International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

AI-BASED RECRUITMENT AND SELECTION: BIAS, FAIRNESS AND TRANSPARENCY

Bhargavi Dasgupta
E.Tanushree
K.pranitha
Department: MBA
Institution: Geethanjali College of Engineering and Technology

Academic Year: 2025–2027

Abstract

Companies now use artificial intelligence (AI) at many steps of hiring: showing job ads, reading résumés, ranking applicants, running online tests, scheduling interviews and analysing video interviews. These tools can save time and handle thousands of applications. But they also raise worries about bias, fairness, transparency, privacy and accountability.

This paper looks at these issues, with a focus on India. It uses published research and official guidance, and it designs a simple survey study of job applicants, MBA students and HR professionals. The survey measures awareness, perceived bias, perceived fairness, transparency and trust.

The literature shows two key points. First, AI can repeat old inequalities if it learns from past hiring decisions. Second, a highly accurate system is not automatically a fair one. The paper suggests practical safeguards: job-related validation, representative data, testing for each group, clear communication with candidates, human review, appeal routes, vendor accountability and regular audits.

Important note: Real survey responses have not yet been collected. The tables in Section 8 use a *simulated* (made-up) dataset of 120 respondents, only to show how the analysis will look. They are **not real findings** and must be replaced with genuine data.

Keywords: Artificial Intelligence; Algorithmic Recruitment; Selection; Algorithmic Bias; Perceived Fairness; Transparency

1. Introduction

1.1 Background

Recruitment and selection shape the quality and diversity of an organisation's workforce. Online applications have grown so much that employers rely on AI tools to source candidates, parse résumés, match skills to job descriptions, run online tests, analyse interviews and suggest shortlists.

AI can cut repetitive work and highlight job-relevant information. However, AI does not act on its own. People decide what data to collect, what "success" means, which variables to include and how to use the system's output. If past hiring or performance data reflect unequal opportunities, the AI may learn and repeat those patterns. Bias can also come from incomplete data, measurement errors, proxy variables (for example, a postcode standing in for caste or income), inaccessible test formats and blind trust in vendor claims.

1.2 Statement of the Problem

AI hiring is often called "objective" because it applies the same rules to everyone. But being consistent is not the same as being fair. A system can consistently disadvantage people from groups that are under-represented in its training data. Candidates may also not know that AI is being used, what is being assessed, or how to challenge a wrong result. Employers therefore have a double duty: use technology well, and protect equal opportunity, privacy and human judgement.

1.3 Why This Study Matters

- **For MBA students:** it links HR strategy, ethics, analytics and technology governance.
- **For HR managers:** it shows that buying an AI tool needs more than a check on its features.
- **For applicants:** it concerns fair access to jobs and the ability to question decisions.
- **For Indian organisations:** digital hiring is spreading across sectors and regions.

1.4 Scope and Key Terms

The study covers AI tools that automate or assist sourcing, screening, assessment and selection. Not every Applicant Tracking System (ATS) uses AI; some only store and route applications.

Term	Meaning in this paper
Bias	A repeated pattern of disadvantage for certain groups
Fairness	Justified, job-related treatment and outcomes
Transparency	Clear information about AI use, criteria, who decides and how to seek review

These ideas overlap but are not the same.

2. Literature Review

2.1 Discrimination by algorithms. Köchling and Wehner (2020) reviewed studies on algorithmic decision-making in HR. They found that algorithms can raise efficiency but also create hidden discrimination and a sense of unfairness. Their advice: examine the data and process behind the algorithm instead of assuming automation is neutral.

2.2 Ethical issues. Hunkenschroer and Lütge (2022) mapped the opportunities and risks of AI recruiting, including fairness, privacy, accountability and the need for ethical oversight. They treat AI hiring as a mix of technology, organisations, vendors and people, not just software.

2.3 Vendor claims. Raghavan et al. (2020) studied companies that sell AI hiring assessments. They warn organisations not to accept claims of "objectivity" or "bias-free" results without checking what the system predicts, what data it learned from, how it was validated and what its limits are.

2.4 Video interviews. Köchling et al. (2021) tested video analysis tools. When some groups were under-represented in the training data, results were less accurate and unequal across gender and ethnic groups. Lesson: high overall accuracy can hide poor results for specific groups. Video, face or voice analysis should be used only when job relevance and validity are proven.

2.5 Broad fairness research. Fabris et al. (2025) surveyed fairness in algorithmic hiring across disciplines. They show how bias can enter at sourcing, screening, selection and evaluation. The real question is not "are algorithms better than humans?" but "does this system, in this setting, give defensible results and can it be governed responsibly?"

2.6 Guidance and law.

- *NIST AI Risk Management Framework (2023)* lists traits of trustworthy AI: validity, reliability, accountability, transparency, explainability, privacy and managed bias. Its four functions are **Govern, Map, Measure, Manage**, which HR teams can use to assign responsibility, understand context, test outcomes and respond to risks.
- *India's Digital Personal Data Protection Act, 2023* sets rules for handling personal data. For hiring, it touches candidate information, notices, lawful processing, security and individual rights, subject to the Act's provisions and commencement dates. Organisations should take current legal advice; this paper is not legal advice.

2.7 Evidence including India. A recent study by Kulkarnic and Chacón (2026) compared applicants' views of AI evaluation in Chile, Germany and India and found that country context shapes perceptions such as opportunity to perform and consistency. So India is already part of the research literature, and this paper does not claim to be the first study of Indian applicants.

2.8 Summary of Selected Studies

Author(s) and year	Focus	Contribution to this paper
Köchling & Wehner (2020)	Systematic review of algorithmic HR decisions	Maps discrimination and fairness risks
Raghavan et al. (2020)	Hiring-assessment vendors	Shows why validation and vendor claims need scrutiny
Köchling et al. (2021)	Fairness of video analysis	Shows how unbalanced data creates unequal outcomes
Hunkenschroer & Lütge (2022)	Ethics of AI recruiting	Identifies ethical risks and mitigation areas
Fabris et al. (2025)	Multidisciplinary survey	Links hiring pipeline, bias sources and governance
NIST (2023)	Voluntary AI risk framework	Offers a governance structure
Kulkarnic & Chacón (2026)	Applicant views in Chile, Germany, India	Shows national context matters

3. Research Gap

What is known. Earlier work shows that AI hiring brings efficiency but also risks of unfair treatment, and that vendor claims and validity must be questioned.

What is still under-studied. Technical fairness and *perceived* fairness are different. A tool may apply the same rules to all, yet applicants may still see the process as unfair if they do not understand it, cannot show their abilities, get no human contact or have no way to question the result. Studies such as Ochmann et al. (2024) examine how transparency affects fairness perceptions. Since newer research already includes India, the remaining opportunity is narrower.

Gap addressed here. This study looks at how several perceptions go together in one defined Indian group: awareness, perceived bias, fairness, transparency, trust and preferred human involvement. It collects views from students, job seekers, employed people and HR professionals using a 25-question survey.

Boundary. The survey measures *opinions*. It does not audit a real algorithm, measure real selection results or prove that any tool discriminates. Findings are respondents' views, not technical proof or evidence of cause, and should not be generalised beyond the sample.

4. Objectives

1 To understand how AI is used in recruitment and selection.

2 To identify perceived sources and forms of bias in AI-assisted hiring.

3 To examine perceptions of fairness in AI screening and selection.

4 To assess whether transparency is linked to candidate trust.

5 To understand how important people find human oversight and the right to request review.

6 To recommend practical steps for responsible, inclusive AI hiring in Indian organisations.

5. Hypotheses

The hypotheses test *association*, not cause and effect, and will be tested only after real data are collected.

Code	Null hypothesis (H0)	Alternative hypothesis (H1)
H1	No significant association between perceived transparency and candidate trust	There is a significant association
H2	No significant association between perceived fairness and willingness to accept AI-assisted selection	There is a significant association
H3	No significant difference in perceived fairness between people with and without prior AI-recruitment experience	There is a significant difference

The exact test depends on the scale, sample size and data distribution. Correlation can be used for suitable composite Likert scores; a t-test or a non-parametric alternative can compare groups. Report significance together with effect sizes and limitations.

6. Research Methodology

Design. Descriptive and analytical, cross-sectional (a snapshot at one point in time), combining secondary research with a primary survey. Optional interviews with HR professionals can add context.

Population and sample. Adult job applicants, MBA or other postgraduate students who have applied for jobs or internships, and HR/recruitment professionals. A practical MBA target is 100–150 valid responses. This is a convenience/purposive sample, not a probability sample, so conclusions apply only to respondents.

Sampling. Convenience sampling to reach eligible people, plus purposive sampling to include HR professionals. Record the recruitment channel, collect minimal identifying information, and keep participation voluntary.

Data sources.

- *Primary:* structured questionnaire (Google Forms or similar); optional interviews.
- *Secondary:* journal articles, conference papers, legal materials and guidance such as NIST.

Instrument. Demographic and experience questions, then five-point Likert items (1 = Strongly Disagree to 5 = Strongly Agree). Constructs: awareness/experience, perceived bias, perceived fairness, transparency, trust and human oversight. Pilot the questions with a small group first.

Ethics. Give an information statement (purpose, voluntary nature, time needed). Do not collect names, phone numbers, employer names or sensitive details unless essential and approved. Explain how data will be stored and reported. Let participants stop before submitting. Follow institutional ethics rules and data-protection law.

6.1 The 25-Question Questionnaire (Summary)

Participation is voluntary, responses are used only for academic research, and respondents should not give names or direct identifiers.

Section	Questions	Topic	Example
A	Q1–Q4	Demographics	Age group, gender, qualification, employment status
B	Q5–Q8	Awareness and experience	Have you experienced an AI-based recruitment process?
C	Q9–Q12	Bias and discrimination	Can AI recruitment systems discriminate against candidates?
D	Q13–Q16	Fairness	Is AI recruitment fairer than human recruitment?
E	Q17–Q20	Transparency and trust	Should organisations tell candidates when AI is used?
F	Q21–Q25	HR oversight and ethical AI	Should HR review AI decisions before final selection?

Q7, Q8 and Q23 allow multiple selections; Q25 is open-ended. Most opinion questions use the five-point agreement scale; others use Yes/No/Maybe or categorical options.

7. Data Analysis and Interpretation (Simulated Illustration)

Warning: All figures below come from a **simulated dataset (N = 120)** created to show how results would be presented. They are *not* evidence about real applicants, students or HR professionals. Replace them with genuine data before submission.

Percentages are out of 120. For multiple-response questions (Q7, Q8, Q23), percentages can add up to more than 100%. "Agree" combines *Agree* and *Strongly agree*; "Disagree" combines *Disagree* and *Strongly disagree*.

7.1 Demographic Profile (simulated)

Variable	Largest group	Other groups
Age	20–25: 60 (50.0%)	26–30: 18.3%; 31–40: 17.5%; Above 40: 7.5%; Below 20: 6.7%
Gender	Female: 60 (50.0%)	Male: 46.7%; Prefer not to say: 2.5%; Other: 0.8%
Education	Postgraduate: 62 (51.7%)	Undergraduate: 30.0%; Diploma: 9.2%; Other: 5.8%; Doctorate: 3.3%
Employment	Student: 39 (32.5%)	Job seeker: 22.5%; Employed: 20.8%; Other: 11.7%; HR professional: 6.7%; Self-employed: 5.8%

7.2 Awareness and Experience (simulated)

Question	Result
Q5. Aware of AI in recruitment	Yes 45.0%; Somewhat 41.7%; No 13.3%
Q6. Experienced an AI-based process	No 60.0%; Yes 27.5%; Not sure 12.5%

Q7. Where respondents heard about it: Social media 54.2%; College/University 49.2%; Job portals 45.0%; Workplace 30.0%; Friends/Family 27.5%; Other 6.7%.

Q8. Familiar AI activities: Résumé screening 75.8%; Candidate shortlisting 71.7%; Online assessments 57.5%; Candidate matching 55.8%; AI video interviews 46.7%; AI chatbots 46.7%; None 5.0%.

Reading: In this simulation, most respondents know about AI hiring, but only about one in four has personally experienced it. Résumé screening and shortlisting are the best-known uses.

7.3 Bias and Discrimination (simulated)

Question	Agree (incl. strongly)	Neutral	Disagree (incl. strongly)
Q9. AI systems can discriminate	65.0%	19.2%	15.8%
Q10. AI may show bias by gender, age or education	76.7%	13.3%	10.0%
Q12. AI may unfairly reject qualified candidates (e.g., employment gaps)	59.1%	21.7%	19.2%

Q11. Can biased historical data influence AI decisions? Yes 63.3%; Maybe 20.8%; Not sure 9.2%; No 6.7%.

Reading: In this simulation, most respondents believe AI can be biased, and most accept that old data can shape its decisions.

7.4 Fairness (simulated)

Question	Result
Q13. AI is fairer than human recruitment	Agree 28.3%; Neutral 20.8%; Disagree 50.8%
Q14. AI can reduce personal bias and favouritism	Agree 50.0%; Neutral 27.5%; Disagree 22.5%
Q16. Equal opportunity regardless of background	Agree 91.7%; Neutral 5.8%; Disagree 2.5%

Q15. Preferred method: Combination of AI and human 69.2%; Completely human 20.0%; No preference 6.7%; Completely AI 4.2%.

Reading: In this simulation, opinion is split on whether AI is fairer than humans, but a clear majority prefers a mix of AI and human judgement.

7.5 Transparency and Trust (simulated)

Question	Result
Q17. Organisations should inform candidates when AI is used	Yes 79.2%; No 11.7%; Maybe 9.2%

Question	Result
Q18. Understand how AI evaluates résumés	Do not understand 36.7%; Partially 33.3%; Not sure 21.7%; Completely 8.3%
Q19. Trust in AI-based decisions	Trust 25.0%; Neutral 35.0%; Distrust 40.0%
Q20. Right to an explanation after rejection	Yes 79.2%; Maybe 13.3%; No 7.5%

Reading: In this simulation, few people say they fully understand AI evaluation, trust is low, and most want disclosure and explanations.

7.6 HR Role and Ethical AI (simulated)

Question	Agree (incl. strongly)	Neutral	Disagree (incl. strongly)
Q21. HR should review AI decisions before final selection	90.8%	7.5%	1.7%
Q22. Organisations should regularly audit AI for bias	90.0%	5.8%	4.1%
Q24. AI should support, not replace, HR professionals	91.6%	5.8%	2.5%

Q23. Most important safeguards: Human supervision 81.7%; Transparent selection criteria 77.5%; Equal employment opportunities 71.7%; Regular bias audits 63.3%; Candidate data protection 63.3%; Regular monitoring of AI systems 62.5%; Clear explanations for rejection 56.7%.

Q25. Overall opinion (simulated themes): AI is useful if monitored by humans 26.7%; Human judgement should remain important 24.2%; AI may reduce favouritism but can contain bias 24.2%; Transparency and explanation are essential 20.8%; Limited knowledge or no clear opinion 4.2%.

7.7 Plan for Testing Hypotheses (after real data)

Because the data are simulated, no hypothesis can be accepted or rejected now. After genuine data are collected:

Relationship	Questions	Possible test
Transparency and trust	Q17–Q20	Cross-tabulations; ordinal association tests if coded properly (do not mix response formats automatically)
Fairness and acceptance	Q13–Q16	Descriptive comparisons and an association test suited to the variable types
Prior experience and fairness	Q6 with Q13 and Q14	Chi-square or Mann–Whitney U, depending on coding and assumptions

7.8 Overall Caution

The simulated pattern only shows how an MBA paper can discuss bias, fairness, transparency and HR oversight. Any apparent majority or relationship is an artefact of how the data were generated. To complete the study: collect real responses, export them from Google Forms, and replace every simulated count, percentage, interpretation and chart with recalculated results.

8. Findings (from the Literature)

These are literature-based themes, **not survey results**.

1 AI can improve administrative efficiency, but efficiency does not prove a hiring decision is valid or fair.

2 Historical data and proxy variables can carry old inequalities forward.

3 Overall accuracy can hide uneven errors or outcomes for different groups.

4 Transparency helps applicants understand, trust and challenge decisions.

5 Human oversight works only when reviewers have the authority, information and skill to question the algorithm.

6 Fair hiring needs continuous monitoring across the whole hiring process, not a one-time software check.

After data collection, add respondent-specific findings supported by frequencies, charts and statistical tests.

9. Suggestions

1 **Keep AI use job-related.** Avoid inferring emotions, voice, accent or personality from faces or speech unless strong validity evidence exists.

2 **Audit the data.** Check training and assessment data for representation, quality, historical bias and missing groups; document sources and limits.

3 **Validate each tool** for the specific role and applicant pool. Measure overall performance *and* results for each group; investigate gaps rather than relying on a single fairness metric.

4 **Tell candidates.** Give clear notice of AI use, the stage it supports, the data assessed and how to ask for review.

5 **Keep humans responsible.** Trained decision-makers should own final decisions and be able to override AI with recorded reasons.

6 **Provide accessible alternatives** or reasonable accommodations for candidates who cannot use a given digital format.

7 **Offer an appeal channel** to correct wrong data, technical errors or unfair decisions.

8 **Audit regularly.** Review after launch and whenever the role, applicant pool, model, vendor or data changes; track adverse impact and model drift.

9 **Hold vendors accountable.** Require documentation on validation, limits, data handling, subgroup testing, security and incident reporting, with audit and termination rights in contracts.

10 **Protect privacy by design.** Collect only necessary data, limit access and retention, secure it and follow Indian data-protection requirements.

These steps match the NIST approach of governing, mapping, measuring and managing AI risks. Legal duties depend on jurisdiction and on when relevant provisions take effect.

10. Conclusion

AI can help organisations handle large volumes of applications and give recruiters structured information. But it should never be treated as automatically objective or fair. The quality of an AI-assisted decision depends on relevant and representative data, a valid assessment, the right performance targets, a transparent process and the way people use the results. Bias can enter at many stages and can grow when recommendations are accepted without scrutiny.

This paper reviewed key academic and institutional work and designed a study of applicant, student and HR-professional perceptions in India, focusing on transparency, fairness, trust and human oversight. Since real survey data are not yet available, no hypothesis is confirmed.

The central message: responsible AI recruitment combines efficiency with job-related validation, regular fairness audits, clear communication, privacy safeguards, accessible assessments and accountable human review. AI should **assist** HR judgement, not replace it.

11. References

Fabris, A., Baranowska, N., Dennis, M. J., Graus, D., Hacker, P., Saldivar, J., Zuiderveen Borgesius, F., & Biega, A. J. (2025). Fairness and bias in algorithmic hiring: A multidisciplinary survey. *ACM Transactions on Intelligent Systems and Technology, 16*(1), Article 16. https://doi.org/10.1145/3696457

Hunkenschroer, A. L., & Lütge, C. (2022). Ethics of AI-enabled recruiting and selection: A review and research agenda. *Journal of Business Ethics, 178*, 977–1007. https://doi.org/10.1007/s10551-022-05049-6

Köchling, A., Riazy, S., Wehner, M. C., & Simbeck, K. (2021). Highly accurate, but still discriminatory: A fairness evaluation of algorithmic video analysis in the recruitment context. *Business & Information Systems Engineering, 63*, 39–54. https://doi.org/10.1007/s12599-020-00673-w

Köchling, A., & Wehner, M. C. (2020). Discriminated by an algorithm: A systematic review of discrimination and fairness by algorithmic decision-making in the context of HR recruitment and HR development. *Business Research, 13*, 795–848.

https://doi.org/10.1007/s40685-020-00134-w

Kulkarnic, S., & Chacón, A. (2026). Applicants' perceptions of AI in personnel selection across Chile, Germany, and India. *The International Journal of Human Resource Management*. Advance online publication. https://doi.org/10.1080/09585192.2026.2750359

Ministry of Law and Justice, Government of India. (2023). *The Digital Personal Data Protection Act, 2023* (Act No. 22 of 2023). https://www.meity.gov.in/writereaddata/files/Digital%20Personal%20Data%20Protection%20Act%202023.pdf

National Institute of Standards and Technology. (2023). *Artificial intelligence risk management framework (AI RMF 1.0)* (NIST AI 100-1). U.S. Department of Commerce. https://doi.org/10.6028/NIST.AI.100-1

Raghavan, M., Barocas, S., Kleinberg, J., & Levy, K. (2020). Mitigating bias in algorithmic hiring: Evaluating claims and practices. *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, 469–481. https://doi.org/10.1145/3351095.3372828

Ochmann et al. (2024) is cited in Section 4 from the original paper; add its full reference from your source before submitting.