Ethical Challenges in AI Recruitment: Beyond Technical Bias to the Reproduction of Social Inequalities

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Abstract

Recruitment processes play a central role in shaping access to employment and social mobility. The increasing use of artificial intelligence in these processes is beginning to change how candidates are evaluated, raising questions about whether regulatory frameworks are sufficient to address emerging challenges. Current regulatory approaches remain focused on the technical aspects of AI, while giving less weight to the social conditions that shape access to employment. The article employs qualitative analysis to examine how AI-driven recruitment processes, though often presented as neutral, are influenced by candidates' social and economic backgrounds. It examines how existing patterns of human decision-making can be reproduced through AI systems, particularly as these models rely on historical data and extend existing selection practices. The analysis draws on qualitative data on retraining trajectories and career transitions in the Romanian IT sector. It further shows that access to employment is strongly shaped by differences in access to resources, enabling certain candidates to bypass selection processes more effectively than others. AI systems tend to reinforce these patterns by operating within opaque decision-making structures, thereby contributing to the persistence of unequal outcomes. The findings indicate that screening based on easily measurable criteria is central to hiring practices, whether carried out by human recruiters or AI systems, often limiting candidates' ability to demonstrate their full potential. By bringing together social and technical perspectives, the article highlights how these disadvantages remain embedded in recruitment processes, even when criteria appear neutral. The paper argues for greater regulatory involvement in guiding AI toward more robust and fair evaluation practices and suggests a shift in regulatory approaches toward addressing broader inequalities, enhancing transparency, and promoting more meaningful forms of evaluation in recruitment.

Keywords

Artificial Intelligence; recruitment; algorithmic decision-making; labor market inequality; automation

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Introduction

Over the last decades, the emergence of information technologies has been redefining the mechanisms governing work across different segments of the labour market (Huws, 2014). Beyond transformations in labour structure, these developments have extended into recruitment and selection processes through increasing digitalization, transforming hiring practices while introducing new capacities for large-scale evaluation. These changes vary across the labour market, from internal applicant tracking systems and decision-support tools to external digital recruitment platforms (Ajunwa & Greene, 2019; Koivunen et al., 2019). In the current context, the expanding use of automated tools in recruitment and the growing use of artificial intelligence in candidate assessment require analytical examination. While AI adoption in recruitment remains in a transition period, academic perspectives and regulatory frameworks have focused on technological bias in algorithms, without considering the structural conditions through which recruitment data and evaluative criteria are socially produced (Zajko, 2021).

Our research approach emphasizes that AI adoption in recruitment should be understood in relation to the social and institutional conditions through which it operates. Artificial intelligence models rely on historical data and are trained on existing decision-making patterns. Consequently, their deployment may reinforce existing structural inequalities. To address these dynamics, we use qualitative data on retraining trajectories and career transitions in the Romanian information technology sector, where recruitment practices are understood as an essential gatekeeping mechanism shaping occupational mobility. The qualitative data collected on retraining trajectories are particularly relevant for understanding the future implications of AI-driven transformations in the labour market. Increasing occupational mobility and advanced digital competencies become central conditions for securing employment. This approach allows us to examine how transitions into technical professions are not determined solely by retraining strategies but are also shaped by recruitment practices rooted in existing social structures. In this context, although regulatory frameworks emphasize human oversight in recruitment, the decision-making mechanisms continue to reproduce inequality and may further polarize the labour market.

1. Literature review

One of the significant technological developments in recruitment has been the growing reliance on automation, with applicant tracking systems (ATS) increasingly used across organizations. These systems were perceived as practical tools for improving recruitment efficiency while reducing human bias in selection processes (Trumble, 2025). The role of applicant tracking systems has expanded within organizations, covering job postings, application screening, and the automation of administrative tasks (Vallas & Kovalainen, 2019). Applicant tracking systems, even when analyzing neutral variables, have been shown to reproduce biases related to candidates' socio-demographic characteristics (Vallas, 2013). Subsequent research suggests that the expansion of automated hiring tools tends to polarize labour markets by relying on surface-level forms of competency assessment. As automation excludes resumes that do not align with predefined or standardized profiles, organizations increasingly prioritize high-profile candidates from passive external sources to cover job vacancies, thereby intensifying polarization within labour markets (Vallas & Kovalainen, 2019). Rather than offering enhanced objectivity or expanded opportunities, this form of automation can be understood primarily as a mechanism for reducing organizational workload, with limited effects on hiring outcomes and fairness (Trumble, 2025). In organizational practices, most automated recruitment systems operate through preliminary keyword-matching assessments rather than qualitative evaluations of candidates' experience or competencies (Navarro, 2025).

Recent advances in artificial intelligence, particularly machine learning, mark a qualitative shift by extending algorithmic evaluation and decision-making across multiple stages of candidate assessment. As Raghavan et al. (2020) argue, a broad understanding of algorithmic outputs and the objectivity of AI recruitment systems requires analyzing the context, quality of input data, and design of training models. In contemporary recruitment practices, AI solutions are commonly implemented through two main types of assessment approaches: (1) custom assessments and (2) customizable or pre-built assessments. A similar typology is identified by Ajunwa (2020) in her analysis of algorithmic hiring systems, distinguishing between standardized algorithms that employers can purchase or license and those developed by software providers to meet specific organizational requirements. The custom assessments approach relies on the availability of sufficient and representative data within organizations. Concerns associated with this model arise from the configuration and potential biases of participants used in training models, which can influence the quality of outputs applied in organizational contexts. Customizable or pre-built assessment tools reduce reliance on organizations' data but assume comparability across job roles and labour markets, potentially overlooking cultural and institutional differences (Raghavan et al., 2020).

Taken together, these developments in automation and algorithmic systems intensify concerns about the objectivity of recruitment processes. First, operational models that process applicant data beyond the scope of individual decision-making may reinforce inequalities embedded in training data. Second, decision processes that prioritize statistical patterns over human contextual judgment may neglect relevant individual or situational factors. Third, inequalities may arise not only from biased datasets but also from system design. While digital technologies expand the quantity and complexity of data used in recruitment algorithms, existing social inequalities are expected to be reproduced. In other words, when systems are designed around limited or abstract assumptions of social equality, their implementation can generate disadvantages for vulnerable groups (Gerdon et al., 2022).

Academic analyses and research approaches have been oriented toward questions of impartiality and equality reproduced through the adoption of new technologies in the field of recruitment (Agbasiere & Nze-Igwe, 2025). The current academic paradigm addressing inequalities arising from artificial intelligence adoption in recruitment has been framed around biases emerging from technical outputs. As Zajko (2021) argues, these approaches tend to prioritize technical bias mitigation or correction while failing to account for the structural inequalities within which AI systems operate. Many researchers address these issues primarily as technical bias, whereas broader normative considerations of equality and fairness remain secondary. As the previous literature revealed, AI systems rely on historical data that reproduce inequalities or discriminatory patterns, and the transparency of operating models is in many cases limited. Therefore, approaches to recruitment practices should extend beyond technical controls and include legal oversight, ethical considerations, and professional competencies in the use of AI (Koivunen, 2023). A shift toward a social perspective should begin from the assumption that human decision-making is itself subject to bias, which can be reproduced or intensified through algorithms' training data. At the same time, human and algorithmic decision processes are not directly comparable, as algorithms operate on large scales and apply mechanisms that can perpetuate existing patterns of inequality. The adoption of artificial intelligence in hiring constitutes a significant technological transformation that requires legal and regulatory attention, particularly given its potential to generate discriminatory outcomes (Ajunwa, 2020).

In this context, algorithmic decision-making increasingly shapes applicants' access to employment. Given the novelty and the widespread use of this technology, responsibility is distributed across a wide range of actors within the AI value chain, as identified in the AI Act (Regulation (EU) 2024/1689). Although the AI Act represents a significant regulatory step, the legal framework governing AI is still undergoing refinement, with the European Commission's Digital Omnibus initiative proposing adjustments to both the AI Act and the GDPR, both of relevance to this paper. The Digital Omnibus simplify elements of both GDPR and AI Act in order to reduce regulatory complexity. At the time of writing, the proposal is at an advanced legislative stage and the trilogue negotiations are expected to begin. (European Parliamentary Research Service, 2026).

Against this evolving regulatory backdrop, the AI Act adopts a risk-based approach, under which the Union legislator has classified AI systems used in recruitment and selection processes as high-risk pursuant to Article 6, read in conjunction with Annex III (4)(a), of the Artificial Intelligence Act (European Parliament & Council, 2024). This classification acknowledges that such systems may significantly affect individuals' fundamental rights, notably regarding equal treatment and access to employment, and is accompanied by a set of obligations, including requirements relating to risk management, data governance, transparency and human oversight. Nevertheless, doubts remain as to whether the framework that relies heavily on ex ante compliance and internal assessments can adequately address the persistent gap between formal legal safeguards and their real-world application in contexts such as hiring (Veale & Borgesius, 2021).

The AI Act relevance to recruitment is particularly significant, as deployers must inform individuals when they are subject to the use of a high-risk AI system, and affected persons may have the right to a clear and meaningful explanation of the role of that system and the main elements of the decision (Regulation (EU) 2024/1689, Art. 86). In recruitment contexts, concerns relating to transparency and discrimination arise simultaneously across overlapping frameworks of data protection and equality law, creating a fragmented regulatory landscape (Rigotti & Fosch-Villaronga, 2024). Although the AI Act introduces ex ante obligations aimed at transparency and oversight, GDPR safeguards remain limited where systems are not considered" solely automated" under Article 22 (Wachter et al., 2017).

The complementary role becomes particularly important in the context of AI-driven hiring, where certain forms of algorithmic decision are only partially regulated. Seemingly neutral criteria may indirectly reflect protected characteristics and reproduce structural inequalities embedded in historical data even without explicit references to sensitive attributes (Gerards & Zuiderveen Borgesius, 2022; Veale & Borgesius, 2021). Equality law therefore addresses a dimension not fully captured by either the GDPR or the AI Act, namely the impact of decisions on different groups. Even where recruitment systems comply with procedural obligations under the AI Act, they may still produce disproportionate adverse effects that cannot be objectively justified. Ethical issues arise both from decision-making processes and their outcomes, particularly where opaque decision-making or inadequate explanations may reinforce inequalities in access to employment.

However, attempts to identify and address bias create further challenges. Identifying discrimination in AI systems may require the processing of sensitive data, which is restricted under the GDPR, although permitted under certain conditions. Where such data are avoided altogether, the detection of algorithmic discrimination becomes significantly more difficult. Unequal access to employment persists due to structural limitations. Not all forms of exclusion are legally actionable, and AI systems may further obscure how decisions are made (Prince, 2020; Fraser et al., 2022). Moreover, GDPR safeguards under Article 22 may be limited where recruitment decisions involve some degree of human involvement (Wachter et al., 2017). As a result, AI systems may comply with formal legal requirements while still producing unequal outcomes within labour markets already shaped by structural inequalities. Although the current regulatory framework is subject to ongoing refinement, significant gaps remain in addressing the risk that AI-driven recruitment systems may reproduce or amplify existing inequalities. We therefore argue that regulatory approaches must consider the broader social conditions in which AI systems operate, as technologies deepen already uneven access to opportunities. From this perspective, the recruitment process operates as a gatekeeping mechanism of social mobility, and inequality is analyzed not through technical biases in algorithmic decisions or data interpretation but as the reproduction of positions in stratified societies. In this sense, data bias reflects the reproduction of practices within social structures and processes (Zajko, 2022). Research on social mobility and equal access to employment has demonstrated that recruitment decisions are shaped by long processes of institutionalized cultural reproduction of inequality, in many cases long before individuals enter the labour market. As Tilly (1998) argues, patterns of unequal opportunity remain embedded in social structures through processes of exploitation and opportunity hoarding, disproportionately affecting vulnerable groups whose personal characteristics shape access to opportunities within society. These processes shape what are often perceived as neutral variables by maintaining territorial segregation (Marger, 2014), unequal access to educational opportunities (Braham, 2013), and uneven professional trajectories (Farley & Flota, 2017).

Contemporary research on recruitment therefore requires the systematic inclusion of structural dimensions of inequality, such as gender, race, and social class. Rivera (2016) demonstrated that educational background and individual cultural capital play a central role in the reproduction of social class inequalities. Human recruitment practices tend to prioritize cultural similarity over objective measures of competence (Rivera, 2012). The increasing use of digital recruitment tools introduces new forms of ranking, evaluation, and assessment. These systems may advantage certain social groups at the expense of others. Even when these systems operate on the basis of competency models, they remain grounded in human assumptions that have shaped their design (Rivera, 2020). This perspective points to a duality in which both human and algorithmic recruitment processes operate within broader structures of social inequality rather than functioning as neutral mechanisms. At the same time, the development of competencies contributes to the accumulation of what can be described as "digital capital" within certain segments of the labour market, enabling individuals to benefit from strategic knowledge of algorithmic systems, including keyword optimization, preparation for digital assessments, and the navigation of automated screening processes (Xu et al., 2025). As a result, many labour market narratives emerge around perceptions of unfair outcomes, limited opportunities to demonstrate competencies, and the continued importance of personal networks within organizations for successful job offers (Armstrong, 2023). In the current structural context, AI systems may replicate unequal labour-market outcomes or reorganize them into what Hughes et al. describe as "algorithmically mediated inequality regimes". At the same time, legal and regulatory responses to AI-based hiring practices remain uneven and insufficiently developed, often failing to account for labour market conditions shaped by individuals' social and economic backgrounds. This regulatory gap may further contribute to the reinforcement of existing inequalities (Hughes et al., 2025).

2. Research methodology

The current multidimensional analysis of the literature examines the implications of artificial intelligence for recruitment practices, framing them as a gatekeeping mechanism shaping occupational mobility. This is particularly important, as AI is simultaneously transforming recruitment practices and reshaping the structure of competencies within the labour market. The methodological approach draws on qualitative data derived from a larger research project conducted by one of the authors (unpublished PhD thesis, Mechanisms of Occupational Mobility in the IT Sector and Their Social Effects). The data used in this article were extracted from a subset of the broader research project, with only specific segments selected for the present analysis. The main research project was designed using a grounded theory approach, which enabled the development of analytical categories through an iterative coding process. Participants were initially recruited via job platforms (e.g. LinkedIn) and through snowball sampling, based on their relevance to the research focus, with subsequent selection following the analytical categories emerging during the analysis. Based on data extracted from a sample of 36 semi-structured interviews, with an average duration of approximately one hour and twenty minutes, the current analysis was structured around three main categories: competence acquisition processes, strategies for obtaining professional roles in the IT sector, and internal recruitment practices within companies. The sample includes three groups: recruitment specialists and HR managers (10 participants), relevant for explaining decision-making processes in recruitment and selection; individuals undergoing or having undergone career transitions for at least six months but who have not yet secured employment in the IT labour market (9 participants), relevant for understanding experiences of navigating recruitment systems and the adaptive strategies involved in accessing fields with limited prior experience; and individuals who successfully integrated into the IT sector following retraining processes (17 participants), allowing for comparisons between factors influencing successful entry into different areas of the IT sector. Participants were recruited primarily from urban areas, particularly technological centers such as Bucharest, Cluj-Napoca, and Iași.

3. Research findings

The current labour market is entering a period of structural transformation driven by the evolution of information technology. Changes in competencies continue to be debated, with some estimates suggesting impacts on nearly half of the active workforce. These developments may amplify vulnerabilities across different segments of work and employment structures (World Economic Forum, 2025). Currently, AI adoption in the labour market is associated with shifts in demand across tasks, including declines in some activities and increased demand for tasks that complement AI (Hampole et al., 2025). These structural changes directly influence educational systems, competency development, and occupational mobility between jobs (International Labour Organization, 2024). As artificial intelligence is reshaping competency requirements, recruitment and selection processes remain essential in ensuring equitable outcomes in occupational mobility. On these assumptions, we argue that future structural changes in work may amplify inequalities already embedded in recruitment practices. The empirical evidence collected from retraining and career transitions allows us to identify a mechanism of labour market duality that shapes occupational trajectories despite individual efforts to acquire specific competencies.

As illustrated in *Figure 1*, the current diffusion of AI generates two main axes of transformation. The first axis refers to structural changes in the labour market, particularly in job structures and competency requirements. The uneven development of AI-related competencies, mainly concentrated among core employees, creates differentiated capacities for adaptation to changing labour-market conditions and contributes to increasing inequalities in occupational mobility, especially under potential conditions of organizational restructuring. The second axis refers to the growing use of algorithmic tools in recruitment processes, where screening procedures tend to favour candidates with specific professional experience. Although current regulatory frameworks rely on human oversight in algorithmic recruitment, our qualitative data suggest that these practices continue to reproduce inequalities. As shown in our data, recruiters often rely, when analysing resumes, on variables such as previous experience, company prestige, and educational background, frequently rejecting candidates who do not meet predefined criteria. In this context, candidates whose resumes reflect limited field-specific experience, even when they possess intensive training in the domain, enter these processes from disadvantaged positions, given that both algorithms and human evaluators tend to favour already established profiles. Candidates in occupational transition must therefore develop alternative strategies to access better employment opportunities or at least maintain stable occupational trajectories. Within this segment, a privileged minority is better positioned to navigate these opportunities due to the resources derived from their social position. Drawing on Bourdieu theoretical framework (1986; 1990), we argue that access to labour-market positions depends not only on the individual capacity to acquire specific competencies but also on the ability to mobilize different forms of capital, such as economic, social, and cultural. These forms of capital, derived from individuals' social position, can improve outcomes in navigating screening procedures or, in some cases, help individuals bypass initial stages of recruitment. As illustrated in Figure 1, in the absence of digital capital or extensive experience in specific domains, other individual resources become increasingly important in determining access to superior labour market positions.

Economic capital represents an essential factor in shaping opportunities in the labour market, especially in the context of resumes that do not meet recruitment criteria. As previous studies demonstrate, economic resources significantly influence employment outcomes. Research by Friedman and Laurison (2019) shows that financial capacities functions as a form of protection, especially at the beginning of a career, by enabling the development of more secure career trajectories.

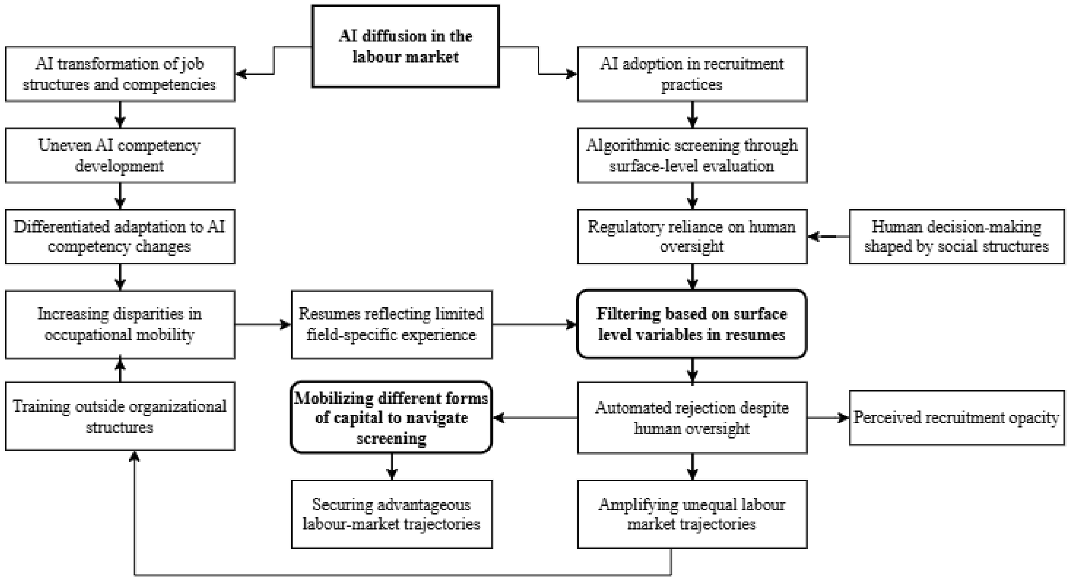

Figure no. 1. Diagram Mechanisms of Inequality Reproduction in AI Diffusion Across the Labour Market

At the same time, our findings suggest that, in the context of applying for positions across different fields of expertise, individuals with limited experience but higher levels of economic capital are better able to navigate these transitions by sustaining longer periods between jobs. Additionally, access to financial resources contributes to improved outcomes by ensuring access to advanced training and formal credentials, increasing the chances of success in initial screening.

Social capital, on the other hand, constitutes an important resource that enables actors to bypass both human and algorithmic screening practices. Individuals with stronger networks are more able to access opportunities through recommendations and internal referrals within companies. These mechanisms are particularly relevant in the context of recruitment “black boxes”, which result from large-scale selection processes rather than direct evaluations of competencies. While some candidates submit applications without receiving responses, social ties may facilitate access through referrals. The mobilization of social capital is therefore important in shaping recruitment outcomes, as many candidates are filtered out during the early stages without the opportunity to demonstrate their competencies. At the same time, the absence of social capital and the perception of unfair or opaque recruitment processes push many candidates to seek alternative pathways through online communities. These practices highlight the limitations of large-scale recruitment systems and unequal access to positions across social categories.

Recruitment decisions are often based on surface-level evaluations that privilege candidates with greater economic and social resources. Although these practices rely on variables commonly treated as neutral, such as experience, education, or credentials, they may still contribute to unequal outcomes across social groups. This contributes to perceptions of limited transparency, especially when applications are filtered at early stages. Under current labour market conditions, intensified by structural transformations, this research highlights the limitations of large-scale recruitment models that are often assumed to be neutral but continue to produce unequal outcomes. Our central argument emphasizes the need for regulatory frameworks in which technological development operates to the advantage of candidates. AI development remains in a transitional phase, nevertheless, a proactive approach may enable better direct evaluation of competencies at early stages and reduce reliance on formal indicators and resume-based screening.

Conclusions

Based on the experiences of social actors involved in retraining and career trajectories in new professional fields, we formulate the conclusions of this research. The increasing use of artificial intelligence in recruitment may serve as an optimization mechanism for organizations, however, the objectivity of recruitment outcomes tends to remain unequal. As the labour market continues to undergo structural transformation, an increasing number of individuals may experience similar processes of retraining and professional career transitions. In this context, the question is whether current regulatory and academic positions will maintain a focus on correcting technical biases in AI-based recruitment or whether they will integrate broader social considerations in order to proactively address inequalities in the labour market. While many initiatives, such as the European Commission's classification of competencies, qualifications, and occupations (ESCO), aim to support better matching between candidates' competencies and labour market opportunities, direct application to recruitment screening practices remains limited.

This study has several limitations that should be acknowledged. The qualitative analysis focuses on retraining trajectories and career transition within the Romanian IT sector, which limits the extent to which the findings can be generalized across different labour markets or occupational contexts. In addition, the research relies primarily on participants' experiences and perceptions of recruitment processes rather than direct access to organizational AI systems datasets. Future research could therefore examine recruitment practices across different sectors and national contexts. It could also explore more directly how organizations implement AI systems and how regulatory developments influence recruitment outcomes over time.

This article draws on a literature assessment and qualitative research to outline several directions for future research and legal regulation: (1) the current legislative framework should not only address algorithmic biases but also consider the structural production of social inequalities; (2) approaches relying on human decision-making require further research and proactive integration within regulatory frameworks; and (3) emerging regulatory approaches to AI technologies in large-scale recruitment should prioritize competency-based assessment, reduce reliance on variables treated as neutral, and ensure transparent communication of outcomes.

Generative Artificial Intelligence (GenAI) usage statement:

ChatGPT (version 5.0) was responsibly used for language inadvertences. After this process, the authors reviewed and edited the content as needed and take full responsibility for the content of the present article.

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