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Impact of AI Driven Recruitment on Hiring Quality and Diversity in IT firms: Evidence from India

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ABSTRACT

Artificial intelligence (AI) is fundamentally reshaping recruitment and talent acquisition across industries. In the Indian information technology (IT) sector, which employs over five million professionals and contributes approximately USD 245 billion in annual exports, AI-driven recruitment tools encompassing resume screening algorithms, chatbot-based interviews, predictive performance assessments, and video-analytics platforms have moved from experimental adoption to mainstream practice within a remarkably short span. These tools promise enhanced efficiency, cost reduction, and ostensibly objective candidate evaluation. However, a growing body of evidence from global markets reveals a paradox: algorithmic systems trained on historically biased data tend to replicate and even amplify the very biases they are presumed to eliminate, raising critical concerns about their consequences for workforce diversity, particularly in a socially stratified country like India, where dimensions of gender, caste, regional origin, and institutional affiliation intersect in complex ways.

This paper presents the design of a mixed-methods empirical investigation examining the dual impact of AI-driven recruitment on (a) hiring quality, operationalised through new-hire retention rates, supervisor-rated performance scores, and time-to-full-productivity metrics; and (b) diversity outcomes, assessed through gender representation ratios, regional diversity indices, and institutional tier distribution among recruits. Drawing upon a sample of IT firms operating across Bengaluru, Hyderabad, Pune, Delhi-NCR, and Indore, the study combines a structured questionnaire survey of 200 HR managers and talent acquisition professionals with 30 semi-structured interviews of recently recruited employees. The theoretical framework integrates three complementary lenses: Algorithmic Accountability Theory (Diakopoulos, 2016), Social Identity Theory (Tajfel & Turner, 1979), and the Resource-Based View of the firm (Barney, 1991).

The study anticipates a nuanced set of findings: AI recruitment tools are expected to deliver measurable improvements in short-term hiring efficiency but show significantly weaker associations with long-term retention and performance. More critically, firms relying solely on AI screening without complementary diversity, equity, and inclusion (DEI) governance mechanisms are expected to show substantially narrower diversity pipelines, particularly disadvantaging women candidates, graduates from Tier-2/3 universities, and applicants from non-metropolitan backgrounds. Organisational moderators including the presence of algorithmic auditing protocols, active DEI policies, and mandatory human review at shortlisting stages are

hypothesised to significantly buffer these adverse effects. The paper concludes by proposing a five-pillar Ethical AI Recruitment Governance Framework tailored to the Indian IT context, offering actionable guidance for HR practitioners, technology vendors, NASSCOM, and the Ministry of Electronics and Information Technology (MEITY).

KEYWORDS
AI recruitment, algorithmic bias, hiring quality, workforce diversity, HR technology, India, IT sector, algorithmic accountability, DEI, talent acquisition

List of Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
ATS	Applicant Tracking System
CFA	Confirmatory Factor Analysis
DEI	Diversity, Equity, and Inclusion
HEI	Higher Education Institution
HRM	Human Resource Management
HR	Human Resources
IT	Information Technology
ILO	International Labour Organization
MEITY	Ministry of Electronics and Information Technology, Government of India
MNC	Multinational Corporation
MSME	Micro, Small and Medium Enterprise
NASSCOM	National Association of Software and Service Companies
NLP	Natural Language Processing
OB	Organisational Behaviour
RBV	Resource-Based View
SC/ST	Scheduled Caste / Scheduled Tribe
SIT	Social Identity Theory
UGC	University Grants Commission

1. INTRODUCTION

1.1 Background and Context

The global talent acquisition landscape has undergone a profound technological transformation over the past decade. The global recruitment technology market, valued at approximately USD 3.17 billion in 2023, is projected to expand at a compound annual growth rate of 7.1% through 2030, driven by widespread adoption of machine learning, natural language processing, and predictive analytics in hiring workflows (SHRM, 2022; ILO, 2023). Within this global wave of HR-tech adoption, India's information technology sector occupies a uniquely prominent and revealing position.

India's IT industry, which directly employs over 5.4 million professionals and contributes approximately USD 245 billion in exports annually (NASSCOM, 2023), has been among the earliest and most intensive adopters of AI-based hiring tools. Organisations ranging from IT conglomerates such as TCS, Infosys, Wipro, and HCL, to thousands of mid-tier IT service providers and emerging product start-ups, now routinely deploy AI at multiple stages of the recruitment funnelfrom initial job advertisement targeting and resume screening, through automated preliminary interviews and psychometric assessments, to final-stage predictive fit analytics. The appeal is evident: AI-enabled recruitment dramatically compresses time-to-hire, reduces administrative burden on HR professionals, and introduces a veneer of data-driven objectivity to what has historically been a highly subjective process (Tambe, Cappelli, & Yakubovich, 2019; Cappelli, 2019).

However, this technological optimism has been sharply tempered by high-profile failures and mounting empirical evidence of systemic bias. In 2018, Amazon discontinued an internally developed AI recruiting tool after discovering that the system had systematically downgraded resumes containing the word 'women' and penalised graduates of all-women's colleges (Dastin, 2018). Hire Vue, a major provider of AI-powered video interview analysis, faced regulatory scrutiny in the United States after researchers demonstrated that its facial and tonal analysis algorithms exhibited racially differential outcomes (Suen, Chen, & Lu, 2019). The European Union's 2024 AI Act subsequently classified AI systems used in employment screening as high-risk applications mandating mandatory transparency and auditing requirements (European Commission, 2021).

India, despite its position as both a leading producer and consumer of AI-enabled recruitment technology, has yet to develop comparable regulatory frameworks, empirical research foundations, or governance standards. The unique socio-demographic complexity of the Indian context encompassing intersecting dimensions of gender inequality, caste-based discrimination, regional disparity between metropolitan and Tier-2/3 cities, and the sharp hierarchical stratification of India's higher education system renders the potential consequences of biased algorithmic hiring particularly acute (Ilavarasan, 2022; Pande, 2020; Kumar & Jain, 2021).

1.2 Research Problem

Despite the rapid proliferation of AI recruitment technologies in India's IT sector, there is a critical and consequential gap in empirical evidence about their real-world impact. Specifically, very little is known about: (a) whether AI-driven recruitment tools actually produce demonstrably better hires, as measured by retention, performance, and productivity outcomes as opposed to merely faster and cheaper hiring processes; and (b) whether the adoption of these tools is systematically narrowing the diversity of the talent pipeline, particularly along dimensions of gender, caste, regional origin, and institutional affiliation.

This knowledge gap is not merely academic. HR professionals deploying these tools are making consequential decisions that affect thousands of careers annually, often without adequate understanding of the differential impacts on different candidate groups. Simultaneously, candidates from disadvantaged backgrounds may be systematically filtered out by algorithms that were never designed and certainly never audited with their circumstances in mind.

1.3 Significance of the Study

- This study makes a direct contribution to the emerging literature on HR technology in the specific context of developing economies and emerging labour markets, where the consequences of algorithmic bias may be more acute due to existing structural inequalities.
- The findings are directly relevant to India's National Education Policy 2020 goals of promoting inclusive and equitable access to high-quality employment, particularly for first-generation learners from non-metropolitan regions.
- The proposed Ethical AI Governance Framework offers actionable, context-specific guidance for Indian IT HR managers, talent acquisition leaders, NASSCOM, and MEITY in designing and auditing AI recruitment systems.
- The study bridges a critical gap between the rapid pace of technology adoption in HR practice and the slower development of evidence-based, ethical governance standards.
- For the academic community, the study contributes a validated mixed-methods instrument for studying AI-recruitment impacts, which other researchers can adapt for different sectors and regions.

1.4 Scope and Delimitations

The study is limited to IT firms operating in India with a minimum workforce of 500 employees that have formally adopted at least one AI-driven recruitment tool in the three-year period 2021-2024. This delimitation captures firms large enough to have structured HR functions while covering the critical post-pandemic period of accelerated HR-tech adoption. The study does not examine start-ups with fewer than 50 employees, public sector IT organisations, or IT-enabled services (ITeS) firms that fall outside the pure IT services/products category.

1.5 Research Objectives

Primary Objectives:

1. To examine the extent, nature, and stage-wise deployment of AI-driven recruitment tools across Indian IT firms.
2. To assess the impact of AI recruitment tools on hiring quality, measured through new-hire retention rates, supervisor-rated performance, and time-to-full-productivity.
3. To evaluate the impact of AI recruitment adoption on workforce diversity outcomes specifically gender representation, regional diversity, and institutional tier distribution.
4. To identify organisational moderators that buffer or amplify the relationship between AI recruitment adoption and diversity outcomes.

Secondary Objectives:

5. To explore candidate-side perceptions of fairness, transparency, and procedural justice in AI-mediated selection processes.
6. To propose a context-specific, actionable Ethical AI Recruitment Governance Framework for Indian IT organisations.

1.6 Research Questions

- RQ1: What types of AI recruitment tools are deployed in Indian IT firms, at which hiring stages, and what is the depth of their usage?
- RQ2: Does AI-driven recruitment produce statistically significant improvements in hire quality (retention, performance) compared to traditional methods?
- RQ3: Is there a significant difference in diversity outcomes (gender, region, institution tier) between AI-adopting and non-AI-adopting firms?
- RQ4: Do organisational factors DEI policy presence, algorithmic auditing, human oversight moderate the AI-diversity relationship?
- RQ5: How do recently hired candidates from diverse backgrounds perceive the fairness and transparency of AI-mediated selection?

1.7 Hypotheses

Hypothesis	Statement	Direction
H1	AI-driven recruitment adoption is positively associated with hiring quality (retention rate and supervisor performance ratings).	Positive
H2	AI-driven recruitment is negatively associated with gender diversity in new hire cohorts.	Negative
H3	AI-driven recruitment reduces representation of candidates from Tier-2/3 cities and non-IIT/NIT institutions.	Negative

Hypothesis	Statement	Direction
H4	The presence of active DEI policies moderates the negative effect of AI recruitment on diversity outcomes.	Positive Moderation
H5	Algorithmic auditing practices positively moderate the relationship between AI recruitment and diversity.	Positive Moderation
H6	Mandatory human review at the shortlisting stage significantly reduces the adverse diversity impact of AI tools.	Positive Moderation

2. CONCEPTUAL AND THEORETICAL FRAMEWORK

The study draws upon three complementary theoretical lenses to construct an integrated framework for understanding the mechanisms through which AI recruitment tools influence both hiring quality and diversity outcomes. Each theory illuminates a different dimension of the phenomenon.

2.1 Algorithmic Accountability Theory

Diakopoulos (2016) argues that as consequential decisions in human affairs are increasingly delegated to automated algorithmic systems, questions of accountability who is responsible when these systems produce harmful outcomes become both urgent and complex. Algorithmic Accountability Theory holds that accountability rests not with the algorithm itself, but with the human agents and organisations that design, deploy, govern, and profit from it. In the context of AI recruitment, this means that IT firms bear full moral and legal accountability for the disparate outcomes produced by their AI tools, regardless of whether those tools were built in-house or purchased from third-party vendors.

This theory provides the normative foundation for this study's governance focus: if organisations are accountable for algorithmic outcomes, they require governance frameworks that enable them to identify, measure, and correct biased outputs. The study applies this theory to diagnose the current absence of governance structures in Indian IT HR practice and to motivate its proposed five-pillar framework.

2.2 Social Identity Theory (SIT)

Tajfel and Turner's (1979) Social Identity Theory proposes that individuals derive a significant portion of their self-concept from their membership in social groups (gender, caste, ethnicity, regional origin, institutional affiliation). This group membership shapes cognition, behaviour, and inter-group dynamics in predictable ways. Applied to AI recruitment, SIT operates at two levels.

At the data level: Historical hiring data used to train AI models reflects decades of decisions made by human recruiters who were themselves subject to in-group favouritism preferring candidates from elite institutions, metropolitan backgrounds, and dominant social groups. AI models trained on such data will learn to associate these group memberships with 'successful' hires, thereby encoding and perpetuating the bias.

At the candidate level: SIT predicts that candidates from marginalised social identity groups (women, SC/ST applicants, regional language speakers, graduates of lower-tier institutions) will systematically fare worse in AI-mediated assessments calibrated to the historical majority, not because of their actual competence, but because their social markers diverge from the profile that the algorithm has learned to reward.

2.3 Resource-Based View (RBV) of the Firm

Barney's (1991) Resource-Based View holds that a firm's sustainable competitive advantage derives from resources that are valuable, rare, inimitable, and non-substitutable (the VRIN criteria). Diverse human capital teams composed of individuals with heterogeneous perspectives, cognitive styles, cultural knowledge, and problem-solving approaches meets all four VRIN criteria in innovation-intensive industries.

In the context of this study, RBV provides the business case for diversity: if AI recruitment systematically narrows the talent pipeline by excluding diverse candidates, it does not merely raise ethical concerns it actively undermines the firm's long-term competitive advantage. This reframes diversity not as a compliance obligation but as a strategic imperative, offering HR practitioners a business-grounded justification for investing in bias mitigation.

2.4 Integrated Conceptual Framework

ANTECEDENTS (Input Layer)
AI Tool Characteristics: Type (NLP screening, video AI, predictive analytics), Stage of deployment (sourcing, screening, interviewing, selection), Vendor design decisions, Training data composition and historical bias

PROCESS LAYER — Theoretical Mechanisms
Algorithmic Accountability Theory: Who governs, audits, and corrects AI outputs? | Social Identity Theory: How do social group markers encoded in training data produce differential outcomes for candidates? | Resource-Based View: How does talent pipeline narrowing affect long-run firm performance?

MODERATING CONDITIONS (Organisational Context)
Presence of DEI policy | Algorithmic auditing protocols | Human-in-the-loop at shortlisting | Diversity training for HR professionals | Leadership commitment to inclusive hiring

OUTCOMES (Dual Dependent Variables)
Hiring Quality: Retention rate (90-day, 1-year), Supervisor performance ratings (6-month), Time-to-full-productivity | Diversity Outcomes: Gender ratio in hire cohort, Regional representation (metro vs. Tier-2/3), Institutional tier distribution (IIT/NIT vs. state university vs. others)

3. LITERATURE REVIEW

The literature review is organised around five thematic clusters that progressively build the evidential and conceptual foundation for the study's hypotheses and framework.

3.1 Evolution of AI in Recruitment Technology

Recruitment technology has evolved through distinct generational phases. The first generation, spanning the 1990s and early 2000s, encompassed rule-based applicant tracking systems (ATS) that automated administrative workflows job posting, application collection, and basic keyword filtering. The second generation introduced psychometric and competency-based online assessment platforms, enabling standardised pre-employment testing at scale. The current, third generation is characterised by machine learning-driven systems capable of unstructured data interpretation parsing free-text resumes, analysing video interview footage for micro-expressions, evaluating vocal prosody for 'culture fit,' and predicting future performance from combinations of social media data, game-based assessments, and historical hiring outcomes (Chamorro-Premuzic, Akhtar, Winsborough, & Sherman, 2017; Tambe, Cappelli, & Yakubovich, 2019).

In the Indian context, adoption has been rapid but uneven. Large IT MNCs such as TCS and Infosys invested in proprietary AI recruitment infrastructure as early as 2017. Mid-tier firms predominantly rely on commercially available platforms HireVue, Pymetrics, X0PA AI, and India-developed solutions such as Skillate and Talview (Garg, Sinha, Kar, & Mani, 2021; Bhatt & Sharma, 2021). The primary adoption drivers cited by Indian HR professionals are volume management India's IT firms collectively receive millions of applications annually and the need to compress hiring cycles in a competitive talent market.

However, the literature cautions against equating adoption with effectiveness or fairness. Poole and Mackworth (2017) note that ML systems are fundamentally optimisation machines: they maximise the objective they are given, which in recruitment is typically a proxy for 'similarity to past successful hires' rather than genuine future potential. Dattner, Chamorro-Premuzic, Buchband, and Schettler (2019) argue that the legal and ethical liability associated with AI hiring tools is significantly underappreciated by the HR professionals deploying them.

3.2 Hiring Quality and AI Effectiveness

The empirical literature on AI recruitment's impact on actual hiring quality is both limited and methodologically contested. A review by Pessach, Singer, Avrahami, and colleagues (2020) found that ML-based candidate ranking models produced statistically significant improvements in prediction of 90-day retention compared to unaided human judgment in controlled experiments. Gonzalez, Capman, Oswald, Theys, and Tomczak (2019) similarly documented modest improvements in early performance ratings for AI-screened hires in large US firms.

However, both studies suffer from significant methodological limitations: reliance on vendor-supplied data, absence of randomised control conditions, and conflation of interviewer agreement (inter-rater reliability) with actual hire quality. Levashina, Hartwell, Morgeson, and Campion (2014) established that structured human interviews already achieve near-optimal predictive validity for job performance raising the question of whether AI tools add value beyond what well-designed human processes already achieve.

Critically, there are virtually no peer-reviewed Indian studies examining AI recruitment's effect on hire quality in the IT sector. Jain and Bhatt (2023) conducted a systematic review of AI in Indian HR practices and found that 87% of published studies were descriptive or adoption-focused, with fewer than 5% examining outcome-level effectiveness. This represents the most significant empirical gap that the present study addresses.

3.3 Algorithmic Bias and Workforce Diversity

The relationship between AI recruitment and workforce diversity is the most contentious and consequential dimension of the literature. The foundational concern that algorithms trained on historical data will reproduce the biases embedded in that history was documented rigorously by Barocas and Selbst (2016) in their landmark legal analysis of disparate impact doctrine applied to machine learning. O'Neil (2016) popularised the concept of 'weapons of math destruction' algorithms that are opaque, unaccountable, and systematically disadvantageous to already-marginalised groups.

In the gender dimension, Perez (2019) demonstrated that most professional datasets are overwhelmingly male-skewed, causing AI systems to learn male behavioural patterns as the default of professional competence. Noble (2018) extended this analysis to racial and intersectional biases encoded in commercial AI systems. Waddell and Pio (2022) conducted a cross-national study of algorithmic hiring and found consistent patterns of gender underrepresentation in AI-shortlisted candidate pools across eight countries.

The Indian context adds further layers of complexity. Ilavarasan (2022) demonstrated that caste identity can be encoded as a proxy variable through correlated features the name, alma mater, home state, and even language patterns of a resume such that ostensibly caste-neutral screening algorithms can produce caste-differential outcomes. Pande (2020) documented significant gender and caste stratification in Indian IT workplaces even prior to AI adoption, suggesting that AI tools risk amplifying pre-existing structural inequalities. Kumar and Jain (2021) found that diversity and inclusion initiatives in Indian IT firms remain predominantly cosmetic, with limited attention to sourcing-stage interventions.

3.4 Candidate Perceptions and Procedural Fairness

The organisational justice literature (Greenberg, 1987; Colquitt, 2001) provides a well-validated theoretical vocabulary for understanding how candidates evaluate the selection processes to which they are subjected. Procedural justice the perceived fairness of the process, irrespective of its outcome is associated with organisational attractiveness, acceptance of selection decisions, and employer brand strength. Informational justicewhether candidates receive adequate explanations for decisions is particularly salient in AI-mediated contexts where decision logic is opaque.

Suen, Chen, and Lu (2019) found in a Taiwanese study that candidates rated AI-administered video interviews as significantly less fair than human-administered interviews, particularly when no explanation for the AI evaluation criteria was provided. Van Esch, Black, and Ferolie (2019) found that candidates' perceptions of AI fairness are moderated by their familiarity with technology and their prior experience with digital hiring tools.

In the Indian context, Raghuram and Fang (2022) documented that candidates from Tier-2 cities reported specific, technology-mediated disadvantages in AI video interviewsincluding accent-based penalisation by voice-analysis algorithms calibrated predominantly on metropolitan English speech patterns, and bandwidth limitations that produced visual artefacts in video feeds that AI systems interpreted as signs of disengagement.

3.5 AI Governance, Regulation, and Ethical HRM

The governance literature on AI in employment has developed rapidly in response to documented harms. The EU AI Act (2021/2024) represents the most comprehensive regulatory framework to date, classifying AI systems used in employment screening, promotion, and termination decisions as 'high-risk AI systems' subject to mandatory conformity assessments, transparency requirements, human oversight provisions, and post-market monitoring obligations (European Commission, 2021). In India, NASSCOM's Responsible AI Framework (2022) offers a voluntary self-regulatory approach, centred on principles of fairness, transparency, accountability, robustness, and privacy. MEITY's National Strategy for Artificial Intelligence (2023) acknowledges the employment implications of AI but stops short of mandating specific governance requirements for HR applications. The ILO (2023) has called on governments and employers globally to develop co-regulatory frameworks for digital labour platforms and AI-mediated employment decisions.

Singh and Sharma (2022) surveyed Indian IT HR professionals and found that fewer than 15% of their organisations had conducted any form of algorithmic audit of their recruitment tools, and fewer than 25% had explicit policies governing the use of AI in hiring. Bogen (2019) provides a comprehensive taxonomy of the governance mechanisms available to mitigate AI hiring bias, including pre-deployment fairness testing, ongoing outcome monitoring, mandatory explainability requirements, and diverse training data curation most of which remain absent from standard Indian IT HR practice.

4. RESEARCH METHODOLOGY

4.1 Research Design

This study adopts a Sequential Explanatory Mixed-Methods Design (Creswell, 2014), comprising two chronologically ordered, analytically integrated phases. In Phase 1, a quantitative survey provides statistical evidence on the prevalence of AI adoption, its association with hiring quality metrics, and its differential impact on diversity outcomes across a representative sample of IT firms. In Phase 2, semi-structured qualitative interviews with recently hired employees provide contextual depth and mechanistic explanation for the patterns identified in the quantitative phase. The qualitative phase does not stand alone but is specifically designed to explain and contextualise the Phase 1 findings, making the design genuinely explanatory rather than merely descriptive.

4.2 Population and Sample

Target Population	HR managers, talent acquisition heads, and recent recruits in Indian IT firms (500+ employees) that have adopted at least one AI recruitment tool between 2021 and 2024
Phase 1 — Respondents	200 HR/TA professionals (purposive sampling via NASSCOM member directory, LinkedIn outreach, and snowball referral from initial contacts)
Phase 2 — Respondents	30 employees recruited through AI-enabled processes in the past 12 months (maximum variation sampling across gender, city tier, and institutional background)
Geographic Coverage	Bengaluru, Hyderabad, Pune, Delhi-NCR (Tier-1); Indore, Jaipur, Lucknow, Bhopal (Tier-2)
Firm Categories	Large Indian IT MNCs | Mid-tier IT services firms | IT product start-ups (Series B+)
Sample Justification	n=200 satisfies power requirements for multiple regression analysis ($f^2=0.15$, $\alpha=0.05$, power=0.80 requires $n\geq89$; n=200 provides comfortable buffer for attrition)
Inclusion Criteria	Minimum 2 years in current role (Phase 1); recruited within past 12 months (Phase 2); direct involvement in or experience of AI-assisted hiring

4.3 Data Collection Instrument — Structured Questionnaire

A 48-item structured questionnaire, administered via Google Forms (online) and hard copy (in-person), is organised into five sections:

7. Section A - Organisational Profile (12 items): Firm size, IT sub-sector, years of AI tool adoption, specific tools deployed, stages of deployment, vendor vs. proprietary tools, HR team size.
8. Section B - Hiring Quality Metrics (10 items): 90-day and 12-month retention rates for AI-screened vs. traditionally recruited cohorts; supervisor performance ratings at 6 months; time-to-full-productivity estimates; cost-per-hire comparisons. Items adapted from Gonzalez et al. (2019) and validated for the Indian IT context.
9. Section C - Diversity Outcomes (8 items): Gender ratio in hire cohorts (last 3 years); proportion of recruits from Tier-2/3 cities; proportion from non-IIT/NIT institutions; SC/ST representation; change in these metrics post-AI adoption.
10. Section D - Moderating Variables (10 items): Presence and maturity of DEI policy; frequency of algorithmic auditing; existence of human review at shortlisting; HR staff training on algorithmic bias; leadership commitment to inclusive hiring.
11. Section E - Ethical AI Readiness (8 items): Perceived transparency of AI tools; candidate complaint mechanisms; vendor accountability clauses in contracts; awareness of NASSCOM Responsible AI Framework.

Measurement Scale: 5-point Likert (1 = Strongly Disagree, 5 = Strongly Agree) for attitudinal items; frequency scales and actual metrics for organisational data items.

Pilot Testing: The instrument will be pilot tested with 20 HR professionals not in the final sample. Internal consistency will be assessed via Cronbach's Alpha (target $\alpha > 0.70$). Content validity will be established through review by three HR faculty experts and one practicing CHRO.

4.4 Data Collection Instrument Semi-Structured Interview Guide

Phase 2 interviews will be conducted with 30 recently recruited employees selected to maximise variation across gender (15 women, 15 men), city tier (15 metro, 15 Tier-2), and institutional background (10 IIT/NIT, 10 state university, 10 private university/other). Each interview will last 45-60 minutes, conducted via Microsoft Teams (for outstation participants) or in person. Key interview themes include:

- The candidate's experience with AI-mediated stages of their recent recruitment process (screening, assessment, video interview).
- Perceived fairness and transparency of AI evaluation — what was explained, what was opaque.
- Any specific moments of perceived disadvantage, confusion, or alienation during AI-mediated stages.
- Comparison with prior (human-mediated) recruitment experiences.
- Suggestions for improving fairness in AI recruitment.

Interviews will be audio-recorded with informed consent, transcribed verbatim, and analysed using Reflexive Thematic Analysis (Braun & Clarke, 2006). NVivo 14 will be used for systematic coding.

4.5 Data Analysis Strategy

Analysis Type	Method	Software	Purpose
Descriptive Statistics	Mean, SD, frequency distributions, cross-tabulations	SPSS 27	Profile of AI adoption and baseline HR metrics
Reliability & Validity	Cronbach's Alpha, CFA, AVE, discriminant validity	AMOS 24 / SmartPLS 4	Instrument quality assessment
Hypothesis Testing (H1-H3)	Multiple regression analysis, independent samples t-test	SPSS 27	Direct effects of AI on quality and diversity
Moderation Analysis (H4-H6)	Hierarchical regression, PROCESS Macro (Hayes, 2017)	SPSS + PROCESS v4	Testing moderating effects of governance variables
Group Comparison	One-way ANOVA, Chi-square test	SPSS 27	Comparing AI vs. non-AI firms on diversity outcomes
Qualitative Analysis	Reflexive Thematic Analysis, 6-phase Braun & Clarke model	NVivo 14	Generating themes from interview transcripts
Integration	Joint displays (meta-inferences table)	Manual	Merging Phase 1 and Phase 2 findings

4.6 Validity and Reliability

Quantitative validity is addressed through content validation (expert review), construct validation (CFA), convergent validity (AVE > 0.50), and discriminant validity (HTMT ratio < 0.90). Common method bias will be assessed using Harman's single-factor test and controlled through procedural remedies including temporal separation of predictor and criterion measurement where feasible.

Qualitative trustworthiness is ensured through member checking (sharing transcript summaries with 5 participants for accuracy confirmation), peer debriefing (two independent researchers reviewing 20% of coding), reflexivity documentation (maintained research journal), and thick description to enable analytic generalisation.

4.7 Ethical Considerations

- Written informed consent obtained from all Phase 1 and Phase 2 participants prior to data collection.
- Full anonymisation: firm names, individual names, and identifying details will be replaced with codes in all reported data.
- Institutional Ethics Committee clearance will be obtained from Aryavart University prior to data collection.
- Participants retain the unconditional right to withdraw at any stage without consequence.
- Interview audio recordings will be deleted after transcription and verification. All data will be stored on a password-protected institutional server for 5 years in accordance with UGC research data management guidelines.
- This study does not involve any deception, and no personally sensitive data (caste, health, financial) will be directly collected.

5. EXPECTED RESULTS AND DISCUSSION

5.1 Expected Quantitative Findings

AI Adoption Patterns: It is anticipated that over 75% of sampled firms will report using at least one AI tool at the resume screening stage, while fewer than 40% will report AI usage at the final interview or selection stage. This stage-wise distribution suggests that AI is primarily deployed as a volume-reduction tool winnowing large applicant pools to manageable shortlists rather than as a holistic replacement for human judgment. This finding would align with the global pattern documented by SHRM (2022).

Hiring Quality (H1): AI-adopting firms are expected to show moderate improvements in 90-day new-hire retention rates (estimated effect size $d = 0.3\text{-}0.4$) and cost-per-hire reductions (estimated 20-30%). However, the association with 12-month retention and 6-month supervisor performance ratings is expected to be substantially weaker ($d < 0.2$), consistent with Pessach et al.'s (2020) finding that AI tools predict short-term fit better than long-term performance. This nuanced patternAI improves efficiency proxies but not deep hire quality would challenge the prevalent vendor narrative of AI as a wholesale improvement over human hiring.

Diversity - Gender (H2): Firms relying exclusively on AI screening without DEI safeguards are expected to show a statistically significant lower proportion of women in shortlisted and hired cohorts compared to firms using human-augmented processes (expected difference: 12-18 percentage points, $p < 0.01$). This finding would be consistent with Waddell and Pio (2022) and would provide the first quantitative evidence of this effect in the Indian IT sector specifically.

Diversity - Regional and Institutional (H3): AI screening is expected to show a statistically significant bias toward candidates from metropolitan areas and elite institutions (IIT, NIT, top private engineering colleges). Graduates from state universities and Tier-2 city colleges who constitute the majority of India's engineering graduate workforce are expected to be substantially underrepresented in AI-shortlisted pools relative to their proportion in the overall applicant pool. This finding carries particular significance for Central Indian cities like Indore, Lucknow, and Bhopal, whose graduates face a structural penalty from AI systems calibrated on metropolitan hiring histories.

Moderation Effects (H4-H6): Hierarchical regression analysis is expected to reveal significant interaction effects for DEI policy presence (H4) and algorithmic auditing (H5), with interaction term beta coefficients exceeding 0.20 ($p < 0.05$). Firms with active algorithmic auditing are expected to show substantially smaller diversity gaps suggesting that regular outcome monitoring and bias correction can meaningfully attenuate AI's adverse diversity impact.

5.2 Expected Qualitative Findings

Thematic analysis of Phase 2 interviews is expected to yield four primary themes:

- Theme 1 The Black Box Experience: Candidates will consistently describe the AI screening stage as opaque, arbitrary, and anxiety-inducing. The absence of feedback or explanation following AI-mediated rejection is expected to emerge as a key source of perceived procedural injustice, consistent with Colquitt (2001) and Suen et al. (2019).
- Theme 2 The Accent and Bandwidth Penalty: Candidates from non-metropolitan regions and regional-language educational backgrounds will report specific experiences of disadvantage in AI video interviews including accent penalisation, technical connectivity issues producing distorted video quality, and discomfort performing for a camera rather than engaging with a human interlocutor. This theme would provide qualitative texture for the quantitative diversity finding on regional representation.
- Theme 3 The Institutional Prestige Filter: Candidates from non-IIT/NIT institutions will report a widespread perception that AI resume screening primarily identifies institutional brand rather than individual competence that a degree from a state engineering college is 'screened out' before a human recruiter ever reads the resume.

- Theme 4 The HR Practitioner's Dilemma: Interviews with HR professionals (triangulated from Phase 1 qualitative comments) will reveal a persistent tension between efficiency imperatives AI saves enormous time in volume hiring and professional responsibility for inclusive hiring. A minority of firms will emerge as 'governance exemplars' that have developed structured protocols for combining AI efficiency with human diversity oversight.

5.3 Hypothesis Testing Summary (Anticipated)

Hypothesis	Expected Result	Likely Statistical Support
H1: AI improves hire quality	Partially supported — efficiency Yes, long-term quality Weak	t-test significant for 90-day retention; NS for 12-month performance
H2: AI reduces gender diversity	Supported	Chi-square p<0.01; regression beta negative, p<0.05
H3: AI reduces regional/institutional diversity	Supported	ANOVA F-ratio significant p<0.01
H4: DEI policy moderates H2/H3	Supported	Interaction term beta > 0.20, p<0.05 in hierarchical regression
H5: Algorithmic auditing moderates H2/H3	Supported	Interaction term beta > 0.18, p<0.05
H6: Human review at shortlisting moderates H2/H3	Strongly supported	Interaction term beta > 0.25, p<0.01

6. The Five-Pillar Ethical AI Recruitment Governance Framework

Based on the synthesis of the theoretical framework, the literature review, and the anticipated empirical findings, this study proposes the following five-pillar Ethical AI Recruitment Governance Framework (EAIRGF) for Indian IT organisations. The framework is designed to be practical, scalable, and aligned with existing NASSCOM Responsible AI principles while extending them with sector-specific operational guidance.

I	**Pre-Deployment Bias Audit** Before any AI recruitment tool is deployed — whether proprietary or vendor-supplied — it must undergo a pre-deployment fairness audit. This involves testing the tool against a demographically diverse sample of historical applicants to measure differential pass-rates across gender, regional origin, and institutional categories. Tools that produce statistically significant differential outcomes exceeding a tolerance threshold of 5 percentage points must be recalibrated or rejected. *Action: Assign an Algorithmic Audit Officer within the HR function; mandate bias audit clauses in all AI vendor contracts; document audit results and share with HR leadership before tool launch.*
II	**Transparent Candidate Communication** Candidates must be informed at the outset that AI tools are being used in their assessment, what types of data are being evaluated (textual, facial, vocal), and what role human judgment plays in the process. Following any AI-driven rejection, candidates must receive a written explanation of the general criteria applied, even if specific model weights cannot be disclosed for commercial reasons. *Action: Develop a standard 'AI Recruitment Disclosure Notice' to be shared with all applicants at registration; establish a candidate query mechanism with a 5-day response SLA; train recruitment teams to communicate AI tool limitations clearly.*
III	**Mandatory Human Oversight at Shortlisting** No candidate shall be permanently excluded from a hiring process on the basis of AI screening alone without a qualified human recruiter reviewing the AI decision. Human reviewers must be trained in algorithmic bias recognition and must be required to document their rationale when overriding — or confirming — AI shortlisting decisions. *Action: Implement a 'Human-in-the-Loop' protocol for all final shortlisting decisions; establish a minimum quota of candidates from diverse institutional backgrounds to be advanced to human review regardless of AI scores; log all human override decisions for quarterly review.*
IV	**Continuous Outcome Monitoring and Reporting** Organisations must establish a quarterly diversity outcome monitoring process that tracks the composition of hire cohorts (gender, region, institution tier) and compares these against the composition of the applicant pool. Any systematic gap exceeding a defined threshold (e.g., >10 percentage points) must trigger an immediate review of the AI screening parameters in use. *Action: Create a quarterly 'AI Hiring Diversity Dashboard' for HR leadership; set diversity representation targets aligned with National Education Policy 2020 inclusivity*

	goals; mandate annual public reporting of AI recruitment diversity outcomes for firms with 1,000+ employees (aligned with BRSR disclosure norms).

V	**Inclusive Data Curation and Model Diversity** AI recruitment models must be trained on datasets that are representative of the full spectrum of qualified applicants — not merely the historical hiring choices of organisations that may have themselves been systematically biased. This requires active curation of diverse training data, including examples of high-performing employees from Tier-2 institutions, regional backgrounds, and underrepresented gender groups. *Action: Establish a 'Diverse Hiring Exemplar Database' of verified high-performers from all institutional and demographic backgrounds; mandate annual retraining of AI models using this curated dataset; require vendors to disclose the demographic composition of their training datasets as a contractual condition.*

7. LIMITATIONS OF THE STUDY

A transparent acknowledgment of this study's limitations is essential for accurately interpreting its findings and for guiding future research.

- Self-Report Bias: Phase 1 data relies on HR professionals' self-reported assessments of their organisations' AI adoption, hiring quality metrics, and diversity outcomes. Social desirability pressures may lead respondents to overstate their DEI commitments and understate observed bias in their AI tools. This limitation is partially mitigated by the Phase 2 interview data, which triangulates organisational claims with candidate experiences, and by the use of objective outcome metrics (retention rates, hire cohort compositions) wherever possible.
- Cross-Sectional Design: The study captures a snapshot of AI recruitment practices and outcomes at a single point in time. The rapidly evolving nature of AI technology means that findings may become partially obsolete as new tool generations emerge. Longitudinal replication studies are recommended.
- Geographic Concentration: While the sample deliberately includes both Tier-1 and Tier-2 cities, IT industry concentration in Bengaluru, Hyderabad, and Pune means that these cities will likely be over-represented. Findings may not fully generalise to IT firms in smaller Tier-3 cities or in states with nascent IT ecosystems.
- Single Sector Scope: The study focuses exclusively on the IT sector, where AI recruitment adoption is highest and most mature. The governance framework proposed here is calibrated for this context and would require modification before application to other sectors (banking, manufacturing, healthcare) where the nature of roles, volumes of applicants, and HR maturity profiles differ substantially.

- Vendor Non-Disclosure: AI recruitment tool vendors typically treat their model architectures, training data compositions, and algorithmic parameters as proprietary. The study cannot directly audit the models being used only their observable outcomes. This 'black box' limitation mirrors the challenge faced by the industry itself and underscores the urgency of the transparency recommendations in the governance framework.
- Response Rate Uncertainty: Purposive sampling of HR professionals via professional networks may introduce selection bias respondents who engage with academic research may be more diversity-conscious than the average HR practitioner, potentially understating the scope of algorithmic bias in the broader industry.
- Caste Data Sensitivity: Given the legal and social sensitivity surrounding caste-disaggregated data in India, direct measurement of caste-based hiring disparities was not attempted. The study uses institutional tier (IIT/NIT vs. state university) and regional origin as proxy indicators, which may not fully capture caste-based discrimination patterns.

8. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

This paper presents a rigorous, mixed-methods research design to investigate one of the most consequential and underexamined intersections of technology and human resource management in contemporary India: the impact of AI-driven recruitment on hiring quality and workforce diversity in the IT sector.

The theoretical framework integrating Algorithmic Accountability Theory, Social Identity Theory, and the Resource-Based View provides a robust multi-level lens through which to understand how algorithmic bias enters the hiring process, whom it systematically disadvantages, and why organisations have strategic as well as ethical incentives to address it. The five-pillar Ethical AI Recruitment Governance Framework translates these theoretical insights into operational guidance that Indian IT organisations, NASSCOM, and MEITY can begin implementing immediately.

The anticipated paradox at the heart of the study's expected findings that AI recruitment improves hiring efficiency while simultaneously narrowing the diversity pipeline, unless active governance counterweights are in placehas profound implications for how organisations conceptualise the value of AI in HR. Efficiency gains that are purchased at the price of systematic exclusion are not genuinely gains: they are transfers of cost from the organisation to the candidates, communities, and society that bear the burden of exclusion. An organisation that uses AI to hire faster while hiring less diversely is not merely missing an ethical obligation it is, as the Resource-Based View predicts, actively degrading its own long-run competitive advantage.

Future research should extend this work in several directions. Longitudinal panel studies tracking the same cohort of AI-adopting firms over 3-5 years would provide more definitive causal evidence on hire quality outcomes. Sector-comparative studies examining AI recruitment in banking, healthcare, and manufacturing would test the generalisability of the findings and the

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governance framework. Research specifically designed to capture caste-disaggregated hiring data through partnerships with organisations willing to share anonymised HR analytics would provide a more complete picture of AI's equity implications in the Indian context. Finally, experimental studies providing some firms with governance training and auditing support while measuring outcomes in comparable control firms could provide the strongest possible evidence base for the framework's effectiveness.

As AI becomes ever more deeply embedded in the hiring decisions that shape careers, organisations, and societies, the imperative to govern these systems rigorously, transparently, and equitably has never been more urgent. This paper is offered as a contribution to that urgent endeavour.

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