakening concerns that remain implicit but are equally important.

3.2 Middle Stage: Application Sourcing and Candidate Screening

The core risks in the middle stages of recruitment are concentrated in two respects: the redistribution of opportunity visibility and the limited explainability of screening outcomes.

In terms of the degree of standardization, platforms and automated tools can be used for matching and recommendation. These tools operate based on job descriptions, resume texts, and behavioral data. In this way, organizations can reach potential candidates more efficiently. Once applications are submitted to the system, artificial intelligence can be used to extract information, verify relevant conditions, and conduct preliminary ranking. These operations transform applications into candidate lists that are easier to process. Work that previously depended on manual review on a case-by-case basis is thereby converted into structured evaluation and prioritization. As a result, processing efficiency is improved, and procedural consistency is also enhanced (Zhang et al., 2025).

However, unlike the early stages of recruitment, this stage involves a more hidden risk. The problem does not primarily lie in the accuracy of screening itself, but in the possibility that algorithms may narrow the candidate pool in advance. As a result, some candidates may find it more difficult to obtain further evaluation. In the application sourcing stage, algorithms also shape who is more likely to see a vacancy and who is more likely to enter the employer's candidate pool. Candidates who do not fit established profiles, are less active on the platform, or come from non-mainstream backgrounds may already face reduced opportunities before formal screening begins. More importantly, the optimization goals of these systems are often short-term, volume-driven performance metrics that prioritize efficiency rather than fairness or diversity (Lane et al., 2024). As a result, groups that have historically been more likely to convert are repeatedly prioritized, while atypical candidates may be marginalized at an early stage.

In the preliminary screening stage, although a high degree of standardization can improve consistency and accelerate processing, this does not mean that the process is neutral in itself. Screening outcomes may reproduce existing biases. At the same time, they may also be shaped by resume presentation, keyword use, and system logic. As a result, candidates who are better able to navigate automated hiring tools, for example, by using online coding assessment practice or a resume scanner, may gain an

advantage. However, such advantages do not necessarily reflect stronger job fit, as these strategies did not have a significant, positive impact on hiring success (Armstrong & Metaxa, 2025). Therefore, the issue at this stage concerns not only who is screened out, but also whether the logic underlying exclusion and retention can genuinely be explained. In addition, it is necessary to consider whether this form of structured processing may reinforce certain established preferences invisibly.

3.3 Later Stage: Final Selection and Hiring Decision

The risks in the later stages of recruitment are concentrated primarily in two dimensions: future-oriented judgment and explainability. In addition, tasks at these stages are themselves difficult to standardize fully. They also have the most direct impact on candidates' rights and interests. Accordingly, the central question is no longer whether AI can be used to improve processing efficiency, but how it should be positioned in the final selection: as a tool that supports evaluation, or as one that independently adjudicates candidates.

Under a more cautious mode of use, AI may be assigned a supportive role. For example, it can help organizations select more acceptable assessment methods. It can also be used to generate structured interview questions and position-related scoring criteria. In addition, AI can integrate records and scores generated across different assessment stages and highlight both consistency and conflicts among evaluation results. In such contexts, the primary role of AI is to support structured evaluation and enhance procedural consistency. At the same time, it can help interviewers identify relevant evidence more clearly. AI is therefore not used to replace human decision-makers in directly determining hiring outcomes. Because this supportive role does not directly determine a candidate's future value, AI may be used with caution in this context.

More controversial, however, is the assignment of an adjudicative role to AI. In some organizations, techniques such as facial expression recognition, voice analysis, and linguistic feature analysis are used in video interviews or digital assessments. These techniques automatically identify personality traits and predict interview performance from asynchronous video interviews. Such algorithmic assessments are being increasingly used in hiring procedures (Koutsoumpis et al., 2024). Existing studies have generally questioned the theoretical foundations and the validity of these tools' measurements. This is because facial expressions, vocal characteristics, and speech patterns are often shaped by cultural background, situational pressure, and individual differences. They therefore cannot necessarily be reliably mapped onto occupational potential or job performance (Koutsoumpis et al., 2024). In addition, such systems often lack explainability. As a result, organizations may find it difficult to clearly explain the basis of their judgments, while candidates have limited opportunities to challenge the outcomes effectively. Consequently, the attribution of responsibility and procedural legitimacy becomes further blurred.

From the perspective of the four-dimensional framework, the later stage requires particular caution because the conditions least favorable to the independent exercise of AI discretion are concentrated there. To begin with, the final selection is not a highly standardized task. Although structured tools can be used to improve consistency, their core still involves holistic comparison, contextual understanding, and

normative judgment. Next, future-oriented judgment is strongest at this stage. The organization is not simply confirming what qualifications a candidate already possesses, but inferring whether the candidate will be able to perform the role, adapt to the organization, and continue to perform well in the future. Then, the final selection has the greatest impact on candidates' rights and interests, and the consequences of misjudgment are also the most direct. Furthermore, it is precisely in this high-risk and high-uncertainty context that explainability is often weakest. As a result, organizations may find it difficult to explain the basis of system-generated conclusions and to provide sufficient opportunities for appeal and error correction. Precisely because these four dimensions create the most concentrated accumulation of risks in the later stage, AI should not be granted an independent adjudicative role at this stage.

4. The Boundaries of AI Applicability in Recruitment and Governance Implications

In recruitment practice, standardization, future-oriented judgment, opportunity visibility, and explainability do not operate as independent evaluative criteria. Rather, they function as interrelated conditions that must be weighed simultaneously. Among them, the degree of standardization is primarily associated with efficiency and consistency. Opportunity visibility and explainability are more directly connected to fairness, procedural legitimacy, and the allocation of responsibility. By contrast, future-oriented judgment concerns whether organizations can retain flexibility in assessing candidate potential, job adaptability, and changing future demands under uncertainty. The difficulty is that these objectives cannot be fully satisfied in all tasks simultaneously. If an organization places excessive emphasis on standardization and processing efficiency alone, complex evaluations may be compressed into rules that are easier to operationalize. As a result, fairness and the explainability of outcomes may be compromised. Conversely, if an organization overemphasizes procedural protection across all tasks or places overly cautious restrictions on future-oriented judgment, the supportive value of artificial intelligence in lower-risk tasks may be weakened. In addition, there is an interplay between future-oriented judgment and explainability. The more an organization attempts to explain inferences about the future based on existing data, the more likely such assessments are to become further anchored in experience. As a result, the capacity to identify atypical candidates or emerging competency needs may be weakened.

For this reason, the focus of governance in AI-enabled recruitment does not lie in mechanically adopting or prohibiting a particular technology. Rather, it lies in the ongoing calibration of the relationship among the four dimensions in relation to task characteristics. Based on this calibration, the functional role of AI, the level of human intervention, and the intensity of procedural safeguards should also be adjusted accordingly. This means that the human role in AI-enabled recruitment should not be understood merely as a final review. More importantly, human involvement should begin at the role-definition stage. Specifically, human decision-makers need to determine which tasks may be properly supported by AI, which may permit only limited filtering, and which must remain areas of human-centered judgment. Because recruitment contexts are inherently open and uncertain, it is difficult for organizations to establish a fully structured and standardized procedure in advance that can be directly applied across all

scenarios. Therefore, responsible governance does not treat human involvement merely as a remedy for algorithmic shortcomings. Rather, it requires continuous adjustment of the degree of human intervention and the boundaries of AI use to improve efficiency without undermining candidates' opportunities, fairness, and procedural safeguards.

To present the applicable boundaries identified by the four-dimensional framework across different stages of recruitment more intuitively, Table 1 summarizes the characteristics of the four dimensions and the suggested roles of AI at each stage of the recruitment process. The table is not intended to provide a fixed set of schemes for mechanical application, but rather to serve as a judgment tool that helps organizations identify the functional boundaries of AI in specific contexts.

Table 1. Boundaries of AI Applicability Across Different Stages of Recruitment Under the Four-dimensional Framework

Recruitment Stage	Standardization	Future-oriented Judgment	Opportunity Visibility Risk	Explainability Requirement	Recommended Role of AI
Early stage	High	Medium	Medium	Medium	Supportive tool
Middle stage	High	Low to medium	High	High	Limited filtering tool
Later stage	Low	High	Low	Very high	Auxiliary reference tool

As shown in Table 1, the appropriate placement of AI in recruitment varies across tasks. More specifically, it depends on how tasks are configured across the four dimensions: standardization, future-oriented judgment, opportunity visibility, and explainability. In general, for tasks characterized by a high degree of standardization and a weak degree of future-oriented judgment, AI is more appropriately assigned supportive or limited filtering functions. By contrast, for tasks closer to final hiring decisions, stricter limits should be placed on AI's independent authority. At the same time, stronger human judgment and more robust procedural safeguards should be retained.

Therefore, the key issue in AI-enabled recruitment is not whether the technology itself can be used, but within what boundaries it should be used. The four-dimensional framework proposed in this paper does not seek to replace organizational judgment. Rather, it aims to provide a clearer analytical basis for positioning AI across different recruitment tasks. Responsible AI recruitment should be understood as a process of continuously calibrating the boundaries among efficiency, opportunity, fairness, and responsibility.

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