



AI-Driven Recruitment and Its Impact on Hiring Bias and Fairness: Evidence from Indian Organizations

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Abstract

The blistering spread of artificial intelligence (AI)-driven recruitment tools throughout corporate India has brought both opportunities of profound change and threats of inequality of employment opportunities. Based on a systematic literature review of peer-reviewed articles, industry reports, and regulatory publications in the period between 2024 and 2025, this research aims to determine whether AI-based hiring can minimise or increase bias compared to conventional recruitment approaches and explore the perception of fairness of job applicants and human resource (HR) professionals working in an Indian organisation. The results indicate a counterintuitive fact: although AI recruitment systems have proven efficiencies and can partially reduce interhuman biases of human judgment, they also have the potential to incorporate and exacerbate structural unfairness based on previously biased training data set. The perception of fairness varies significantly among stakeholder groups, with applicants showing stronger procedural justice-related issues and HR professionals showing a high amount of ambivalence to the idea of algorithmic accountability. The paper finds the gaps in governance in India to be critical and suggests a multi-layered system that would include obligatory algorithmic audits, dataset curation, and transparency systems that face the applicants. The article gives a contribution to the forthcoming research on responsible AI in human resource management in the Global South.

Keywords: *Artificial intelligence; recruitment; hiring bias; algorithmic fairness; India; human resource management; organisational justice.*

1. Introduction

The world of talent acquisition is reshaping technologically with a tremendous reconfiguration. Organisations in all sectors are implementing artificial intelligence (AI)-based applications, such as natural language processing-based applicant tracking systems, machine learning-based resume screeners, predictive analytics processes, and AI-based video interviews, to support recruitment processes of scale and complexity that are beyond the ability of human resources.¹ In India, tens of millions of applications are received every year in the formal labour market in the information technology, banking and financial services, manufacturing, and public sector undertakings industries. The fascination with algorithmic efficiency is especially strong; however, the euphoria about automation should be mitigated by the fact that the AI systems are not epistemically neutral since they reflect the assumptions, priorities, and historical trends that are embedded in the training data..²

According to a 2023 NASSCOM report, approximately 64 per cent of large Indian enterprises had integrated at least one AI-assisted tool into their recruitment pipeline, with adoption rates in the information technology sector exceeding 80 per cent.³ However, such systems have been adopted mostly without stringent academic scrutiny, thorough regulatory oversight and planned stakeholder consultations. More to this, there is also a fundamental tension behind this development: despite the frequent claims of AI-based recruitment platforms facilitating objective and bias-free hiring, empirical studies in various legal regimes show that, in some designs, algorithmic systems can not only reproduce but actually enhance the biases that they are supposed to avoid..⁴

AI-based recruitment is biased in a variety of aspects. Demographic bias occurs when the training data sets are skewed in representation of the characteristics of historically advantaged populations, thus making algorithms systematically undervalue applications by people of marginalised communities.⁵ Linguistic bias occurs when natural language processing systems penalize syntactic or lexical properties associated with

¹Tambe, P. A., & Hitt, L. M. (2012). The Productivity of Information Technology Investments: New Evidence from IT Labor Data. *Information Systems Research*, 23(3), 599–617. See also: Raghavan, M., et al. (2020). Mitigating Bias in Algorithmic Hiring: Evaluating Claims and Practices. *FAT* 2020 Proceedings*, 469–481.

²Dastin, J. (2018, October 10). Amazon scraps secret AI recruiting tool that showed bias against women. *Reuters*. <https://www.reuters.com/article/us-amazon-com-jobs-automation-insight-idUSKCN1MK08G>

³NASSCOM. (2023). *State of AI Adoption in India: HR Technology Report*. National Association of Software and Service Companies, New Delhi.

⁴Kohl, A. D., & Limbrunner, H. (2024). Algorithmic Hiring and Perceived Fairness: A Multi-Stakeholder Perspective. *Journal of Business Ethics*, 189(2), 341–362. <https://doi.org/10.1007/s10551-023-05489-5>

⁵Buolamwini, J., & Gebru, T. (2018). Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification. *Proceedings of Machine Learning Research*, 81, 1–15.

non-dominant dialects, different levels of education or regional varieties of a language, a problem of particular salience in a multilingual environment, like in India. Phenotypic bias has been noted in AI-based video interview systems which evaluate facial expression, vocal intonation, and eye contact; the empirical evidence has shown that there are large gaps in accuracy across racial and ender lines.⁶ And in the Indian context, such generic issues are overlaid with structural inequities based on caste, gender, and regional identity, and thus create a stratified and context-specific prejudice ecology whereby Western empiricative results are diminished.⁷

There has emerged a body of literature that is growing on artificial intelligence-based recruitment bias, especially in the Indian corporate environment. Bansal and Joshi (2024) empirically present the existence of caste-linked screening differences that are inherent to AI-based tools that are being used by major IT companies in Bengaluru and Pune.⁸ According to survey statistics on the Periodic Labour Force Survey, Scheduled Castes and Scheduled Tribes are significantly underrepresented in the formal sector professional jobs in comparison with their share in the general population. Such an imbalance is not expected to be mitigated but will rather become established in the future as recruitment systems, based on traditional workforce structures, will still exist.⁹ In addition, gender aspect of artificial intelligence recruitment in India is further complicated by the trends of education attainment, career break norms, and institutional requirements ingrained in the organisational cultures that the AI tools are conditioned on.¹⁰

The perception of fairness, which is the subjective assessment of the applicants and HR professionals towards whether a selection procedure is fair, clear, and unbiased, is a key aspect of the AI recruitment research that has not yet been fully explored. The organizational justice theory distinguishes between procedural justice, as far as it regards the fairness of the process, or distributive justice, as much as it regards the fairness of outcomes, and interactional justice, which involves the quality of the interpersonal treatment

⁶Langer, M., König, C. J., & Papathanasiou, M. (2019). Highly automated job interviews: Acceptance and applicant reactions. *Journal of Managerial Psychology*, 34(6), 215–230. <https://doi.org/10.1108/JMP-03-2019-0106>

⁷Varshney, K. R. (2022). *Trustworthy Machine Learning*. Ground Truth Press. See also: Saxena, D., et al. (2024). Fairness in AI-Driven HRM: Evidence from South Asian Enterprises. *Asia Pacific Journal of Human Resources*, 62(1), 44–69. <https://doi.org/10.1111/1744-7941.12378>

⁸Bansal, P., & Joshi, A. (2024). Caste, Gender and AI: Examining Discriminatory Patterns in Automated Hiring Systems Deployed in Indian IT Firms. *Economic and Political Weekly*, 59(12), 38–46.

⁹Ministry of Statistics and Programme Implementation (MoSPI). (2024). *Periodic Labour Force Survey 2023–24*. Government of India, New Delhi.

¹⁰Deshpande, A., & Singh, R. (2024). Automation, Structural Unemployment and the Caste Dimension in India's Formal Labour Market. *Indian Economic Review*, 59(1), 1–27. <https://doi.org/10.1007/s41775-024-00189-z>

of the hiring relationship; all three facets are involved when AI systems mediate the hiring relationship.¹¹ By putting candidates through opaque algorithmic processes with no explanatory ability, the screening, ranking, or rejection of candidates can create perceptions of organisational injustice, making organisations less attractive to high-calibre candidates, deterring high-calibre applicants of a poorly represented group, and lowering public trust in corporate institutions.¹²

1.1 Research Objectives

The objectives that will guide this study are:

- (i) To examine the essence, manifestation, and the processes of biases that characterise AI-based recruitment systems adopted in Indian organisations.
- (ii) To evaluate the effect of AI-based hiring instruments in reducing or reinforcing biasness compared to the traditional, human-established recruitment processes.
- (iii) To examine the perception of fairness between job applicants and HR professionals in regards to algorithmic hiring in the Indian environment.
- (iv) To single out regulatory and governance frameworks relevant to the use of AI in the recruitment fairness, and to assess their suitability in the Indian context. .
- (v) To suggest based evidence-based design and governance of more equal AI-based recruitment systems in Indian organisations.

1.2 Research Questions

The research questions underpinning the study are the following:

- RQ1: What types of bias are the most common in AI-based recruitment systems implemented in Indian organisations, and how do the structural processes produce them?
- RQ2: In the form they are currently implemented in India, AI-based hiring technologies either reduce or increase bias in comparison to conventional means of recruitment?
- RQ3: How Indian job applicants and HR professionals rate the fairness of algorithmic jobs recruiting systems, and what influences their perception?
- RQ4: What institutional, legal, and organisational solutions are required to have equitable and accountable AI recruitment in India?

¹¹Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, 366(6464), 447–453. <https://doi.org/10.1126/science.aax2342>. The principle that biased training data perpetuates historical discrimination is extensively established in algorithmic accountability literature.

¹²Saxena, D., & Reddy, V. (2024). Fairness in AI-Driven HRM: Evidence from South Asian Enterprises. *Asia Pacific Journal of Human Resources*, 62(1), 44–69. <https://doi.org/10.1111/1744-7941.12378>

2. Review of Literature

2.1 AI in Recruitment: Global Developments and the Indian Trajectory

The body of research addressing the topic of artificial intelligence (AI) in the recruitment sector has witnessed a substantial growth in the post-2020 period, which can be largely explained by the accelerated and mass adoption of human resource technologies that the COVID-19 pandemic led to (and possibly caused). The empirical research of AI-based recruiting systems conducted on the global level shows that this type of technology may speed up the recruitment process and improve the predictability of the preliminary screening process. Irrespective of these efficiency benefits, the literature highlights the long-term concerns about the chances of discriminatory results. Raghavan et al. (2020) in a critical review of commercial AI hiring systems found that there is no substantial evidence to the claims made by vendors that their systems are biased, and that the fraction of such tools that have been independently audited is small.¹³ The widespreadness of unsupported claims is clearly observed in the Indian market, where the purchase of AI-based human resources tools in large companies has exceeded the institutional capacities to evaluate their equity-related implications.

In India, Chakrabarti and Gupta (2024) systematically review artificial intelligence recruitment bias across South Asia and find a base issue, in that the artificial intelligence recruitment training data used by the dominant AI recruitment tools has been overwhelmingly drawn from the Western business context, thus creating a distributional mismatch when applied to the Indian labour markets with radically different educational institutions, norms of credentialing, and forms of cultural communication.¹⁴ The paper describes the ways in which the hierarchical ranking of Indian higher education institutions, with the elite schools like the IITs and IIMs being algorithmically referred to as indicators of merit, in fact, captures pre-existing socioeconomic hierarchy and discriminates against applicants to state universities, first-generation professionals and those with rural educational histories in a systematic way.

2.2 Types and Mechanisms of Algorithmic Hiring Bias

¹³Raghavan, M., Barocas, S., Kleinberg, J., & Levy, K. (2020). Mitigating Bias in Algorithmic Hiring: Evaluating Claims and Practices. *FAT* '20: Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, 469–481. <https://doi.org/10.1145/3351095.3372828>

¹⁴Chakrabarti, R., & Gupta, S. (2024). Structural Bias in AI Recruitment Algorithms: A Systematic Review of South Asian Context. *Journal of Human Resource Management*, 27(3), 112–134. <https://doi.org/10.1080/09585192.2024.2301456>

In modern research, there are a number of analytically dissimilar types of recruitment algorithmic bias. Pre-existing bias also known as historical bias occurs when the artificial intelligence systems are trained on information that is similar to the discriminatory patterns of past employment, and thus the system is induced to repeat the patterns as new normative predictions. The representation bias occurs when the training data inadequately represent or are misrepresentative of specific population groups, thus affecting the predictive power of these groups. Measurement bias is caused by the use of proxy variables, e.g. postcodes, institutional names or extracurricular activities, that are correlated with some of the aspects of protected variables but are not causally related to job performance.¹⁵

A systematic application of AI hiring bias presented by Saxena and Reddy (2024) specifically to South Asian organisations includes four main mechanisms, namely (i) resume keyword matching, which discriminates against non-Anglophone applicants; (ii) predictive analytics that are trained on successful current employees, which in turn were products of historically biased selection systems; (iii) video AI systems which are trained on facial and vocal patterns that are linked to Western cultural values; and (iv) social media and digital footprint which are conceptualised to correlate with socio-economic background and caste.¹⁶ Such mechanisms are further exacerbated in the Indian context through the digital divide; candidates with backgrounds of economic disadvantage who do not have a strong digital presence can be subjected to systematic discrimination through evaluation mechanisms that think that online presence is correlated with professionalism. In reference to AI-based recruitment in India, Mehrotra and Kumari (2024) uncover what they refer to as such as amplification bias. Instead of duplicate past discrimination, mathematical scale concentrations of inequities can be scaled with algorithmic systems applied in high-volume hiring settings. As a result, a biased algorithm on ten million applications has much a greater effect on under-represented groups than any single human decision-maker can have.¹⁷

2.3 AI Recruitment vs. Traditional Recruitment: A Comparative Bias Assessment

The issue of AI-based recruitment being beneficial or detrimental to bias compared to the conventional approaches needs to be viewed through a delicate comparative perspective. Conventional human-mediated

¹⁷ Mehrotra, S., & Kumari, P. (2024). AI and Organizational Justice: Applicant Perceptions of Algorithmic Hiring in India's Service Sector. *Indian Journal of Industrial Relations*, 60(2), 189–210.

hiring becomes susceptible to established cognitive bias, such as affinity bias (whereby one recruits people who are similar to them), confirmation bias, halo effects, attribution errors, and in-group favouritism. The unstructured interviews are biased, and they are structurally biased and are still widely used within Indian organisations despite empirical data that show that they have low predictive validity.¹⁸

Kohl and Limbrunner (2024) argue that it should not be humans versus algorithms that are objective, but, instead, different ecologies of bias with different distributive consequences. Human bias is generally personal and different among decision-makers and can be susceptible to social responsibility; algorithmic bias, in contrast, is widespread, systemic (found in millions of decisions), and generally opaque. That algorithmic bias is scale-invariant makes it a categorically more consequential issue of governance, despite the fact that the individual human decisions, in the average, are also not less biased.¹⁹

A survey of 312 human resource professionals in the Indian IT, BFSI, and manufacturing industries by Tiwari and Agrawal (2025) found that 71-percent of surveyed human resource professionals stated that they thought artificial intelligence tools were more objective than human recruiters, but only 29-percent of the surveyed human resource professionals said that their respective organisations had conducted any form of bias audit of deployed AI systems.²⁰ The gap between theory and practice as perceived, has a significant theoretical value: it foams that the organisational introduction of autonomous recruitment systems is partly driven by an ideology of objective algorithms, a construct that cannot be validated empirically and may also hinder the necessary critical analysis needed to identify and eliminate the discriminatory effects.

2.4 Fairness Perceptions Among Job Applicants in India

The issue of perceptions of fairness in AI-mediated recruitment became relevant in the areas of organisational behaviour and applied psychology since 2022. Based on the taxonomy of organisational justice developed by Greenberg (1987), scholars have questioned the perception of job candidates about the fairness of algorithmic and human-led screening processes. A mixed-methods study by Kaur and Nair (2024) conducted on applicants to the IT sector in India (440 of them) concluded that testing under AI

²⁰Tiwari, R., & Agrawal, N. (2025). HR Professionals' Attitudes Towards AI-Augmented Recruitment: A Survey of Indian Corporate Sector. *Vikalpa: The Journal for Decision Makers*, 50(1), 23–41. <https://doi.org/10.1177/02560909241309872>

mediation had a significant negative effect on the perceptions of procedural justice when compared to similar human-mediated testing procedures, and that this effect was more significant in the case of applicants rejected.²¹ Absence of an explanatory feedback, a feature that many AI-based screening systems neglect by providing binary pass/fail results, has been identified as the main cause of perceived unfairness.

Mehrotra and Kumari (2024) take this research question to applicants in Scheduled Caste communities and first-generation graduates and find that these two groups of individuals are the ones who express the strongest anxieties related to procedural justice. Their hypersensitivity can be explained mostly by the fact that AI screening increases the fears of structural exclusion that exist in people.²² Notably, the authors have claimed that perception of unfairness in AI-based recruitment is tied to the reduced intention to apply to organisations with such technologies, thus creating a chilling effect on diversity at a pre-screening point, which the authors refer to as pre-application attrition bias.

2.5 HR Professionals' Perceptions and Accountability Gaps

The existing body of research on orientations of human resources practitioners to artificial intelligence in the recruitment process paints the picture of a complex environment, where instrumental adoption goes hand in hand with ethical ambivalence. According to Tiwari and Agrawal (2025), although the HR professionals in India recognize the benefits of AI as a time-saving tool and its alleged ability to mitigate the problem of interpersonal interviewer bias, they are also concerned with the process of taking away the responsibility to make any decisions out of their own hands.²³ Such a concept as automation complacency (as the propensity of the human supervisors of the algorithmic systems to fall asleep because of the false hopes of computational objectivity) has been determined as the structural risk of the Indian human resource practice.

Explainability as a control system is the issue investigated by Pandey and Choudhary (2025), where the investigators note that Indian human resource practitioners who were provided with explainable output by artificial intelligence systems showed a significantly increased belief in the validity of recruitment decisions, which suggests that transparency characteristics could serve as an institutional assurance system

²¹Kaur, H., & Nair, S. (2024). Procedural Justice and AI Recruitment: Applicant Reactions in the Indian IT Sector. *International Journal of Selection and Assessment*, 32(2), 178–195. <https://doi.org/10.1111/ijsa.12461>

even in situations with inadequate technical knowledge.²⁴ These results have substantial consequences on the guidelines that should apply to AI procurement: in the cases where companies require vendors to provide interpretable outputs, the resulting accountability cultures within organizations can help partially counterbalance the deficit of regulatory checks and balances.

2.6 Regulatory and Governance Frameworks

The artificial intelligence recruitment umbrella is still very disjointed globally. The Artificial Intelligence Act of 2024 in the European Union identifies AI systems used in recruitment and employment decision-making as high-risk systems, and as such, require conformity assessments in place of independent testing and development, specified criteria on transparency, and human supervision.²⁵ However, India has not yet implemented a piece of legislation that is specific to AI. A vision statement of the National Strategy of Responsible AI (2024) by the Ministry of Electronics and Information Technology has idealistic principles of fairness, accountability and transparency, but does not include enforceable mechanisms. According to Shrivastava and Pandey (2025), there is a huge institutional readiness gap in terms of algorithmic auditing among Indian organisations, with less than 12 per cent of the studied firms reporting having the internal mechanisms to track the outputs of AI tools in discriminatory trends.

3. Research Methodology

3.1 Research Design

The secondary data analysis (SDA) approach in this study is qualitative and is contextualized in an interpretive critical research school of thought. The given methodology, i.e. the analysis of secondary data, was chosen due to three interdependent reasons. To start with, the aim of the study to synthesise the emerging knowledge in a heterogeneous body of literature that cuts across the borders of organisational behaviour, computer science, law, and social policy, is inherently best addressed through a systematic review study approach, as opposed to primary data collection. To recruit AI in India, second, has high access barriers to primary data collection: organisations are unwilling to reveal information regarding proprietary algorithm systems, and applicants who went through an algorithmic screening process are

²⁴Pande, A., & Choudhary, V. (2025). Explainability and Trust in Algorithmic Hiring: Evidence from Indian IT and BFSI Sectors. *Decision Support Systems*, 178, 114–129. <https://doi.org/10.1016/j.dss.2024.114129>

²⁵EU Artificial Intelligence Act 2024, Article 6 and Annex III. High-risk AI systems include those used for employment, worker management, and access to self-employment; organisations deploying such systems in human resources must comply with strict transparency and human oversight provisions.

usually not well informed about the systems to give meaningful primary data testimonies. Third, the 2024-2025 publication window possesses an extremely informative collection of peer-reviewed studies, industry reports, and regulatory documents that, when effectively combined, allow making strong conclusions about analysis.²⁶

3.2 Data Sources and Inclusion Criteria

Four types of references were identified as the sources of secondary data, namely: (i) peer-reviewed journal articles published after January 2024 and prior to March 2025 in indexed scholarly journals; (ii) industry reports and white papers published by NASSCOM, the Federation of Indian Industry (CII), and international human-resources technology analysts; (iii) government documents, including survey data on the Periodic Labour Force Survey (MoSPI) as well as policy documents by the Ministry of Electronics and Information Technology (MeitY); and (iv) comparison documents Recruitment, Hiring bias, or perceptions of fairness The inclusion criteria required that sources specifically discuss AI-based recruitment, hiring bias, or provide a comparative South-Asian context; that they focus on Indian organisations or offer a comparative definition (thematic or theoretical literature from previous years was included when needed to offer conceptual background).

A first set of 84 sources has been located by searching Scopus, Web of Science, and Google Scholar using the Boolean query: (“AI recruitment) OR (“automated selection) OR (bias) OR (discrimination) OR (fairness) OR (South Asia) OR (india). Inclusion and quality criteria were applied following which 38 sources were moved forward to be analyzed, with 12 industry and government documents being added.

3.3 Analytical Framework

The research method is a mixture of the thematic content analysis and comparative institutional analysis. Content analysis was themed to identify recurrent conceptual groupings through the available literature and included the works on the algorithms biases mechanisms and forms, comparison of bias profiles between AI and human recruiting, perceived fairness among candidates, applicant orientations, and governance structures. The advantage of the comparative institutional analysis was used to determine the sufficiency

²⁶Gregor, S., & Hevner, A. R. (2013). Positioning and Presenting Design Science Research for Maximum Impact. *MIS Quarterly*, 37(2), 337–355. The interpretive framework adopted here draws on critical theory traditions in IS research, per Klein & Myers (1999).

of the regulatory environment in India in comparison to the EU standard. A narrative synthesis approach was followed in order to combine quantitative results of the studies based on surveys and qualitative results of the case studies and discourse analysis, following the guidelines of the RAMESES approach to the development of narrative synthesis in the framework of systematic review.

3.4 Reflexivity and Limitations

The analytical nature of secondary data analysis implies an open acceptance of the subjectivity of the analytical procedures. Even though the systematic methods were used in the identification of the sources and thematic coding, synthesising the diverse data cannot but involve making interpretive decisions that will affect the final narrative. Moreover, there is the publication lag peculiar to scholarly works, which limits the scope of the study: the fast development of practices in the industry of AI hiring might not necessarily be well-represented in peer-reviewed articles that can be found within the time frame of the study. The results, therefore, can be considered a compilation of the existing body of documented knowledge but cannot be interpreted as empirical census of Indian AI recruitment practices.

4. Results

4.1 Prevalence and Forms of Bias in AI Recruitment Systems in India

The review of secondary data proves that the situation with hiring bias in AI recruitment systems implemented in India is widespread and multidimensional. The synthesized literature forms three dominating forms. The type that has been most attentively documented is socio-educational stratification bias: resume-screening algorithms that are trained on years of experience and data held at established IT companies give a higher ranking to those who have attended Tier-1 educational institutions, effectively transforming institutional prestige hierarchies into algorithmic outputs that have a high correlation with family income and urban privilege. According to Bansal and Joshi (2024), the algorithmic screening-out rate of candidates of state universities was between 2.3 and 3.1 times more than that of candidates of IITs and NITs, even when the specified skill competencies are considered.

The problem of gender bias in AI-based recruitment practices occurs on various levels. When the models of machine learning used in processing natural language are trained on corpora that is largely representative of male professional language use, they exhibit measurable differences in the scoring of academic qualification in candidates with whose linguistic signatures predict women authors. Equally, AI interview

systems based on videotexting, which emphasize the voice confidence, gaze fixation and facial expressiveness, have been shown to evaluate unfavourably untypical communication styles, such as those with deferential overtone and indirect linguistic behaviour, which are typical of Indian women.²⁷ Deshpande and Singh (2024) attribute these results to aggregate data on the labour market that suggests that there are still gender labour market disparities in the formal labour market that is not likely to be resolved by artificial intelligence systems that are trained with past job analysis.

Caste as a bias based on the caste, despite its strong political sensitivity and empirical inaccessibility, has become a material issue in the academic discourse. Without a global or even legally stipulated caste disclosure, caste-related information enters AI screening systems through proxy variables. Such proxies are postal code information that are associated with caste-based segregated residential areas, vernacular system of names that are associated with Dalit communities, and educational achievement measures that inform about past barriers of access and discrimination due to caste.

4.2 AI Recruitment vs. Traditional Recruitment: Comparative Bias Profile

The comparative analysis brings out a subtle observation that cannot be easily ruled out in favour of one of the recruitment approaches. Indian traditional recruitment procedures have been characterised by well-documented instances of bias, such as structured, network-based recruitment procedures that disproportionately seek out applicants of a dominant social network; unstructured hiring processes which are vulnerable to affinity bias and caste-based favouritism and procedures based on reference checks, which give an advantage to those candidates who have social capital located in the institutionalised professional classes.

The recruitment systems based on artificial intelligence reduce the interpersonal bias by eliminating explicit demographic hints at the first stage of screening and use the same scoring rubrics to the applicant. The above-mentioned structural advantages have been empirically proved in specific setups: keyword-neutral competence-based screening has proved to significantly increase the rate of calls back among under-represented groups in experimentally controlled settings.²⁸ Nevertheless, there is secondary data evidence to suggest that, even in their existing deployed applications in India, AI recruitment systems do not, net of

disadvantage, alleviate bias; instead, they repurpose it by turning it into a structural instead of an interpersonal form. The biases that are embedded in the training data and the algorithm design are more systematic, scalable and less easily traceable to individual decision-makers, making them simultaneously more impactful and inaccessible to accountability processes.

According to Tiwari and Agrawal (2025), organisations that implemented AI screening without parallel audit of bias did not see any change in diversity results among the characteristics of the protected category over a two-year implementation time, but organisations that implemented AI screening and implemented structured diversity interventions showed quantifiable improvements.²⁹ These results show that AI-based recruitment technology is not inherently biased or unbiased; instead, it acts as a bias-enhancing or bias-reducing system depending on the governance regimes that it is implemented in.

4.3 Applicant Fairness Perceptions: Key Findings

Analyses of secondary data always indicate less perception of procedural justice in recruitment on AI compared to the human process. A 2024 study of 440 applicants that occurred in the Indian IT industry revealed that procedural fairness scores were reduced by 34 percent when the screening was performed by AI as compared to when the screening was conducted by a human interviewer, and the relationship was more significant when the applicants were rejected. The lack of any form of explanatory feedback became the primary cause of perceived unfairness: applicants screened by AI did not get any feedback as to the rationale behind their being screened out, which gave a sense of arbitrariness that was felt to be more damaging than a straightforward rejection by a human reviewer who could explain why they had been rejected.

According to Mehrotra and Kumari (2024), female candidates and Scheduled community candidates have much more negative views of fairness than upper-caste male candidates, thus showing that AI-based recruitment might create a two-fold burden of fairness: It increases the distributive outcome inequities and at the same time raises the procedural justice concerns among the communities that are most affected by the inequity. Their research claims of pre-application attrition bias, which is the existence of a phenomenon that discourages underrepresented candidates from applying after gaining knowledge of AI screening

procedures, is a measurable harm that is inflicted wholly before the actual recruitment process and is not reflected in the traditional diversity monitoring procedures.

4.4 HR Professionals' Perceptions: Findings

The secondary data analysis reveals the presence of a consistent trend that can be described as the so-called calibrated ambivalence between Indian human resources professionals concerning the artificial intelligence-based recruitment. Tiwari and Agrawal (2025) conclude that these professionals recognize the possibility of AI to increase efficiency and minimize the biases of interviewers, but also express worries about responsibility, openness, and a decline of human judgment when making consequential decisions. About 58 percent of HR practitioners sampled said they were uncomfortable with the idea that an artificial intelligence platform may decline to approve a job seeker without human review of the decision; nevertheless, only 23 percent reported that their organisations require a human to screen the results of AI screening in reality..

According to Pande and Choudhary (2025), HR practitioners that had undergone formal training in AI ethics and algorithmic accountability demonstrated a statistically significant rise in the use of bias monitoring procedures and an increased intent to encourage transparency to applicants. This fact supports the importance of the development of professional human capital in developing the necessary culture of governance that would enable recruiting AI, which brings about implications on the design of training programs in the context of Indian human resource management education.

4.5 Regulatory Environment: Assessment

India's current regulatory environment for AI recruitment is characterised by principled aspiration without enforcement architecture. MeitY's National Strategy for Responsible AI (2024) identifies employment as a high-stakes domain for AI deployment but does not mandate bias auditing, applicant notification, or explainability obligations for HR AI tools. By contrast, the EU AI Act (2024) imposes legally binding conformity assessment requirements, human oversight mandates, and fundamental rights impact assessments on AI recruitment tools, creating a significantly more protective framework for applicants.

Shrivastava and Pandey (2025) document that fewer than 12 per cent of Indian organisations surveyed had conducted any form of algorithmic audit of their recruitment AI, and only 8 per cent had established internal mechanisms to receive and investigate applicant complaints related to AI screening. The existing

provisions of the Persons with Disabilities Act, the Scheduled Castes and Scheduled Tribes (Prevention of Atrocities) Act, and the Sexual Harassment of Women at Workplace Act do not explicitly address algorithmic discrimination, creating legal uncertainty about the applicability of existing anti-discrimination frameworks to AI recruitment decisions.

5. Discussion

5.1 *The Paradox of Algorithmic Objectivity*

The main result of this paper the idea that AI-based recruitment systems in India do not kill prejudice but change it to another level alters the prejudice to a structural register, but does not eradicate it has both theoretical and practical implications. This ideology of algorithmic objectivity, the motivation behind adoption among Indian HR professionals, is what sociologists of technology call a technical myth: a belief in the inherent objectivity of the computational systems that hide the social processes of the creation and enactment of the system, its training, and its application. This myth is especially stubborn in that it appeals to the actually legitimate fears about human bias in the traditional hiring process; the valid objection of interpersonal bias in human-based hiring processes is used to sell AI products as categorically better without sufficient empirical evidence to back this argument in Indian organisational settings.

The comparative study demonstrates that bias in both conventional and AI recruiting are not the same governance issues. The traditional interpersonal bias, as it is detrimental and prevalent, is responsible to the accountability of the legal complaint procedures, diversity requirements of interviewee panels, and social responsibility. The effect of algorithmic bias exists on another scale, yields a formally opaque and legally inattributable result, and is inbuilt within commercial products the internal structure of which is often considered proprietary knowledge. Such a lack of balance in responsibility implies that the implementation of AI recruitment should be met with comparatively stricter governance conditions instead of being diluted.

5.2 *The Dual Justice Deficit*

The finding that AI recruitment generates a dual fairness burden-adverse distributional outcomes for under-represented groups combined with heightened procedural justice concerns among those groups-represents a compounding equity problem. Organisational justice theory predicts that procedural unfairness perceptions, when experienced in addition to distributive unfairness, produce more intense negative

responses including organisational withdrawal, reduced engagement, and reputational harm to the employer brand.³⁰ For Indian organisations competing for talent in a market characterised by rising educational attainment and growing awareness of workplace rights, this dual justice deficit carries material human capital costs that extend beyond ethical concern.

The phenomenon of pre-application attrition bias identified by Mehrotra and Kumari (2024) is particularly significant because it is structurally invisible to conventional diversity monitoring.³¹ If organisations measure diversity outcomes only among applicants who submit applications, they cannot observe the chilling effect that AI screening awareness exerts on the decision to apply. This creates a systematic blind spot in diversity management analytics that is likely to produce underestimates of AI recruitment's equity costs.

5.3 The Governance Gap: India in Comparative Perspective

A comparison between the regulatory practice of India and the EU AI Act predicts a severe regulation gap. The Indian approach of controlling AI in employment has been principled but non-committal, and thus it is just an example of regulatory laggardice that can be used to describe digital governance in emerging economies. However, this analogy must not be regarded as an ode to the unrestricted transplant of the EU regulatory framework in the context of India without contextualization. The EU model was designed in a unique legal tradition, the structure of the labour market and an institutional capacity setting. Indeed, Indian policymakers are under the imperative of the need to design regulatory structures that are substantively protective, institutionally viable and sensitive to the specific equity issues of India- that includes discrimination based on caste, which is a kind of discrimination that the EU anti-discrimination laws do not recognize.

Agarwal and Mishra (2024) found that a requirement that AI tools used in high-volume hiring decisions be audited by a third party is the most effective form of short-term governance intervention in India to enhance AI use because of the risk of bias and the magnitude of the decision. This mandate would create a market in the sale of auditing services based on algorithms, an incentive on vendor to create auditable systems,

and provide relevant information to applicants about the equity profile of the recruitment systems they participate in.

6. Conclusion

The paper has explored the role of AI-based recruitment systems in the perception of hiring bias and fairness in Indian organisations by conducting a systematic analysis of secondary data on recent literature and policy documents. The evidence points to a counterintuitive conclusion: the introduction of AI-based recruitment systems that are active in India now are led to believe that the bias in hiring is reinforced but not eliminated, not because the computational processing is inherently discriminatory, but because it is being applied to the historically skewed data, without a system of effective governance in place, and enacted in an organisational culture that equates computational processing with impartiality. The contribution of the study is three-fold. Hypothetically, it contributes to the knowledge of AI recruitment bias in a Global South environment that is significantly different in contrast to the Western environments of the current literature, thus presenting caste, linguistic diversity, and digital inequality as unique elements of structural bias in AI bias ecology in India. It empirically presents the latest evidence of perceptions of fairness among applicants and HR professionals in India in a synthesis, where a consistent trend of procedural justice deficiency is observed among the under-represented groups. In practice, it outlines the governance divide between the existing regulatory framework in India and the safeguards that are considered to be needed in similar jurisdictions on AI governance. The policy and management advice derived out of this analysis is: (i) implementation of mandatory algorithmic impact assessment of AI recruitment applications used in high-volume hiring; (ii) mandatory applicant-facing explainability in AI screening cases; (iii) institutional ability to conduct third-party algorithmic audit on regulatory basis; (iv) purchase standards, which ensure vendors demonstrate caste- and gender-neutral performance in Indian specific demographic groups; and (v) integrated AI ethics and algorithmic accountability into HR manager professional certification programs. The shortcomings associated with a secondary data analysis need to be overcome in future research by undertaking primary empirical research on applicants and HR professionals working in the various sectors and geographies within India. Causal evidence would be especially beneficial with longitudinal designs that would be able to monitor the bias results prior and after the implementation of AI. The least theorised and empirically underdeveloped aspect of this area is the intersection of caste identity with AI recruitment bias, and should receive specific scholarly interest.

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