



AI-Based Hiring Vs Traditional Hiring

An Empirical Study of Recruitment Effectiveness, Procedural Fairness and Candidate Experience

1Kamalesh R, 2Dr. Madhu B K

1MBA Student, 2Research Supervisor

Faculty of Management and Commerce, M. S. Ramaiah University of Applied Sciences, Bengaluru, India

How to Cite this Article:

R, K. (2026). AI-Based Hiring Vs Traditional Hiring. International Journal of Creative and Open Research in Engineering and Management, 2(10), 1-9.
<https://doi.org/10.55041/ijcope.v2i10.053>

License:

This article is published under the terms of the Creative Commons Attribution 4.0 International License (CC BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author(s) and the source are credited.

© The Author(s). Published by International Journal of Creative and Open Research in Engineering and Management.



<https://doi.org/10.55041/ijcope.v2i10.053>

Abstract: Artificial intelligence (AI) is increasingly embedded in recruitment activities such as candidate sourcing, resume screening, shortlisting, communication and initial assessment. This study examines whether AI-supported recruitment practices are associated with perceived recruitment effectiveness, whether transparency and human oversight are associated with procedural fairness, and whether AI-supported practices and human interaction affect candidate experience. A quantitative, descriptive, explanatory and cross-sectional survey design was used. Primary data were collected through a structured closed-ended questionnaire from 101 respondents with awareness, experience or exposure to recruitment and selection. A five-point Likert scale was used. Data were coded in Microsoft Excel and analysed using Jamovi through descriptive statistics, Cronbach's alpha, Pearson correlation, simple linear regression and multiple linear regression. The results did not support any of the three alternative hypotheses. AI-practices/integration showed an almost zero association with perceived recruitment effectiveness ($r = .011$, $p = .910$; $R^2 = .000129$). Transparency/human oversight showed no significant relationship with procedural fairness ($r = -.084$, $p = .406$; $R^2 = .00699$). AI-supported practices and human interaction together explained only 1.05% of the variance in candidate experience ($R^2 = .0105$), and neither predictor was significant. The findings should be interpreted cautiously because several composite measures showed very low internal consistency. The study therefore suggests that AI should not be evaluated simply as a replacement for traditional recruitment; instead, individual AI practices, human safeguards, transparency and interaction should be assessed separately using stronger measurement scales.

Index Terms - Artificial Intelligence Recruitment, Traditional Hiring, Recruitment Effectiveness, Procedural Fairness, Human Oversight, Candidate Experience, Human-AI Recruitment.

I. INTRODUCTION

Artificial intelligence is changing recruitment and selection by supporting activities such as candidate sourcing, resume screening, candidate ranking, communication, interview scheduling and online assessment. Traditional recruitment, in contrast, has historically depended more heavily on recruiters and managers for application review, interviews, verification and final judgement. AI can process large volumes of information quickly and reduce repetitive administrative work, but the use of AI also raises concerns about transparency, algorithmic bias, privacy, accountability, fairness and reduced human interaction.

The present study does not treat AI-based hiring and traditional hiring as mutually exclusive alternatives. It adopts a human-AI perspective in which AI can support data-heavy and repetitive activities while human recruiters retain an important role in interpretation, communication, fairness review and consequential hiring decisions. This framing is consistent with the thesis draft, which identifies the practical question as how technological efficiency and meaningful human involvement can work together.

The research problem is therefore centred on three outcomes: perceived recruitment effectiveness, procedural fairness and candidate experience. Recruitment effectiveness covers speed, quality of shortlisting, consistency and administrative efficiency. Procedural fairness is considered through transparency and human oversight. Candidate experience includes convenience, communication, trust, acceptance and the perceived importance of human interaction.

A. Problem Identification

Although AI-enabled recruitment tools are increasingly available, greater automation does not automatically mean that recruitment becomes more effective, fair or acceptable to candidates. AI may improve administrative efficiency while creating uncertainty about how recommendations are produced and whether candidates receive adequate explanation or opportunities for review. Traditional approaches can preserve human connection and contextual judgement but may require greater time and effort and can also be influenced by personal judgement.

The central problem addressed by this study is the lack of clear empirical evidence, within the selected Indian respondent context, about the relationships between AI-supported recruitment practices and recruitment effectiveness, transparency and human oversight and procedural fairness, and AI-supported practices and human interaction and candidate experience.

B. Criticality of the Problem

The issue is critical because recruitment decisions directly affect access to employment and organisational talent. AI systems can influence who is screened, ranked, contacted or progressed, making questions of fairness and accountability important alongside efficiency. The literature reviewed in the thesis indicates that AI adoption is not solely a technology decision; organisational readiness, recruiter involvement, explainability, candidate acceptance and responsible governance also matter. Indian evidence particularly points toward the need to combine technology with HR capability rather than assuming that automation alone produces better outcomes.

C. Rationale for the Research

Existing research identifies potential benefits of AI in repetitive and high-volume recruitment tasks, but also reports concerns about algorithmic discrimination, transparency, candidate reactions and loss of human involvement. Indian studies have examined AI adoption and recruiter perspectives, while international studies have examined candidate reactions, fairness and human-AI augmentation. The present research brings these strands together by testing three relationships within one quantitative framework and by including respondents with different forms of recruitment exposure.

II. LITERATURE REVIEW

The literature reviewed in the thesis shows a broad movement from purely traditional recruitment toward technology-assisted and hybrid recruitment. Mehrotra and Khanna (2022) reported that AI can streamline talent acquisition in Indian organisations but should not replace human judgement. Bhatt (2023) highlighted information security, return on investment and the usefulness of AI for information-heavy and repetitive tasks. Sattu, Das and Jena (2024) showed that HR readiness and perceived



value influence AI adoption in Indian IT organisations. Rukadikar, Khandelwal and Warriar (2025) described the movement toward hybrid recruitment in which AI supports screening and matching while human recruiters retain interpretive and decision-making roles. Itam et al. (2026) similarly reported that AI is transforming talent-acquisition work while humans remain important for interpreting and applying technology-generated information.

International research provides complementary evidence. Ore and Spasato (2022) identified opportunities and risks in AI recruitment and emphasised that recruiters remain necessary for human decision-making. Van Esch, Black and Arli (2021) found that candidates' attitudes toward AI-enabled applications can influence intentions to apply. Wesche and Sonderegger (2021) found that negative reactions to AI vary by the stage at which AI is introduced, with stronger acceptance for preliminary tasks than later decision stages. Mirowska and Mesnet (2022) reported applicant concerns about AI-based interview evaluation despite recognition of possible consistency and objectivity benefits.

Hunkenschroer and Luetge (2022) identified algorithmic discrimination, privacy, transparency, accountability and fairness as important ethical issues. Gonzalez et al. (2022) found stronger support for human-led and human-supported hiring than AI-led decision making and showed that augmented human-AI approaches can mitigate negative reactions. Fumagalli, Rezaei and Salomons (2022) demonstrated that perceptions of algorithmic and human evaluators differ, with neither method being uniformly perceived as superior. Hohenstein and Jung (2023) emphasised explainability, transparency and human supervision. Rigotti and Fosch-Villaronga (2024) highlighted consistency, job relevance, objectivity and opportunities to demonstrate suitability as dimensions of procedural fairness. Hosain et al. (2025) found positive relationships between perceived AI use, perceived procedural justice, usefulness, ease of use and trust among job applicants.

Table 1. Selected Literature and Relevance to the Present Study

Author(s), Year	Focus	Key Finding / Relevance
Mehrotra & Khanna (2022)	AI recruitment in Indian companies	AI streamlines recruitment; human judgement remains important.
Bhatt (2023)	AI adoption criteria in hiring	Security, ROI and information-heavy tasks influence adoption.
Sattu et al. (2024)	AI adoption among Indian IT HR professionals	HR readiness and perceived value shape adoption.
Rukadikar et al. (2025)	Traditional recruitment and AI interventions	Evidence supports movement toward hybrid recruitment.
Itam et al. (2026)	AI-driven talent acquisition in Indian IT	AI transforms recruitment work; humans remain critical for interpretation.
van Esch et al. (2021)	Applicant reactions to AI applications	Candidate attitudes toward AI can affect application intentions.
Wesche & Sonderegger (2021)	Job-seeker reactions to AI selection	AI is more acceptable in preliminary than later-stage tasks.
Mirowska & Mesnet (2022)	AI interview evaluation	Candidates value human engagement despite AI consistency benefits.
Gonzalez et al. (2022)	Human, AI/ML and augmented hiring	Human-supported and augmented approaches are better received than AI-led hiring.
Rigotti & Fosch-Villaronga (2024)	Fairness in AI recruitment	Transparency, accountability and procedural fairness are central.

III. RESEARCH GAP AND RESEARCH QUESTIONS

Four related gaps motivate the study. First, much of the literature examines either technology adoption or ethical concerns rather than testing recruitment effectiveness, procedural fairness and

candidate experience together. Second, Indian research has established the relevance of AI adoption and organisational readiness, but the perspectives of HR professionals, hiring managers, employees, job seekers and graduates are not always examined together. Third, although transparency and human oversight are widely recommended, fewer empirical studies directly test their association with perceived procedural fairness within one integrated framework. Fourth, research increasingly supports human-AI augmentation, but the practical relationship between AI-supported practices, human interaction and candidate experience remains context dependent.

RQ1: What is the relationship between the extent of AI integration in recruitment activities and perceived recruitment effectiveness?

RQ2: How do transparency and human oversight in AI-supported recruitment influence perceived procedural fairness of hiring decisions?

RQ3: What effect do AI-supported recruitment practices and human interaction have on candidate experience?

IV. RESEARCH OBJECTIVES AND HYPOTHESES

- Objective 1: To determine the relationship between the extent of AI integration in recruitment activities and perceived recruitment effectiveness, including speed, quality of shortlisting, consistency and administrative efficiency.
- Objective 2: To assess the influence of transparency and human oversight in AI-supported recruitment on perceived procedural fairness of hiring decisions.
- Objective 3: To evaluate the effect of AI-supported recruitment practices and human interaction on candidate experience, including convenience, communication quality, trust and acceptance of hiring outcomes.

A. Research Hypotheses

- H0₁: There is no significant relationship between the extent of AI integration in recruitment activities and perceived recruitment effectiveness.
- H1₁: There is a significant positive relationship between the extent of AI integration in recruitment activities and perceived recruitment effectiveness.
- H0₂: Transparency and human oversight in AI-supported recruitment have no significant influence on perceived procedural fairness of hiring decisions.
- H1₂: Transparency and human oversight in AI-supported recruitment have a significant positive influence on perceived procedural fairness of hiring decisions.
- H0₃: AI-supported recruitment practices and human interaction have no significant effect on candidate experience.
- H1₃: AI-supported recruitment practices and human interaction have a significant effect on candidate experience.

V. RESEARCH METHODOLOGY

A. Research Design

The study used a quantitative, descriptive, analytical, explanatory and cross-sectional survey design. A structured closed-ended questionnaire was administered once. Purposive sampling, described in the thesis as a form of convenience sampling, was used to obtain respondents with experience, exposure or informed awareness of recruitment and selection practices.

B. Sample and Data Collection

A total of 101 valid responses were used for analysis. Respondents included HR professionals/recruiters/talent-



acquisition specialists, hiring managers/team leads, employees or working professionals, job seekers, and final-year students or recent graduates. The questionnaire was administered online and responses were exported to Microsoft Excel before statistical analysis in Jamovi.

C. Instrument and Variables

All attitudinal statements used a five-point Likert scale from 1 = Strongly Disagree to 5 = Strongly Agree. The principal constructs were operationalised as follows: H1_AIProxy (Q12–Q16) and H1_Effect (Q17); H2_THO (Q18–Q22) and H2_Fair (Q23–Q24); and H3_AI (Q25–Q26), H3_Human (Q27–Q28) and H3_CE (Q29–Q31), with the negatively worded Q29 reverse-coded for the regression composite).

D. Data Analysis

Descriptive statistics were used to summarise respondent characteristics and response patterns. Cronbach's alpha was used to examine internal consistency. Pearson product-moment correlation and simple linear regression were used for Objectives 1 and 2, while multiple linear regression was used for Objective 3. Normality and regression diagnostics were examined, including multicollinearity for the H3 model.

E. Conceptual Model

Predictor / Explanatory Construct	Outcome	Primary Test
AI integration / AI-supported recruitment practices	Perceived recruitment effectiveness	Pearson correlation + simple linear regression
Transparency + human oversight	Perceived procedural fairness	Pearson correlation + simple linear regression
AI-supported recruitment practices + human interaction	Candidate experience	Multiple linear regression

Figure 1. Conceptual relationships tested in the study

AI Integration → Recruitment Effectiveness
 Transparency + Human Oversight → Procedural Fairness
 AI-Supported Practices + Human Interaction → Candidate Experience

VI. DATA ANALYSIS AND RESULTS

A. Descriptive Results

The descriptive results show mixed rather than uniformly positive attitudes toward AI-enabled recruitment. Composite means reported in the thesis were 2.99 for H1_AIProxy, 2.91 for recruitment effectiveness, 2.97 for transparency/human oversight, 3.11 for procedural fairness, 2.88 for AI-supported practices, 3.17 for human interaction and 2.92 for candidate experience. This pattern indicates that respondents were not strongly positive about AI recruitment as a complete system.

For individual items, the clearest positive response in Objective 1 concerned the usefulness of AI for handling large application volumes: 44.6% agreed or strongly agreed. By contrast, responses were less favourable for claims about reduced shortlisting time and improved consistency. For candidate experience, 37.6% agreed or strongly agreed that AI could provide faster communication, while 43.6% disagreed or strongly disagreed that AI-supported recruitment makes the application process more convenient. A substantial 50.5% disagreed or strongly disagreed that a balanced AI-human combination improves candidate experience, although 42.2% agreed or strongly agreed that they would be comfortable with AI recruitment under appropriate human oversight.

Table 2. Composite Descriptive Statistics

Construct	Mean	SD	Interpretation
H1_AIProxy	2.99	0.545	Near midpoint; mixed perception
H1_Effect	2.91	1.18	Mixed perception of effectiveness
H2_THO	2.97	0.565	Near midpoint
H2_Fair	3.11	0.954	Slightly above midpoint
H3_AI	2.88	0.884	Mixed/neutral perception
H3_Human	3.17	0.819	Relatively more positive
H3_CE	2.92	0.732	Mixed candidate-experience perception

B. Reliability

The reliability analysis produced an important methodological finding. The H1 AI-practices/integration proxy had Cronbach's $\alpha = .111$; transparency/human oversight had $\alpha = .00506$; procedural fairness had $\alpha = .162$; AI-supported practices had $\alpha = .0128$. These coefficients are far below the conventional .70 benchmark and indicate that the grouped items did not behave as internally consistent measures in this sample. The thesis therefore appropriately treats the inferential findings with caution and recommends stronger measurement scales in future work.

Table 3. Reliability Results

Scale	Items	Cronbach's α	Assessment
AI-practices/integration proxy	Q12–Q16	.111	Very low internal consistency
Transparency + human oversight	Q18–Q22	.00506	Very low internal consistency
Procedural fairness	Q23–Q24	.162	Very low internal consistency
AI-supported practices	Q25–Q26	.0128	Very low internal consistency

C. Hypothesis Testing

Hypothesis	Statistic	Result	Decision
H1: AI integration → recruitment effectiveness	$r = .011$; $p = .910$; $R^2 = .000129$	Not significant	Do not reject H_{01}
H2: Transparency/human oversight → procedural fairness	$r = -.084$; $p = .406$; $R^2 = .00699$	Not significant	Do not reject H_{02}
H3: AI practices + human interaction → candidate experience	$R^2 = .0105$; $p = .328$ and $.659$	Neither predictor significant	Do not reject H_{03}

Objective 1 — AI Integration and Recruitment Effectiveness

Pearson correlation between H1_AIProxy and H1_Effect was $r = .011$ with $p = .910$. The supporting simple regression produced $R^2 = .000129$, with $B = .0246$ and $\beta = .0114$, $p = .910$. The 95% confidence interval for the predictor coefficient included zero. Therefore, the data do not establish a statistically significant relationship between the operationalised AI-practices/integration proxy and perceived recruitment effectiveness.

Objective 2 — Transparency, Human Oversight and Procedural Fairness

The relationship between H2_THO and H2_Fair was weakly negative and non-significant ($r = -.084$, $p = .406$). Simple regression produced $R^2 = .00699$ and $B = -.141$, $\beta = -.0836$, $p = .406$. The 95% confidence interval ranged from $-.477$ to $.194$ and included zero. Thus, the proposed positive relationship between transparency/human oversight and procedural fairness was not established in this sample.



Objective 3 — AI Practices, Human Interaction and Candidate Experience

The multiple regression model produced $R = .103$, $R^2 = .0105$ and adjusted $R^2 = -.00966$. AI-supported practices had $B = -.0830$, $\beta = -.1002$, $p = .328$, while human interaction had $B = .0403$, $\beta = .0451$, $p = .659$. Both confidence intervals included zero. The model therefore explained only 1.05% of the variance in candidate experience, and neither predictor made a statistically significant contribution. Multicollinearity was not a concern because both predictors had $VIF = 1.03$ and tolerance = .971.

VII. DISCUSSION

The findings provide a conservative picture of AI-supported recruitment. Respondents appear more receptive to AI for specific administrative or high-volume tasks than for broad claims about recruitment effectiveness. This is consistent with the literature reviewed in the thesis, which frequently distinguishes between repetitive preliminary activities and judgement-intensive stages of hiring. The absence of a significant H1 relationship should therefore not be interpreted as evidence that AI is useless; rather, the measured AI proxy did not predict the selected effectiveness outcome in this sample.

The second finding is that transparency and human oversight did not show the expected statistical association with procedural fairness. This result contrasts with the normative and conceptual literature that treats transparency, explainability and human supervision as important safeguards. The thesis notes that several governance items received relatively strong support individually, including bias monitoring, human oversight and opportunities for candidate clarification or review. Consequently, the lack of a composite-scale relationship may reflect the fact that respondents perceive these safeguards as distinct practices rather than as interchangeable components of one construct.

The third finding reinforces the complexity of candidate experience. Human interaction had a positive but very small coefficient, while AI-supported practices had a small negative coefficient, and neither was significant. Descriptive responses nevertheless indicate that human contact and appropriate oversight matter to meaningful segments of the sample. This suggests that the quality, timing and purpose of human interaction may matter more than simply whether a human is present somewhere in an AI-enabled process.

The most important methodological contribution is the evidence that conceptually related recruitment attitudes cannot automatically be combined into reliable composite scales. Very low Cronbach's alpha values indicate that future research should distinguish AI-use intensity, perceived AI benefits, transparency, human review, bias governance, candidate voice, interaction quality and overall candidate experience as separate constructs unless stronger measurement evidence supports aggregation.

VIII. KEY FINDINGS AND CONTRIBUTION

- AI was most positively viewed for handling large application volumes, while broader claims about shortlisting, consistency, matching and overall effectiveness received mixed responses.
- No statistically significant relationship was found between the AI-practices/integration proxy and perceived recruitment effectiveness.
- No statistically significant relationship was found between transparency/human oversight and perceived procedural fairness.

- AI-supported practices and human interaction jointly explained only 1.05% of candidate-experience variance, with neither predictor significant.
- Human interaction had a slightly more positive descriptive profile than AI-supported practices, but this did not translate into a statistically significant regression effect.
- Very low internal consistency across several composite scales is a major caveat and a contribution to the methodological interpretation of the study.
- The findings support evaluating AI and traditional recruitment as complementary components rather than assuming that one should completely replace the other.

IX. CONCLUSION

This study examined AI-based hiring and traditional human involvement through three linked dimensions: recruitment effectiveness, procedural fairness and candidate experience. Based on 101 valid responses, none of the three alternative hypotheses was statistically supported at the .05 level. AI-practices/integration was not significantly associated with recruitment effectiveness; transparency and human oversight were not significantly associated with procedural fairness; and neither AI-supported recruitment practices nor human interaction significantly predicted candidate experience.

These results do not demonstrate that AI, transparency, oversight or human interaction are unimportant. Rather, the relationships proposed in the conceptual model were not established using the operationalised measures and sample. The descriptive findings indicate bounded acceptance of AI for certain administrative tasks and continued interest in human oversight and interaction. A more defensible organisational approach is therefore to use AI selectively for appropriate recruitment activities while retaining meaningful human review, explanation and decision authority at consequential stages.

X. RECOMMENDATIONS AND FUTURE RESEARCH

- Use a larger and more representative sample, ideally including more HR professionals, recruiters, talent-acquisition specialists and hiring managers.
- Develop and validate multi-item scales separately for AI-use intensity, perceived effectiveness, transparency, human review, bias governance, candidate voice, interaction quality and candidate experience.
- Use sensitivity analyses and appropriate non-parametric methods when normality assumptions are not satisfied.
- Distinguish access to a human recruiter from the quality of human interaction, including responsiveness, empathy, explanation, opportunity to challenge and meaningful decision authority.
- Examine AI familiarity and direct experience with AI recruitment as possible moderators of candidate attitudes.
- Future studies should incorporate actual recruitment outcomes such as time-to-hire, cost-per-hire, screening accuracy, quality of hire and post-hire outcomes rather than relying only on perceptions.
- Compare AI-supported, traditional human-led and augmented human-AI recruitment using experimental or longitudinal designs to strengthen causal interpretation.

XI. LIMITATIONS

- The attained sample size was 101 rather than the proposed minimum of 150, reducing statistical power and generalisability.



- Purposive/convenience online sampling means the sample is not a probability sample of HR professionals, employees or job seekers in India.
- The questionnaire measured perceptions rather than actual organisational hiring results, algorithm accuracy, cost, time-to-hire or post-hire outcomes.
- Several constructs had very low internal consistency, which can attenuate correlations and regression coefficients.
- Several constructs contained only two items, limiting content coverage and reliability stability.
- H1_AIPProxy is a perceived-practices proxy rather than a direct organisational measure of actual AI integration.
- Several composite variables were significantly non-normal according to Shapiro–Wilk tests, and non-parametric sensitivity tests were not available in the analysed output.
- The cross-sectional design identifies associations but cannot demonstrate that AI practices, transparency or human interaction cause changes in recruitment outcomes.
- Respondents differed in their direct experience with AI-enabled recruitment, so perceptions may reflect personal experience, general awareness or expectations.

XII. ACKNOWLEDGMENT

The author expresses gratitude to the faculty, research supervisor, respondents and all those who supported the completion of the study at M. S. Ramaiah University of Applied Sciences, Bengaluru.

REFERENCES

- [1] Bhatt, P. (2023). AI adoption in the hiring process – important criteria and extent of AI adoption. *Foresight*, 25(1), 144–163. doi:10.1108/FS-07-2021-0144.
- [2] Fumagalli, E., Rezaei, S., & Salomons, A. (2022). OK computer: Worker perceptions of algorithmic recruitment. *Research Policy*, 51(2), Article 104420. doi:10.1016/j.respol.2021.104420.
- [3] Gonzalez, M. F., Liu, W., Shirase, L., Tomczak, D. L., Lobbe, C. E., Justenhoven, R., & Martin, N. R. (2022). Allying with AI? Reactions toward human-based, AI/ML-based, and augmented hiring processes. *Computers in Human Behavior*, 130, 107179. doi:10.1016/j.chb.2022.107179.
- [4] Horodyski, P. (2023). Applicants' perception of artificial intelligence in the recruitment process. *Computers in Human Behavior Reports*, 11, 100303. doi:10.1016/j.chbr.2023.100303.
- [5] Hosain, M. S., Amin, M. B., Debnath, G. C., & Rahaman, M. A. (2025). The use of artificial intelligence (AI) in the hiring process: Job applicants' perceptions of procedural justice. *Computers in Human Behavior Reports*, 19, 100713. doi:10.1016/j.chbr.2025.100713.
- [6] Hunkenschroer, A. L., & Kriebitz, A. (2023). Is AI recruiting (un)ethical? A human rights perspective on the use of AI for hiring. *AI and Ethics*, 3, 199–213. doi:10.1007/s43681-022-00166-4.
- [7] Hunkenschroer, A. L., & Luetge, C. (2022). Ethics of AI-enabled recruiting and selection: A review and research agenda. *Journal of Business Ethics*, 178(4), 977–1007. doi:10.1007/s10551-022-05049-6.
- [8] Itam, U. J., Shukla, N., Toni, M., Kesavan, K. R., & Mishra, K. (2026). AI-driven talent acquisition in Indian IT firms: A qualitative study of automation, impacts, and skill requirements. *SN Business & Economics*, 6, Article 347. doi:10.1007/s43546-026-01325-z.
- [9] Lee, C. H., & Cha, K. J. (2023). FAT-CAT—Explainability and augmentation for an AI system: A case study on AI recruitment-system adoption. *International Journal of Human-Computer Studies*, 171, 102976. doi:10.1016/j.ijhcs.2022.102976.
- [10] Mehrotra, S., & Khanna, A. (2022). Recruitment through AI in selected Indian companies. *Metamorphosis*, 21(1), 31–39. doi:10.1177/09726225211066220.
- [11] Mirowska, A., & Mesnet, L. (2022). Preferring the devil you know: Potential applicant reactions to artificial intelligence evaluation of interviews. *Human Resource Management Journal*, 32(2), 364–383. doi:10.1111/1748-8583.12393.
- [12] Ore, O., & Sposato, M. (2022). Opportunities and risks of artificial intelligence in recruitment and selection. *International Journal of Organizational Analysis*, 30(6), 1771–1782. doi:10.1108/IJOA-07-2020-2291.
- [13] Ravikumar, P. (2025). Adapting to stay: A review of AI in recruitment, work–life balance, and the future of HR. *International Journal of Indian Psychology*, 13(3), 3568–3573. doi:10.25215/1303.324.
- [14] Rigotti, C., & Fosch-Villaronga, E. (2024). Fairness, AI & recruitment. *Computer Law & Security Review*, 53, 105966. doi:10.1016/j.clsr.2024.105966.
- [15] Rukadikar, A., Khandelwal, K., & Warriar, U. (2025). Reimagining recruitment: Traditional methods meet AI interventions—A 20-year assessment (2003–2023). *Cogent Business & Management*, 12(1), 2454319. doi:10.1080/23311975.2025.2454319.
- [16] Sattu, R., Das, S., & Jena, L. K. (2024). Should I adopt AI during talent acquisition? Evidence from HR professionals of Indian IT organisations. *Journal of Organizational Effectiveness: People and Performance*, 11(4), 1005–1022. doi:10.1108/JOEPP-05-2023-0186.
- [17] Seppälä, P., & Małecka, M. (2024). AI and discriminative decisions in recruitment: Challenging the core assumptions. *Big Data & Society*, 11(1), 1–12. doi:10.1177/20539517241235872.
- [18] van Esch, P., Black, J. S., & Arli, D. (2021). Job candidates' reactions to AI-enabled job application processes. *AI and Ethics*, 1, 119–130. doi:10.1007/s43681-020-00025-0.
- [19] Wesche, J. S., & Sonderegger, A. (2021). Repelled at first sight? Expectations and intentions of job-seekers reading about AI selection in job advertisements. *Computers in Human Behavior*, 125, 106931. doi:10.1016/j.chb.2021.106931.
- [20] Yadav, A., & Nigam, A. (2025). Navigating AI adoption in recruitment for driving organizational performance: A systematic literature review. *Delhi Business Review*, 26(1), 65–78. doi:10.51768/dbr.v26i1.261202506.

APPENDIX: CORE QUESTIONNAIRE CONSTRUCTS

Section	Items	Construct / Purpose
C	Q12–Q17	AI integration/practices and recruitment effectiveness
D	Q18–Q24	Transparency, human oversight and procedural fairness
E	Q25–Q31	AI-supported practices, human interaction and candidate experience
F	Q32–Q34	Overall recruitment preference and responsible-AI orientation

The full questionnaire in the thesis uses a five-point Likert scale for attitudinal statements and includes respondent-profile and recruitment-exposure questions. The technical paper reports only the core constructs required for the empirical model.