

RESEARCH ARTICLE

The Promise and Perils of AI in Talent Acquisition: Efficiency, Ethics, and Stakeholder Trust***Dr Kartik Chandra Das, **Dr. Suman Kalyan Chaudhury, ***Dr Apoorva Behera***Assistant Professor PM&IR, Utkal University, Vanivihar 751004**Faculty Member, Department of Business Administration, Berhampur University, Odisha**Asst. Professor, Department of Business Administration, Berhampur University, Odisha***ABSTRACT**

Artificial intelligence (AI) is transforming the way companies recruit and hire new employees by automating the hiring process, facilitating data-driven decision-making, and streamlining the hiring process. Even with these benefits, issues such as algorithmic bias, transparency, ethical governance, and candidate trust still make it hard to use AI for hiring responsibly. This study experimentally investigates the advantages and challenges of AI-driven recruitment processes in the Indian IT sector by incorporating perspectives from both HR experts and job applicants. A cross-sectional survey approach was employed to gather data from 432 respondents, which were subsequently analysed utilising descriptive statistics, t-tests, ANOVA, correlation, and regression. The results show that using AI reduces time-to-hire, lowers hiring costs, and improves the quality of candidate selection. However, the results also show that people remain concerned about algorithmic bias, a lack of transparency, and reduced confidence, especially among job seekers who have previously used AI-based hiring systems. The research emphasises the significance of hybrid AI-human decision-making models underpinned by ethical governance frameworks and transparent AI procedures. This research contributes to the AI-in-HRM literature by providing real-world evidence from a growing economy and offering managers and policymakers practical guidance on using AI to hire fairly, openly, and effectively.

Keywords: Artificial intelligence; Talent acquisition; Recruitment automation; Algorithmic bias; Ethical HRM

ARTICLE INFO**Received:** [27/07/2026]**Accepted:** [04/08/2026]**Published:** [25/08/2026]**Issue Period:** July – August 2026 (Bi-Monthly)**DOI:** <https://doi.org/10.56293/IJMSSSR.2026.6324>**Copyright:** © 2026 The Author(s). Published by IJMSSSR. This is an Open Access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY 4.0) License.**Introduction**

The unparalleled growth of open and agentic “Artificial Intelligence” (AI) tools and their applications in organisations have become inescapable and imminent (Hosseini & Seilani, 2025). The AI deployment in human resource practices, particularly in manpower acquisition, has gathered heightened attention from

practitioners and policymakers. In the domain of recruitment and selection, AI applications have efficiently facilitated the analysis of larger volumes of data, the automation of routine tasks, and an increase in decision-making accuracy. The computational intelligence in recruiting has brought us Application Tracking Systems (ATS), resume screening software, chatbot development, and predictive analytics. Such applications streamline hiring workflows and ensure efficient talent acquisition activity, including time-to-hire metrics (Chong et al., 2026; Simsek et al., 2020)

In knowledge-intensive, highly competitive industries, including the Information Technology (IT) sector, the adoption of AI is influenced by the war for talent. Companies are encountering myriad issues that increase recruitment costs, including creating HR inventory on tight timelines, maintaining consistency, and overcoming human biases during the screening phase (Aparna & Kumar, 2025; Thivnuja, 2026). In the context of skill scarcity and a high volume of talent acquisition over a relatively short period, there is increasing deployment of predictive AI tools that serve as a strategic lever to enhance recruiting effectiveness (Allal-Chérif et al., 2021).

The most debated discourse on AI convergence in human resource management concerns algorithmic bias and an ultra-mechanical approach to candidate selection (Kelan, 2024). AI technologies are implemented to reduce bias and to gather sufficient scientific evidence to support prudent decisions. Ironically, in the present scenario, algorithm-driven decisions amplify inequities and promote engineering choices and downstream decision rules (Wang et al., 2022). Recent evidence on AI-applied recruitment lifecycle suggests that biases are pervasive across all stages, from the selection of training data through model deployment to the human understanding needed for technical controls and governance mechanisms (Sartori & Theodorou, 2022).

AI-assisted hiring decisions are often criticised on the dimensions of transparency, accountability, and explainability (Rajendra & Thuraisingam, 2026; Sartori & Theodorou, 2022). The existing research suggests that explainable AI (XAI) capabilities, including agnostic explanation models and feature extraction techniques, are paramount for procedural sanctity and justifiable decision making in the context of employment (Surendra et al., 2026; Tian et al., 2023). Evidence gathered from systematic reviews of AI hiring literature shows that explainability is an inseparable socio-organisational element of trust, auditability, and compliance (Dadaboyev et al., 2025; Mori et al., 2025a).

Although mapping the candidate experience and the credibility of selection attributes in an AI environment increases responsiveness and standardisation, it also raises humanitarian issues in hiring decisions. Excessive automation has laid the foundation for perceptual biases among candidates, including unfair, impersonal, and highly mechanical perceptions, particularly when feedback and explanations are adequate (Afrin et al., 2025). Recent research suggests that the fairness and acceptance of AI-assisted selection among applicants depend on the suitability of explanations and appropriate feedback, as well as the justifiability of the procedure. The fair perception and acceptance of algorithm-driven hiring strengthen engagement, increase completion rates, and coagulate employer brand.

The scalability of AI applications in hiring necessitates scholarly enquiry into the level of effectiveness and the ethical challenges associated with excessive automation and standardisation. The available literature is limited in explaining candidates' perception and trust in AI applications during the hiring process. There is very limited literature on a growing-economy context like India, with a high-growth labour market (Aggarwal, 2018). The present study examines these gaps through an empirical investigation of AI recruitment practices in the Indian IT sector. Through empirical examination, the study provides a detailed description of AI-assisted hiring practices in the Indian IT sector. The study offers a balanced assessment of both opportunities and hindrances. The novelty of this study lies in synthesising the perceptions of HR professionals and job seekers regarding the effectiveness of AI-driven recruiting practices. The study attempts to address the following research questions:

RQ1: To what extent does the adoption of AI-powered recruitment systems improve hiring efficiency, quality of candidate selection, and overall recruitment outcomes within the IT sector?

RQ2: How do ethical concerns, algorithmic transparency, and candidate experience influence trust and stakeholder perceptions of AI-driven recruitment processes?

The two research questions provide the conceptual foundation for formulating the study's hypotheses.

Research Question 1 (RQ1) examines whether AI-powered recruitment systems improve recruitment efficiency, reduce hiring costs, enhance candidate selection quality, and contribute to better recruitment outcomes in the IT sector. Accordingly, **Hypotheses H1a, H1b, H2a, H3a, and H3b** were formulated to empirically assess the operational and strategic benefits of AI adoption in talent acquisition. In contrast, **Research Question 2 (RQ2)** explores the ethical, behavioural, and perceptual dimensions of AI-enabled recruitment by investigating how algorithmic bias, transparency, ethical concerns, stakeholder trust, and candidate experiences influence the acceptance and effectiveness of AI-driven hiring. This research question is addressed through **Hypotheses H2b, H4a, H4b, H5a, H5b, H6a, and H6b**, which examine the effects of fairness, transparency, ethical governance, stakeholder perceptions, and trust-building mechanisms on AI adoption. Collectively, these hypotheses operationalise the two research questions and provide a comprehensive empirical framework for evaluating both the performance advantages and the ethical challenges of AI-driven recruitment within the Indian IT sector.

The paper's logical and scientific flow is presented as follows. Section II explores the relevant literature on AI-enabled recruitment, focusing on efficiency outcomes, algorithmic bias, ethical considerations, and candidate experience, and identifies key research gaps. Section III focuses on the research methodology, including the research design, sampling framework, data collection procedures, and analytical techniques employed in the study. Section IV presents the empirical results and statistical analysis. Section V discusses the findings in relation to existing literature and theoretical perspectives. Section VI concludes the paper by summarising key insights, highlighting limitations, and suggesting directions for future research, followed by managerial and policy implications.

Review of Literature

Strategic Implications of AI in Talent Acquisition

Artificial intelligence (AI) is gradually becoming a strategic driver in talent acquisition (TA), empowering automation of high-volume processes (e.g., sourcing, screening, scheduling) while strengthening more fact-based assessment and workforce planning. The review works emphasise that AI is not merely a tool for operational efficiency; it can reconfigure HR systems and decision criteria, manifesting an analytics-centric, strategically integrated talent system (Priyadarsini & S.S, 2025; Suri & Lakhanpal, 2024). In common parlance, some recent research argues that the strategic value of AI is best realised when the espousal of technology is aligned with organisational governance, management practices, and sustainability objectives.

Emerging Complexities and Ethical Challenges

Ethics-focused research warns that AI-enabled recruiting can introduce risks related to fairness, accountability, transparency, and contestability of decisions, particularly when systems rely on historically biased data, proxy features, or opaque model logic, even though AI is frequently associated with objectivity and consistency (Chen, 2023; Mori et al., 2025b). Applicant-focused research also demonstrates the importance of perceptions of fairness: candidates' acceptance of algorithm-driven hiring is contingent on their judgments of procedural justice, the validity of decision-making procedures, and the availability of clear and justifiable explanations (Haque, 2025). Employer attractiveness and job acceptance intentions may be impacted by candidates' perception of AI evaluators as less reliable than human evaluators, according to experimental findings (Koch-Bayram & Kaibel, 2024).

Interdisciplinary and Operational Gaps

A persistent weakness in the A/B-ranked literature is that numerous studies recognise AI as transformational yet exhibit significant variation in operational specifics, especially with the configuration, auditing, and integration of AI systems within comprehensive TA workflows. Reviews emphasise that HR outcomes are contingent on socio-technical alignment, which encompasses the interplay among AI system design, human judgment, the institutional environment, and governance practices (Chhillar & Aguilera, 2022; Sigfrids et al., 2023). Interdisciplinary perspectives emphasise that for AI to create long-term value for organisations, it must be fully integrated into management practices and ongoing learning. This makes the case even stronger that TA research should examine AI mechanisms, managerial controls, and their actual implementation.

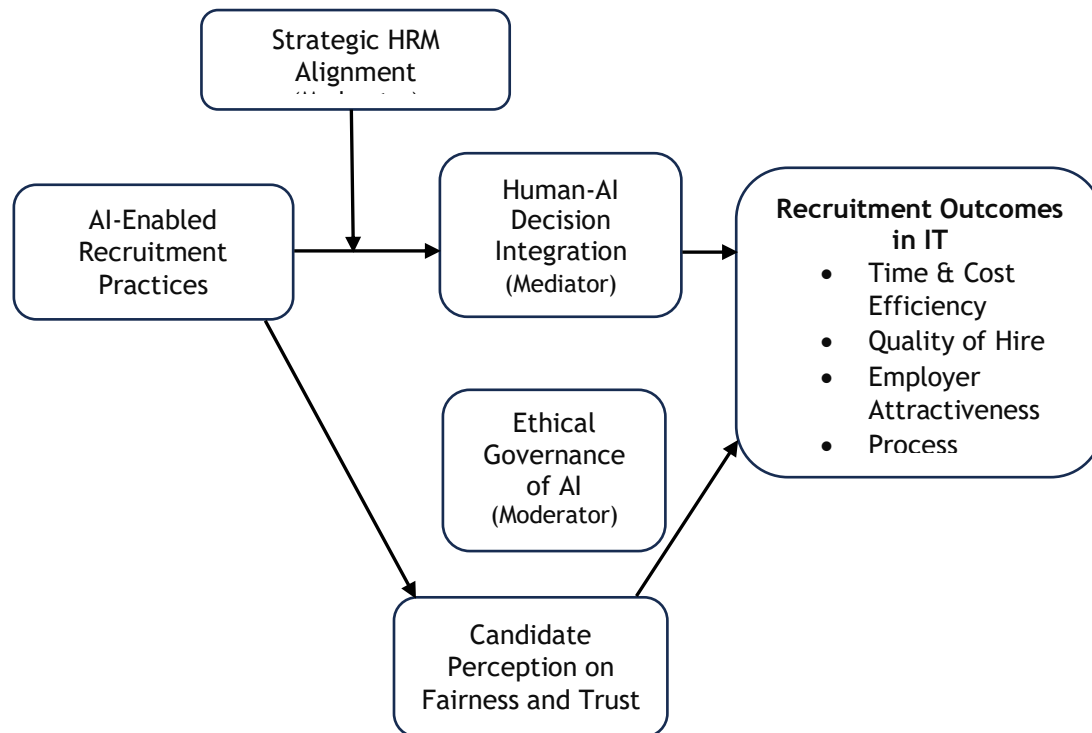
Research Gaps

Based on the aforementioned, the evidence base shows four actionable gaps, which are further supported by practice-oriented and interdisciplinary framing:

1. Mechanistic knowledge of AI-in-TA: More details are needed on how AI recruiting systems put constructs (fit, potential, performance) into action and how people and AI share decisions in real life.
2. Candidate-centric empirical evidence: Additional applicant-focused research is required across labour markets to comprehend perceptions of trust, acceptability, and justice.
3. Ethical operationalisation and governance: Research must progress from theoretical principles to the empirical evaluation of governance systems (auditing, explainability procedures, accountability structures) and their resultant consequences.
4. Strategic HRM integration: More research is needed on how AI affects HR strategy, building skills, and managing legitimacy.

Conceptual Framework

Figure 1 shows the conceptual framework explaining how AI-enabled hiring practices affect hiring outcomes in the IT sector through multiple interacting socio-technical mechanisms. The theory posits that AI-enabled recruitment techniques function as the principal catalyst, influencing hiring efficiency and effectiveness through their interaction with human judgment and organisational processes. The influence of AI on recruiting outcomes is facilitated by the integration of human and AI decision-making, as well as candidates' views of fairness and trust. These factors collectively elucidate the interpretation, implementation, and reception of algorithmic judgments by essential stakeholders. Ethical governance of AI and strategic HRM alignment serve as moderating factors, either reinforcing or undermining these connections by promoting transparency, accountability, and alignment with company strategy. The framework underscores that effective AI-driven recruitment outcomes hinge not only on technological proficiency but also on governance, human oversight, and candidate acceptance.

Figure 1: Conceptual Framework

Source: Prepared by the Authors

Methodology

Research Design and Methodological Justification

This study utilises a cross-sectional descriptive research design to empirically investigate the strategic advantages and challenges of AI-driven recruitment methods in the IT industry. Cross-sectional designs are frequently utilised in human resource management and technology adoption research to assess organisational practices and stakeholder perceptions at a specific point in time, especially in rapidly changing digital environments (HUSELID & BECKER, 1996; Srirangam Ramaprasad et al., 2017). This design facilitates a rigorous evaluation of AI's impact on recruiting efficiency, bias mitigation, ethical considerations, and hiring outcomes among key stakeholders.

The methodological choices are directly aligned with the study's research questions. Research Question 1 investigates the impact of AI adoption on recruiting efficiency and hiring outcomes, necessitating quantitative approaches to evaluate the correlations between technology utilisation and performance metrics (Chapman & Webster, 2003; Walford-Wright & Scott-Jackson, 2018). Research Question 2, which addresses ethical considerations, transparency, and stakeholder trust, requires perceptual data and comparison analysis among stakeholder groups, as advocated in previous AI-in-HRM studies ((Malin et al., 2025)). A survey-based quantitative methodology, supplemented with inferential statistical analysis, is suitable for fulfilling the study objectives.

Sampling Framework and Sample Size

The target group was HR professionals and job seekers in the IT business, mostly in Bangalore, India. The IT sector was chosen because it is highly digitised and has a relatively high rate of adoption of AI-powered hiring tools (Singh et al., 2025; Upadhyay & Khandelwal, 2018). A stratified random sampling technique

was utilised to ensure proportional representation of both stakeholder groups, in line with established standards in comparative HRM research. Of the 500 surveys sent, 432 were valid, indicating that 86.4% of recipients responded. The sample size exceeds the minimum specified by (Alacaci, 2004), allowing the use of inferential statistical techniques with sufficient power and reliability.

Instrument Development and Validation

The data were gathered using a structured questionnaire developed through a comprehensive analysis of prior empirical research on AI-enabled recruiting, HR analytics, algorithmic bias, and ethical AI (Upadhyay & Khandelwal, 2018; Raghavan et al., 2020; Varma et al., 2023). Measurement items were derived from validated scales found in peer-reviewed literature, incorporating contextual changes to account for AI implementation in recruitment settings.

The questionnaire consisted of three sections: (i) demographic features of respondents, (ii) perceived advantages of AI-powered recruiting, and (iii) perceived hurdles and ethical considerations associated with AI-driven hiring. A five-point Likert scale, a common method for measuring attitudes and perceptions in HRM and behavioural research (Jebb et al., 2021), was used to assess all perceptual items.

Content validity was confirmed via expert evaluation by academics and HR professionals specializing in AI and talent acquisition. Cronbach's alpha was used to assess internal consistency, and all constructs were above the suggested threshold of 0.70, indicating reliability (Hair et al., 2019).

Data Collection Procedure

Data were collected via an online survey administered through Google Forms. Researchers in HRM and technology adoption often employ online surveys because they are quick, easy to use, and can reach a wide range of people (Jamali & Asadi, 2010). The survey link was distributed via professional networks, email invitations, and industry forums relevant to the IT sector. People might choose to take part, and their identities were kept secret.

Data Analysis Techniques

We used SPSS software to analyse the data. Descriptive and inferential statistical methods were deployed, aligning with previous quantitative research on AI adoption in HRM (Basu et al., 2023; Lavanchy et al., 2023). Descriptive statistics were employed to summarise demographic characteristics and overall response trends.

We used independent-samples t-tests and one-way ANOVA to examine differences between groups, correlation analysis to examine the relationships between transparency and confidence in AI systems, and regression analysis to examine how AI adoption affects recruitment outcomes. These methods are suitable for analysing relationships and evaluating hypotheses in behavioural and management research (Hair et al., 2019).

Ethical Considerations

The research adhered to existing ethical guidelines. Participants were apprised of the study's objectives, and informed consent was obtained before data collection. Participation was optional, anonymity was preserved, and data were utilised solely for academic study, in accordance with ethical standards for social science inquiry (Wiles et al., 2008).

Results, Analysis, and Interpretation

Profile of the Respondents

This section presents the demographic characteristics of the respondents, followed by an analysis and interpretation of the empirical results. **Table 1** summarises the distribution of respondents across key demographic variables, including gender, age, educational qualification, and current role within the IT sector.

Table 1. Demographic profiles of respondents

Demographic	Category	%
Gender	Male	54%
	Female	46%
Age	Under 25	20%
	25-34	38%
	35-44	30%
	Above 45	12%
Qualification	Postgraduate	40%
	Undergraduate	35%
	Professional Certifications	25%
Current Role	HR Professionals	50%
	Job Seekers	50%

Source: Prepared by the Authors

The sample has a good mix of men and women, with 54% men and 46% women. This near-equal number of people of each gender makes the sample more representative and ensures that all points of view are represented, which strengthens the conclusions. In terms of age, the largest group who answered (38%) was between 25 and 34, and the next largest group (30%) was between 35 and 44. Also, 20% of respondents were younger than 25, and 12% were older than 45. This distribution shows that the survey mostly captured the opinions of young and mid-career professionals, a very important group in the IT business, which is highly technology-dependent. In terms of education, 40% of respondents held master's degrees, 35% held bachelor's degrees, and 25% held professional certifications in HR, recruitment, or information technology. The fact that most respondents had extensive education means they were well-positioned to offer informed opinions on AI-enabled hiring methods. HR professionals said they had about 8 years of work experience, whereas job seekers ranged from new graduates to those with up to 15 years of experience. This wide range of knowledge helps both recruiters and candidates fully comprehend AI-driven hiring.

Finally, the sample was evenly split between HR experts (50%) and job seekers (50%), enabling a fair assessment of AI-powered hiring methods from both sides of the hiring process. The demographic profile indicates that the sample is broad and representative, making the study's results more reliable and applicable to other contexts.

AI in Automating and Enhancing Recruitment Processes

To assess the role of AI in automating recruitment processes, responses related to automation efficiency and time-to-hire were analysed. As shown in **Table 2**, the mean score for AI-enabled automation was **4.1** (SD = 0.82), indicating a high level of agreement among respondents regarding the effectiveness of AI in streamlining recruitment activities.

Table 2. T-Test Analysis for AI in Automating Recruitment Processes

Hypothesis		Values
H1a: AI-powered recruitment significantly reduces the time required for candidate screening and selection	Mean	4.1
	SD	0.82
	t-Statistic	6.25
	p-Value	<0.001

Source: Prepared by the Authors

The t-test results reveal a **statistically significant reduction in time required for candidate screening and selection** ($t = 6.25$, $p < 0.001$). This finding provides strong empirical support for **Hypothesis H1a**, confirming that AI-powered recruitment systems significantly enhance operational efficiency by accelerating early-stage hiring processes.

Benefits of AI-Powered Recruitment

The perceived benefits of AI-powered recruitment were examined in terms of cost efficiency and bias reduction, as presented in **Table 3**. The results indicate that organisations experienced notable cost savings from AI-driven hiring practices, with a mean score of **3.9** ($SD = 0.75$). The corresponding t-test statistic ($t = 4.67$, $p < 0.01$) supports **Hypothesis H1b**, indicating that AI adoption reduces recruitment costs compared to traditional hiring methods.

Table 3. Analysis of the Benefits of AI-Powered Recruitment

Hypothesis	Statement	Mean	SD	t-Statistic	p-Value
H1b	AI-driven hiring leads to cost savings	3.9	0.75	4.67	<0.01
H2a	AI tools reduce human bias in candidate selection	3.8	0.89	3.89	<0.01
H2b	Algorithmic bias negatively impacts diversity	4.2	0.87	-4.12	<0.01

Source: Prepared by the Authors

Regarding reducing prejudice, respondents mostly agreed that AI technologies reduce human bias in candidate selection (mean = 3.8, $SD = 0.89$). The t-test results ($t = 3.89$, $p < 0.01$) support Hypothesis H2a, indicating that AI can facilitate more standardised and objective assessments. There were also worries about algorithmic prejudice, though. A large number of people (46%) thought that algorithmic bias could harm workplace diversity. This was shown by a higher mean score of 4.2 ($SD = 0.87$) and a statistically significant negative t-value ($t = -4.12$, $p < 0.01$). This data supports Hypothesis H2b and underscores the dual character of AI—providing bias reduction while concurrently introducing new fairness issues.

Impact of AI-Powered Recruitment on Hiring Outcomes

The influence of AI-powered recruitment on hiring outcomes was further examined through regression and t-test analyses, as summarised in **Table 4**. The results indicate a strong positive association between AI adoption and the **quality of candidate selection**, with a mean score of **4.0** ($SD = 0.81$). Regression analysis revealed a significant effect ($\beta = 0.38$, $p < 0.01$), supporting **Hypothesis H3a**.

Table 4. Impact of AI-Powered Recruitment on Hiring Outcomes

Hypothesis	Statement	Mean	SD	Test Type	Statistic	P-Value
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	AI-powered recruitment improves the quality of candidate selection	4.0	0.81	Regression	$\beta = 0.38$	<0.01
H3a				t-test		
H3b	Higher satisfaction with recruitment outcomes using AI	3.9	0.85		$t = 5.22$	<0.001

Source: Prepared by the Authors

In addition, organisations utilising AI-driven recruitment systems reported higher satisfaction with recruitment outcomes, as evidenced by a mean score of **3.9** (SD = 0.85) and a statistically significant t-test result ($t = 5.22$, $p < 0.001$). These findings support Hypothesis H3b and indicate that AI adoption not only improves efficiency but also enhances perceived effectiveness and strategic value of recruitment outcomes.

Challenges Associated with AI-Driven Hiring

The study also examined challenges associated with AI-driven hiring, particularly ethical concerns and transparency, as shown in Table 5. The mean score for ethical concerns was **3.6** (SD = 0.91), indicating a moderate level of concern among respondents. ANOVA results ($F = 5.67$, $p < 0.05$) demonstrate that ethical considerations significantly influence organisations' willingness to adopt AI systems, thereby supporting Hypothesis H4a.

Table 5. Analysis of Challenges Associated with AI-Driven Hiring

Hypothesis	Statement	Mean	SD	Test Type	Statistic	p-Value
				ANOVA		
H4a	Ethical concerns influence AI adoption	3.6	0.91		$F = 5.67$	<0.05
				Correlation		
H4b	Lack of transparency reduces trust in AI systems	3.4	0.85		$r = -0.43$	<0.01

Source: Prepared by the Authors

Furthermore, the perceived lack of transparency in AI decision-making emerged as a critical concern. Correlation analysis revealed a moderate negative relationship between transparency and trust in AI systems ($r = -0.43$, $p < 0.01$), as illustrated in Figure 2. This finding validates Hypothesis H4b, indicating that reduced transparency undermines stakeholder trust in AI-powered recruitment processes.

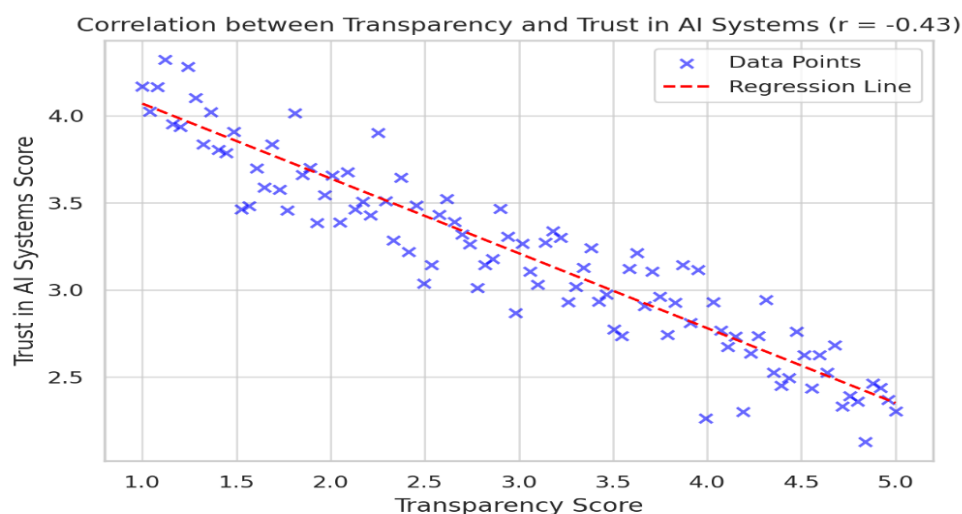


Figure 2. Correlation between Transparency and Trust in AI Systems

Perceptions of HR Professionals and Job Seekers

Differences in perceptions of AI-powered recruitment between HR professionals and job seekers were analysed and are presented in **Table 6**. HR professionals exhibited a significantly more positive perception of AI in recruitment (mean = 4.0, SD = 0.77) compared to job seekers (mean = 3.5, SD = 0.84). The t-test results ($t = 4.85$, $p < 0.001$) provide strong support for **Hypothesis H5a**.

Table 6. Perceptions of HR Professionals and Job Seekers

Hypothesis	Statement	Mean	SD	t-Statistic	p-Value
H5a	HR Professionals	4.0	0.77	4.85	<0.001
	Job Seekers	3.5	0.84		
H5b	Experienced Job Seekers	3.2	0.80	-3.94	<0.01
	Non-Experienced Job Seekers	3.8	0.74		

Source: Prepared by the Authors

Further analysis revealed that **experienced job seekers** had lower trust in AI-based recruitment systems (mean = 3.2, SD = 0.80) than those without prior exposure (mean = 3.8, SD = 0.74). This difference was statistically significant ($t = -3.94$, $p < 0.01$), confirming **Hypothesis H5b**. These results suggest that direct experience with AI-driven hiring may heighten awareness of perceived limitations related to fairness and transparency. The perception of AI adoption is portrayed in the following picture.

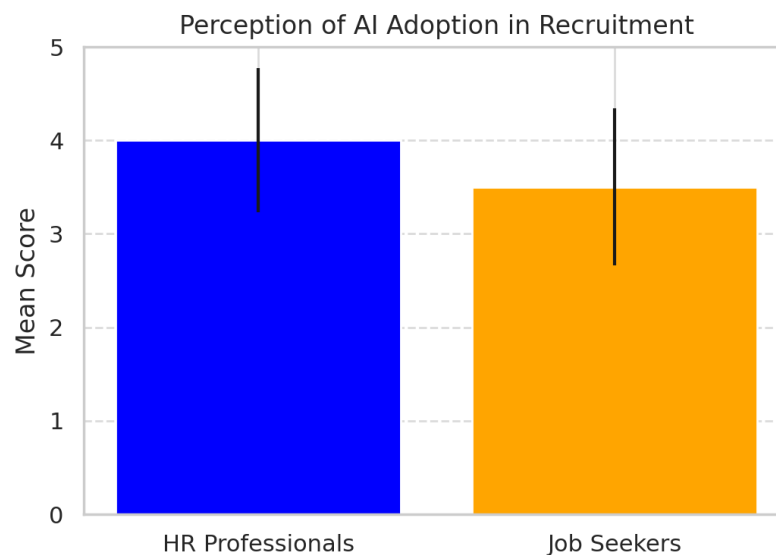


Figure 3. Perceptions of HR Professionals and Job Seekers

Recommendations for Optimising AI-Driven Hiring Practices

Based on the empirical findings, recommendations for optimising AI-driven hiring practices were examined, as summarised in **Table 7**. The analysis indicates that **trust in AI models** plays a significant role in shaping hiring practices, with a mean score of 3.9 (SD = 0.88) and a statistically significant t-test result ($t = 5.41$, $p < 0.05$), supporting **Hypothesis H6a**.

Table 7. Recommendations for Optimizing AI-Driven Hiring Practices

Hypothesis	Statement	Mean	SD	Test Type	Statistic	p-Value
				t-test		
H6a	Trust in AI models influences hiring practices	3.9	0.88		5.41	<0.05
				Regression		
H6b	AI ethics training enhances confidence in AI decisions	3.4	0.85		$\beta = 0.42$	<0.01

Source: Prepared by the Authors

Also, regression analysis indicates that AI ethics training increases confidence in AI-based employment decisions ($\beta = 0.42$, $p < 0.01$), supporting Hypothesis H6b. These results show how important it is to be mindful of ethics, be transparent, and keep learning new skills to use AI-powered hiring systems responsibly and effectively.

Discussion

The current study examined how artificial intelligence (AI) affects hiring, including efficiency, hiring outcomes, ethical issues, and stakeholder perceptions. The study enhances understanding of AI-driven recruitment's transformation of talent acquisition by incorporating perspectives from both HR experts and job seekers within the Indian IT sector, while also presenting novel strategic and ethical challenges.

Efficiency and strategic value creation using AI

The results give solid evidence that using AI in hiring makes operations more efficient and HR more effective in the long run. The strong consensus on automation and efficiency (mean = 4.1, SD = 0.82) and the notable decrease in time-to-hire ($t = 6.25$, $p < 0.001$) validate Hypothesis H1a. These findings are consistent with recent empirical research indicating that AI automates high-volume, repetitive recruitment tasks and expedites decision-making without sacrificing consistency. From a strategic human resource management standpoint, these efficiency improvements facilitate the evolution of HR operations from transactional responsibilities to more strategic duties, encompassing workforce planning and talent analytics (Jackson et al., 2014; Meyer & Xin, 2018).

The validation of Hypothesis H1b strengthens the strategic rationale for using AI. The reported cost savings (mean = 3.9, SD = 0.75) support the idea that AI lowers hiring costs by reducing the need for manual screening and external recruiting agencies (Stone et al., 2024). These results support the idea that AI is a dynamic capability that makes organisations more competitive by enabling better use of their resources and greater efficiency (Zou & Yang, 2026).

A structural tension between bias mitigation and algorithmic bias

The research uncovers a complex and theoretically significant issue concerning AI and prejudice in recruitment. The validation of Hypothesis H2a suggests that AI tools are seen as a way to reduce human bias (mean = 3.8, SD = 0.89). This is in line with earlier studies showing that standardising algorithms can help eliminate inconsistencies arising from different recruiters' judgments (Delecraz et al., 2022). This backs up the idea that AI can help make procedures fairer if it is built and run correctly.

Conversely, the validation of Hypothesis H2b underscores ongoing apprehensions regarding algorithmic bias and the consequences for diversity. Almost half of those who answered said they were worried that AI could undermine diversity efforts. This is in line with research showing that biased training data and unclear algorithms can exacerbate systemic inequities (Delecraz et al., 2022; Panarese et al., 2026). This dichotomy illustrates the overarching socio-technical critique of AI in HRM, highlighting that equitable

outcomes are contingent not solely on algorithms but also on governance frameworks, auditing processes, and human supervision (Naoum et al., 2026; Zhang et al., 2025).

Better hiring results and the ability of humans and AI to work together

The study's affirmation of Hypotheses H3a and H3b indicates that AI-driven recruiting enhances both the calibre of candidate selection and satisfaction with hiring results. The strong regression coefficient ($\beta = 0.38$, $p < 0.01$) implies that AI-driven analytics improve the fit between candidates and jobs. This is in line with research that stresses the predictive power of data-driven hiring tools.

These results substantiate the growing consensus that hybrid human–AI decision–making models surpass both fully automated and fully human methodologies. Scholars contend that human judgment is essential for contextual interpretation, ethical reasoning, and the management of non-standard employment situations (Bolton et al., 2012). The study thus endorses a complementarity perspective, suggesting that AI enhances rather than supplants human skill in recruiting.

Lack of trust, ethical concerns, and lack of transparency

Ethical concerns become a primary limitation on the deployment of AI. The substantial impact of ethical considerations on adoption decisions (Hypothesis H4a) corresponds with previous studies that emphasise transparency, data protection, and responsibility as essential factors for responsible AI utilisation in HRM (Kumar, 2026). The negative association between transparency and trust (Hypothesis H4b) further supports the view that non-transparent AI decision-making undermines stakeholder confidence.

These findings contribute to the literature by empirically illustrating that trust is not an inherent consequence of efficiency improvements. Instead, trust must be deliberately fostered by explicable AI procedures, transparent communication, and ethical governance frameworks (Freiman et al., 2025). Without these protections, companies risk pushback from both recruiters and candidates, which could undermine the long-term validity of AI-driven hiring processes.

Different Stakeholder Views

One of the most important things this study does is compare HR professionals and job seekers. The validation of Hypothesis H5a demonstrates that HR professionals possess markedly more positive views of AI recruiting, aligning with research indicating that organisational stakeholders emphasise efficiency and control advantages (Sandeep & Lavanya, 2026). Conversely, job searchers, especially those previously acquainted with AI-driven recruitment, demonstrated diminished trust (Hypothesis H5b). This discrepancy corresponds with applicant reaction theory, which asserts that perceptions of fairness, transparency, and voice significantly affect candidates' approval of selection methods (Anderson et al., 2010). The results indicate that companies need to actively manage the applicant experience by providing clear explanations, feedback, and opportunities for people to interact to remain desirable to job seekers (Miles & McCamey, 2018).

Implications for Enhancing AI-Driven Recruitment. The confirmation of Hypotheses H6a and H6b yields practical guidance for enhancing AI integration in hiring processes. Trust in AI models and ethics training for HR professionals greatly improve trust in AI-assisted decision-making. This supports earlier research that says ethical competence is an important HR skill in the age of AI (S. et al., 2026). These results bolster the assertion that competent AI implementation requires both technological investment and organisational learning, as well as cultural adaptation. In general, the study adds to the expanding body of literature on AI in HRM by providing empirical evidence from a growing economy and by integrating efficiency, ethical, and stakeholder perspectives. The results show that the long-term benefit of AI in hiring depends

on a balance among technological capacity, ethical governance, and human judgment, not solely on automation.

Conclusion

AI has become a game-changer in hiring, fundamentally reshaping how companies plan and execute their hiring processes. AI-powered solutions like applicant tracking systems, predictive analytics, and conversational chatbots have made hiring much faster and easier by automating repetitive tasks, enabling data-driven decision-making, and accelerating early-stage screening. The results of this study show that using AI in hiring has beneficial effects and helps the IT industry adopt better-organised, scalable hiring methods.

The study also shows that AI-driven hiring has both pros and cons. AI can help reduce certain forms of human prejudice, but algorithmic bias built into training data and model design remains a major problem. Concerns about transparency, explainability, and moral responsibility continue to shape how stakeholders view AI-enabled employment systems and affect their trust in them. Furthermore, the heightened automation of recruiting procedures may negatively impact the candidate experience by diminishing opportunities for human connection, thereby emphasising the necessity of maintaining transparency and communication throughout the hiring process.

This study contributes to the growing body of work on AI in human resource management by examining both its benefits and its limitations in an emerging economy. The results show that AI adoption needs to be balanced and integrated, combining technological efficiency with human judgment, ethical governance, and ongoing oversight. This kind of hybrid AI–human hiring strategy is necessary to ensure fairness, accountability, and continued organisational value. The report also points out a few directions future research could take.

More research is needed to develop strict rules for ethical AI governance, examine the long-term effects of AI-driven hiring on workforce quality and diversity, and assess how well hybrid decision-making models perform across different cultural and organisational settings. By filling these research gaps, scholars and practitioners can make greater use of AI while ensuring that hiring methods are fair, transparent, and focused on the candidate.

Theoretical Contributions

This research significantly enhances theoretical frameworks in the fields of human resource management (HRM), talent acquisition, and AI-driven decision-making. First, it contributes to the AI-in-HRM literature by providing real-world evidence from an emerging market, filling a gap in earlier research, which was largely based on studies from industrialised economies. By examining the Indian IT sector, the study makes AI recruiting theories more relevant and valid in a global context.

Second, the study contributes to the notion of strategic human resource management by viewing AI-powered recruitment as a dynamic capability that enhances hiring and organisational efficiency. The results show that AI enables companies to change their hiring procedures in ways that make them more strategically flexible. This shows that technology is more than just an operational tool; it is also a strategic enabler.

Third, the work advances organisational justice and fairness theories by empirically demonstrating AI's dual role in recruitment. Although AI can mitigate certain forms of human prejudice, the persistent presence of algorithmic bias underscores a fundamental conflict between procedural consistency and distributive fairness. This addition enhances current justice frameworks by illustrating that perceptions of

fairness are influenced not just by outcomes but also by the transparency, explainability, and governance of algorithmic systems.

Fourth, the research enhances human–AI interaction theory by endorsing a hybrid AI–human decision-making paradigm. The results indicate that the best hiring outcomes and stakeholder confidence are achieved when AI tools enhance human judgment rather than replace it. This insight bolsters theoretical assertions that human oversight is essential in intricate, value-driven processes, such as recruitment.

Finally, the study enhances applicant reaction theory by emphasising perceptual disparities between HR professionals and job candidates. The identified disparity in the confidence and acceptability of AI-driven recruitment methods enhances current frameworks for understanding applicant reactions to technology-mediated selection, highlighting the influence of experience, transparency, and perceived control on candidate responses.

These theoretical contributions collectively situate the study at the intersection of HRM, ethics, and AI research, providing a sophisticated framework for understanding how AI-driven recruitment transforms decision-making, equity, and strategic value generation in modern enterprises.

Managerial Implications

The results of this study provide managers, HR leaders, and policymakers seeking to use or improve AI-powered recruitment platforms with several useful ideas. First, the proven efficiency gains, especially lower costs and shorter time-to-hire, show that managers should deliberately use AI technologies to automate routine, high-volume hiring tasks such as screening resumes, narrowing down candidates, and scheduling interviews. HR professionals may then focus their efforts on strategic initiatives such as talent planning, employer branding, and workforce development, thereby making HR's function in organisations more strategic.

Second, the improved quality of candidate selection underscores the importance of using AI-driven analytics in decision-making. Managers should use AI technologies to get data-driven insights, such as talent matching and predictive performance indicators. However, they should still make hiring decisions based on human judgment. This mixed AI–human decision-making strategy lets businesses leverage AI's analytical strengths while still accounting for context, ethics, and experience that algorithms can't.

Third, the study emphasizes the necessity for proactive control of algorithmic bias and ethical hazards. Managers need to understand that AI doesn't automatically eliminate prejudice; instead, it can shift bias from people to systems. As a result, businesses should put in place governance systems such as regular audits of algorithms, training datasets that include a variety of examples, and rules for detecting bias. Setting up cross-functional oversight committees with people from HR, legal, and data science helps strengthen accountability and adherence to rules.

Fourth, trust and openness were found to be very important factors in how HR professionals and job seekers accepted AI. Managers should prioritise using explainable AI technologies and ensure that candidates understand the reasons behind hiring decisions. Being explicit about how AI tools are used, what factors affect conclusions, and how candidate data is handled may greatly increase trust and defend the reputation of the employer brand.

Fifth, the fact that HR professionals and job seekers view things differently underscore the importance of candidate-centric hiring practices. Managers should create AI-driven hiring processes that keep people in the loop at key points, including during interviews and feedback. Adding ways for candidates to provide feedback and ask questions might help shift unfavourable attitudes and improve the candidate experience.

Lastly, the fact that AI ethics training makes managers more confident suggests that companies should invest in ongoing skill development. HR managers can learn to properly run AI systems by taking training courses on ethical AI use, data privacy, and responsible decision-making. These kinds of investments reduce implementation risks and help the company prepare for the long-term use of AI.

In general, the management implications of this study show that AI-driven recruitment is not just a technical problem, but also a strategic and ethical one. Companies that take a balanced approach combining efficiency, openness, ethical leadership, and human oversight are more likely to gain a long-term competitive edge through AI-enabled talent acquisition.

Policy Implications

The results of this study have substantial implications for legislators, regulators, and professional organisations responsible for overseeing the use of AI in hiring and employment processes.

First, the proof of both efficiency improvements and ethical hazards shows that there needs to be clear, uniform rules for how AI can be used in hiring. Policymakers ought to formulate clear directives on algorithmic transparency, equity, data protection, and accountability to ensure that AI-driven recruitment systems operate within permissible ethical and legal parameters.

Second, the study shows that algorithmic bias remains a problem, even when AI systems are used to make decisions less dependent on people's opinions. This result shows that policies should require enterprises to regularly check for bias and examine the effects of AI recruitment tools. Regulatory organisations might require companies to keep records of where they obtain their training data, how they verify it, and how they address bias, especially in fields like IT and tech services, where they hire many people.

Third, job seekers said that being open and honest was a big factor in their trust. So, policymakers should push for or compel the use of explainable AI (XAI) standards in hiring. These kinds of legislation might include granting candidates the right to receive clear reasons for automated decisions, mechanisms to challenge or appeal AI-based outcomes, and rules governing the extent of automation in hiring decisions. These steps would improve procedural fairness and preserve candidates' rights.

Fourth, the study's results underscore the importance of regulations that support HR professionals' learning about AI. Governments, accreditation agencies, and industry associations should support training standards and certification programs that teach HRM professionals to use AI responsibly. Encouraging ongoing professional growth in AI governance would reduce the risks of implementing new rules and make it easier to follow emerging ones.

The policy implications of this study underscore that responsible AI deployment in recruitment necessitates not only organisational initiative but also institutional backing, regulatory clarity, and enforcement measures. Well-thought-out policies can help strike a balance between innovation and fairness, ensuring that AI-driven hiring helps create fair and long-lasting job markets.

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