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IMPACT OF ARTIFICIAL INTELLIGENCE ON RECRUITMENT AND SELECTION

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1. ABSTRACT

AI is being presently used for resume screening, candidate matching, application management, interview scheduled and decision support in recruitment and selection field. The existing paper studies the perceived function and impact of AI in recruitment and selection, particularly in relation to efficiency, screening accuracy, fairness, transparency, candidate experience, data privacy, and the ongoing necessity of human judgement. An observational and analytical research design was adopted. The researchers gathered primary data with the help of a structured questionnaire from 200 respondents consisting of HR professionals, recruiters, job applicants, selected employees, managers, and other employment-related respondents.

The survey data collected were assessed using frequency and percentage analysis, descriptive statistics, one sample t-test, multiple regression analysis, Pearson correlation analysis and Chi-square test of independence. The results show that AI is generally viewed favourably. Utility of AI was rated on average at 4.020 and this score is significantly above neutral ($t = 15.611$, $p < .001$). The regression model was significant ($R = .882$, $R^2 = .777$, $F = 135.462$, $p < .001$) indicating that shortlisting speed, matching accuracy, error reduction, application management and interview scheduling explained 77.7 per cent of the variance in AI overall impact. Significant individual predictors were matching accuracy, shortlisting speed, and interview scheduling. The relationship between transparency and candidate experience was moderately positive as seen in the results. Results obtained from Chi-square show significant association between suggested improvement measures and overall opinion about AI ($\chi^2 = 32.873$, $p = .035$). However, one must take into account small expected counts. The findings provide evidence for a balanced model in which AI may improve operational efficiency, but within set parameters including explainability, privacy protection, bias checks and human oversight.

KEYWORDS: *Artificial Intelligence; Recruitment; Selection; Candidate Experience; Human Oversight.*

2. INTRODUCTION

Recruitment and selection do recruitment and selection is carried out quality. These affect productivity, performance, retention and system – capabilities and the quality of the recruitment inferences. We have often functioned in the way of creating a job advertisement, inviting application, CV screening, test, and interview, reference check, offer making in hiring decisions. When organizations get huge applications, these activities may become time-consuming and repetitive. As a result, AI-based tools are being infused for resume parsing, candidate ranking, skill matching, chatbot communication, interview scheduling, assessment, and workforce planning. Today's HRM research showcases AI as not simply a replacement technology but as an augmentation system that can enhance the speed and consistency of HR decisions where they are complemented with human involvement (Budhwar et al., 2022; Prikshat et al., 2023a).

Computer-assisted hiring can sift through huge datasets quicker than people can and can spot patterns that an individual recruiter cannot examine in a short time. In a real-life context, applicant-tracking systems extract qualifications, experience, keywords, skills, work history and match algorithms match those features with job requirement. Chatbots could reply to frequently asked questions, gather necessary information and supply updates. Interview scheduling tools can set up interviews, while analytical systems can help recruiters find potentially suitable candidates. Research focusing on HR digitalisation shows the close association of AI adoption with automation, data-based decision-making, and changes in HR professionals' roles (Murugesan et al., 2023; Nawaz et al., 2024).

Having speed and scale does not innately guarantee a good hire. A system can reproduce bias contained in historical data, use variables that indirectly disadvantage particular groups, or reject candidates through criteria that are not understood by applicants. Research on AI-enabled recruitment which is ethical indicates that fairness or accountability or explainability or privacy or human responsibly are essential requirements (Hunkenschroer & Luetge, 2022; Drage & Mackereth, 2022; Rigotti & Fosch-Villaronga, 2024). Decisions about recruitment affect access to jobs and the dignity of individuals. Therefore, an algorithm whose accuracy cannot be questioned or explained yet which is useful in operation, could undermine trust.

The answer provided by the candidate is also important in AI recruitment. Candidates might enjoy a more rapid exchange of text, a less demanding and protracted waiting time, yet might also feel a little uneasy when a key employment decision seems to have been made behind the scenes without any significant human interaction. Research conducted on applicant perceptions hints that the effects of AI depend on the type of task, degree of human involvement, information given on system, and perceived quality of test (Schick & Fischer, 2021; Wesche & Sonderegger, 2021; Horodyski, 2023b). HR professionals also assess AI in terms of usefulness, reliability, ease of use, organisational support, and fear of loss of professional control (Horodyski, 2023a).

The Indian job market presents an important context for this issue, as organizations recruit at scale across campus hiring, digital employment platforms, and the IT, services, and start-up, and financial services and other sectors. Indian and India-specific studies are increasingly looking into artificial intelligence (AI) adoption in HRM, digitalisation, candidate engagement, and campus hiring (Basu et al., 2023; Meshram, 2023; Rukadikar & Khandelwal, 2024, 2025b). Recent study of Indian graduates finds that factors such as trust, usefulness, fairness, and technical anxiety shape willingness to use campus recruitment tool powered by AI. This justifies that we need to study both efficiency and human-centred acceptance rather than treating it as merely technical.

The following are the four practical questions addressed in the present study. Are the respondents aware of AI's usefulness in recruitment and selection? Do the efficiency-related factors, namely, how quickly applications are shortlisted, and how accurately matches are made along with the efficiency in error reduction, application management, and interview scheduling contributes to the overall impact of AI? Could it be a good thing if a candidate's experience is more open to discussion? Fourth, what kind of protections are desired for more accountable implementation? The study examines the answers that 200 participants gave and tries to give an academically grounded and practically relevant perspective on the hiring process with the help of AI.

3. LITERATURE REVIEW

The literature has been reviewed in chronological order 2021 – 2025. The selected studies are global research and primarily Indian or India related. Hence, the review will draw on the historical debates, along with the newer context of digitalisation of HR in India.

Table 3.1: Chronological Review of Recent Literature

Author and Year	Objective	Methodology	Key Findings	Relevance to Present Study
Schick & Fischer (2021)	To assess applicants' perceptions of assessment quality when AI is used in personnel selection.	Experimental/scenario-based candidate study.	Perceived quality and acceptance depend on how AI is introduced and used in the selection process.	Supports the candidate-experience and perceived-quality dimensions.
Wesche & Sonderegger (2021)	To examine job-seekers' expectations and intentions after reading about AI-based selection in job advertisements.	Experimental study using recruitment scenarios.	Early disclosure of AI can affect attraction, expectations, and intention to apply.	Shows that communication about AI can influence applicant reactions.
Budhwar et al. (2022)	To review AI-related challenges and opportunities for international HRM.	Critical literature review and research agenda.	AI creates opportunities for automation and analytics, but requires new capabilities, governance, and responsible implementation.	Provides the broader HRM basis for human–AI augmentation.
Drage & Mackereth (2022)	To question whether AI actually removes race and gender bias from recruitment.	Critical and philosophical analysis.	Claims of "debiasing" can hide structural differences and the assumptions built into data and models.	Supports regular bias checking and careful interpretation of fairness.
Hunkenschroer & Luetge (2022)	To review the ethics of AI-enabled recruiting and selection.	Systematic/structured review and research agenda.	Transparency, fairness, privacy, responsibility, and stakeholder trust are major ethical themes.	Directly supports the ethical safeguards examined in the study.
Strang & Sun (2022)	To compare traditional ERP staffing processes with AI recruitment using real-time big data.	Empirical and analytical comparison.	AI-supported recruitment can improve data handling and staffing efficiency, subject to data quality and implementation conditions.	Relevant to application management and efficiency.
Basu et al. (2023)	To synthesise AI–HRM interactions and explain	Systematic review with causal configurational analysis.	AI outcomes depend on combinations of technology, organisational	Shows that technology alone does not

	configurations leading to HR outcomes.		conditions, people, and HR practices.	determine recruitment success.
Horodyski (2023a)	To examine recruiters' perceptions of AI-based recruitment tools.	Survey-based empirical study.	Recruiters value efficiency but remain concerned about reliability, acceptance, and the appropriate role of human judgement.	Supports the recruiter-side view and human oversight.
Horodyski (2023b)	To examine applicants' perceptions of AI in recruitment.	Applicant survey study.	Applicant acceptance differs according to perceived fairness, usefulness, and the nature of AI involvement.	Relevant to fairness, transparency, and candidate experience.
Meshram (2023)	To study the role of AI in organisational recruitment and selection.	Descriptive review/empirical-oriented discussion.	AI supports sourcing, screening, and selection efficiency, but human involvement remains important.	Provides an India-focused account of AI recruitment functions.
Murugesan et al. (2023)	To study the impact of AI on HR digitalisation in Industry 4.0.	Quantitative empirical study.	AI contributes to HR digitalisation and changes the way HR activities are delivered and managed.	Links AI adoption with the digital transformation of recruitment.
Prikshat et al. (2023a)	To propose a framework for AI-augmented HRM antecedents, assimilation, and multilevel consequences.	Conceptual framework grounded in prior literature.	AI value depends on organisational readiness, assimilation, employee response, and multilevel outcomes.	Supports the human-supported rather than replacement approach.
Prikshat et al. (2023b)	To review AI-augmented HRM research and propose a multilevel framework.	Systematic literature review.	The field requires stronger integration of technological, individual, team, organisational, and institutional factors.	Provides a structured basis for future research and governance.
Nawaz et al. (2024)	To examine the adoption of AI in HRM practices.	Quantitative study using HR-related respondents in Chennai, India.	Adoption is shaped by perceived advantages, organisational readiness, and practical implementation factors.	Gives Indian evidence on AI adoption in HR functions.
Rigotti & Fosch-Villaronga (2024)	To analyse fairness challenges in AI-supported recruitment.	Legal and interdisciplinary analysis.	Fairness is context-dependent and requires attention to data, system design, legal duties, and affected persons.	Strengthens the fairness and accountability framework.
Rukadikar & Khandelwal (2024)	To explore adoption of recruitment chatbots and the change process around them.	Qualitative exploratory study.	Chatbot adoption depends on usefulness, user acceptance, organisational change, and human interaction.	Relevant to candidate communication and implementation readiness.
Venugopal et al. (2024)	To examine transformative AI in HRM and workforce planning using topic modelling.	Bibliometric/topic-modelling study.	AI-HRM research is expanding around analytics, planning, decision support, and responsible use.	Places recruitment within broader AI-enabled workforce planning.
Nishanthi et al. (2025)	To map emerging themes and future directions in AI-	Bibliometric analysis.	Research growth centres on automation, predictive analytics, candidate	Shows the recent direction of talent-acquisition scholarship.

	enabled talent acquisition.		experience, ethics, and responsible adoption.	
Rukadikar & Khandelwal (2025a)	To review two decades of traditional recruitment methods and AI interventions.	Longitudinal/scientometric assessment of research from 2003–2023.	AI is changing recruitment, but hybrid methods remain important because selection involves judgement and social interaction.	Supports the study's balanced human–AI model.
Rukadikar & Khandelwal (2025b)	To examine Indian graduates' perceptions of AI-powered campus hiring.	Quantitative survey of 388 graduating students; regression and mediation analysis.	Trust, usefulness, and fairness positively influence engagement, while technological anxiety has a negative effect.	Provides recent Indian evidence directly related to candidate acceptance.

The research published in 2021 and 2022 provided two streams. The first stream looked at applicant reaction and assessment quality. According to Schick and Fischer (2021) and Wesche and Sonderegger (2021), candidates do not simply judge AI recruitment based on speed; candidates also react to disclosure, procedure, assessment quality, and perceived control. The other stream focused on ethics and organisational issues. According to Budhwar et al. (2022), AI was seen as an opportunity and challenge in HRM. Similarly, Hunkenschroer and Luetge (2022) organized the ethical debate surrounding AI usage into transparency, fairness, privacy and responsibility. The term "debiasing" can oversimplify the issue of structural inequality according to Drage and Mackereth (2022). Viewing the tool as an efficient and convenient one to use is easy; however, people may receive it less favourably when the tool's criteria or effects are unclear.

In 2023, research began associating AI with HR digitalisation and implementation. According to a study by Basu et al. (2023), outcomes from AI-HRM are due to configurations of software with organisational and human features. Horodyski (2023a, 2023b) showed that recruiters and applicants may differ in their evaluations of the same tool. Recruiters may stress on workload and utility whereas candidates are more focused on equity, communication and treatment. AI is practically important in sourcing, screening, digital HR processes, and decision support according to Indian contributions by Meshram (2023) and Murugesan et al. (2023). Prikshat and others (2023a, 2023b) proposed a multilevel view in which readiness, assimilation, and employee response shapes the consequences of AI-augmented HRM.

Research into conditions of adoption, fairness as well as certain technologies in 2024. Nawaz et al. (2024) examined AI adoption in HRM in India, while Rukadikar and Khandelwal (2024) studied adoption of recruitment chatbots. Implementation must appear to address training and readiness, process change, and ongoing acceptance. According to Rigotti and Fosch-Villaronga (2024), the concept of fairness is not reducible to a single mathematical measure since employment decisions take place in legal, social and organizational contexts. As per Venugopal et al. (2024), topic modelling indicates a growing connection between workforce planning and HR analytics with responsible AI usage.

The topic of AI talent acquisition is more mature in the 2025 literature. According to Nishanthi et al. (2025), the crucial themes include automation, predictive analytics, candidate experience, and ethics. AI interventions are changing how the recruitment process works, but Rukadikar and Khandelwal (2025a) note that they do not negate the need for human intervention entirely. The relevance of their study on Indian graduates (2025b) lies in the fact that trust, usefulness, fairness, and anxiety affect engagement with campus hiring powered by AI. The dataset of 200 respondents provided for this study will enable it to show statistical analysis of usefulness, efficiency, transparency, candidate experience overall impact and preferred safeguards.

4. RESEARCH GAAP — GENERALLY ACCEPTED ACADEMIC PRACTICES

For this paper, Research GAAP means generally accepted academic practices that foster credible, ethical, transparent, and reproducible research. This is not an accounting standard, and it is used here as an academic quality framework consistent with the format required for the paper. The presentation and interpretation of the study employed the following practices.

- The provided survey analysis retains the statistical values, sample size, variables, hypotheses, frequency distributions of academic integrity. No responses of the type case and no residue values have been invented.
- It explains clearly that information will be used for academic purpose and that response are confidential.
- No personal identity is disclosed – analysis is reported at aggregate level.
- The categories of Likert items are coded in a transparent manner and use the coding from 1 (Strongly Disagree) to 5 (Strongly Agree). The descriptive output for q18 and q19 is reported as supplied and treated as reverse coded concern indicators. The relevant frequency tables are interpreted separately so as not to obscure the apparent direction of coding.
- Each inferential test is linked to an aim and hypothesis as per appropriate statistic process. Statistical significance is evaluated at a level of 5 percent.

- The chi-square output has many expected counts below five; hence the significance is to be interpreted with caution rather than be taken as definitive proof.
- The regression plot accurately visualizes the provided coefficients and confidence intervals. Since case-level residuals were not included, the residual histogram does not exist.
- The recent research is cited in APA-style in-text and references for originality. The paper does not copy the wordings from varied articles and discussions.
- The limitations and scope section states upfront the use of convenience sampling and self-reported perceptions.

4.1 Research Gap

According to current research, AI can automate recruitment, process data, and support matching and scheduling. These factors together indicate acceptance. More specifically, it shows that fairness, transparency, privacy, anxiety, and human contact affect stakeholder acceptance. Nonetheless, the majority of analyses investigate either technical efficiency or ethical issues. The existing empirical research has not collectively addressed the operational aspect of AI, recruitment impact, transparency, candidate experience, and preferred safeguard within a single dataset containing both recruitment-side and candidate-side respondents. The volume of Indian studies is expanding, but much contemporary research centers on the frameworks of adoption, utilization of chatbots, digitalization of HR or campus hiring. Through four tests this study aims to address the above mentioned gap in literature by jointly analysing usefulness, efficiency predictors, transparency, and candidate experience as well as the possibility of allowing improvement measures.

5. STATEMENT OF THE PROBLEM

Increasingly, organisations are using AI-based applications for screening, shortlisting, matching qualifications with jobs, scheduling interviews, and managing large pools of applicants. Though these tools might lower process times and manual efforts, the real value doesn't lie just in automation. When candidates do not understand how decisions are made, biased trends repeat over time, personal information is at risk and human interaction is removed from important stages, the recruitment process can lose trust and legitimacy. HR professionals need to be well equipped to use AI output with some amount of skepticism rather than at its face value. This study thus aims to find out whether respondents perceive AI as useful and efficient in recruitment and selection, whether transparency relates to candidate experience, and whether the combination of human in the loop training, privacy protection, explanation and bias check is needed for it to be effective.

6. SIGNIFICANCE OF THE STUDY

Significant for HR managers, recruiters, candidates, educational institution and technology provider, the study. According to the research findings, it identifies the recruitment activities in which AI is perceived to add the greatest value. In addition, it separates strong efficiency outcomes from weaker perceptions of fairness and transparency. The results of the regression analysis pinpoint which operational factors play a crucial role. The correlations show that the transparency has a positive impact on the candidate experience in the decision-making process. The recommendations include using AI to support decisions, where human responsibility remains, safeguarding data and audit for bias – all of which have real steps that can be taken forward.

From an academic standpoint, the research contributes to the growing academic discourse regarding AI in HRM and responsible hiring practices in India.

7. OBJECTIVES OF THE STUDY

1. To study the role of Artificial Intelligence in recruitment and selection processes.
2. To analyse the impact of AI on recruitment efficiency, candidate screening, and selection accuracy.
3. To examine the perception of HR professionals and candidates towards fairness, transparency, and candidate experience in AI-based recruitment.
4. To provide suitable suggestions for improving the effective use of AI in recruitment and selection.

8. RESEARCH METHODOLOGY

The study uses a quantitative approach and is supported with descriptive and analytical research. The description part shows the demographic profile and average perception of respondents. The analytical component tests whether opinions are significantly above neutrality, if selected efficiency factors predict overall impact, whether transparency is associated with candidate experience, and whether preferences for improvement are related to overall opinion.

The structured questionnaire provided for this study furnished primary data. The survey consists of five demographic questions, 14 five-point perception statements, one multiple-choice question on how to improve, and one on overall impact. Recent journal articles relating to AI, HR digitalisation, recruitment, ethics, fairness, candidate perception and talent acquisition have also been reviewed.

An individual respondent who has a direct or indirect exposure to selection and recruitment is the unit of analysis. The sample consists of 200 valid respondents consisting of HR professionals, recruiters, job applicants or candidates, selected employees, managers or team leaders and others. We used convenience sampling. The report does not claim to be a probabilistic estimate for every organization or applicant, but rather an empirical study of the supplied sample.

Likert scale responses were coded in a way that 1 meant Strongly Disagree and 5 meant Strongly Agree. The analysis employs frequency and percentage tables, mean and standard deviation, one-sample t-test, multiple regression, Pearson correlation and Chi-square test of independence. Hypothesis decisions utilize a significance level of alpha equals .05.

Table 8.1: Summary of Research Methodology

Particular	Description
Research approach	Quantitative
Research design	Descriptive and analytical
Data source	Primary questionnaire data and secondary literature
Sample size	200 valid respondents
Sampling technique	Convenience sampling
Instrument	Structured questionnaire
Scale	Five-point Likert scale and categorical questions
Software/output basis	SPSS-style supplied statistical output
Tools of analysis	Frequency, percentage, descriptive statistics, one-sample t-test, multiple regression, Pearson correlation, Chi-square test
Level of significance	5 per cent ($\alpha = .05$)

9. RESEARCH DESIGN

9.1 Population and Sampling Unit

The population of interest refers to the individuals who are in one way or the other connected with recruitment and selection. This includes candidates, employees, recruiters, human resource professionals, and managers. An individual respondent is the sampling unit. There are 200 cases available in the final dataset.

9.2 Data Collection Instrument

A questionnaire with proper structure was used. This collects gender, age, education, category of respondents and work experience. The usefulness and efficiency of AI Tools are measured in sections B and C. Part D evaluates fairness, transparency, candidate experience, human involvement, and privacy concerns. Part E contains preferred enhancement actions, the role of human judgment and total impact.

9.3 Variables of the Study

Overall Impact AI on Recruitment and Selection (Q22) is the multiple regressions' dependent variable. The independent variables are Q10: speed of shortlisting, Q11: accuracy of matching, Q12: reduction in recruitment error, Q13: management of application process, and Q14: saving of time in scheduling interviews. The correlation test applies transparency (Q16) and candidate experience (Q17). Improvement measure and overall impact category are employed in the Chi square test. The one-sample t-test compares AI usefulness (Q6) to a neutral benchmark.

9.4 Conceptual Framework Chart

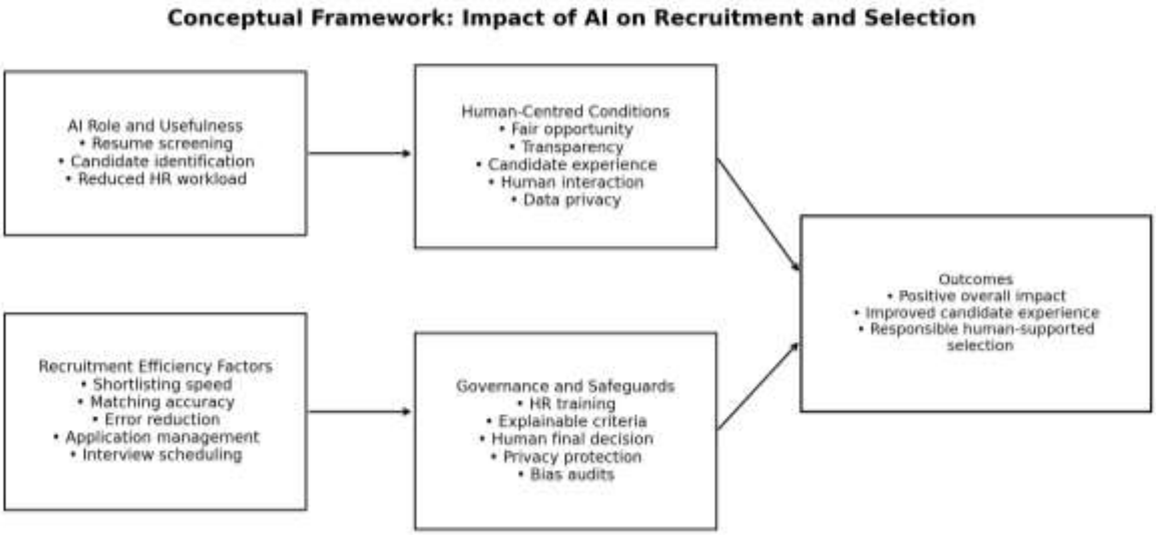

Figure 9.1: Conceptual Framework of the Study

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According to the framework, how AI is perceived and operational efficiency contributes to overall recruitment impact. The conditions that help make process acceptable are fairness, transparency, candidate experience, human interaction and privacy. The measures put in place to safeguard governance affect the applicability of AI in future. The aim is not total automation but an effective selection with accountability through human involvement.

10. HYPOTHESIS FRAMEWORK

Table 10.1: Hypothesis Framework

Hypothesis	Statistical Test	Variables	Statement	Objective
H01 / H11	One-sample t-test	Q6: AI usefulness	H01: Mean usefulness is not significantly above neutral. H11: Mean usefulness is significantly above neutral.	Objective 1
H02 / H12	Multiple regression	Q10–Q14 predicting Q22	H02: Efficiency factors do not significantly influence overall AI impact. H12: They significantly influence overall AI impact.	Objective 2
H03 / H13	Pearson correlation	Q16 and Q17	H03: Transparency and candidate experience have no significant relationship. H13: They have a significant relationship.	Objective 3
H04 / H14	Chi-square independence	Q20 and Q22	H04: Suggested improvements and overall AI opinion are independent. H14: They are significantly associated.	Objective 4

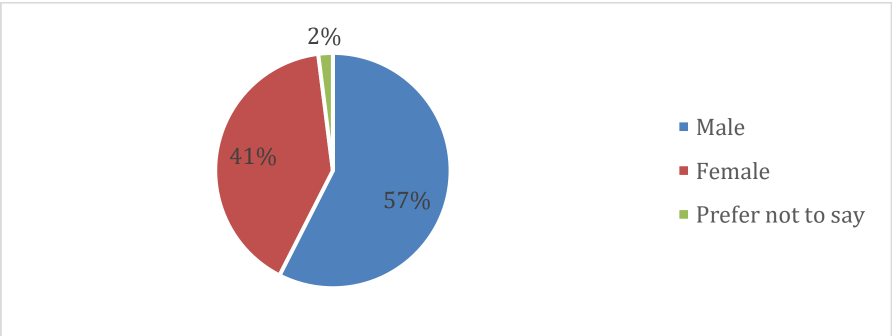
11. RESULTS AND DISCUSSIONS

This is because the same descriptive and inferential values reported with the questionnaire data are now reported. The percentage is based on 200 valid responses. The reported p values are used to make statistical decisions.

11.1 Demographic Profile of Respondents

Table 11.1: Gender-wise Distribution

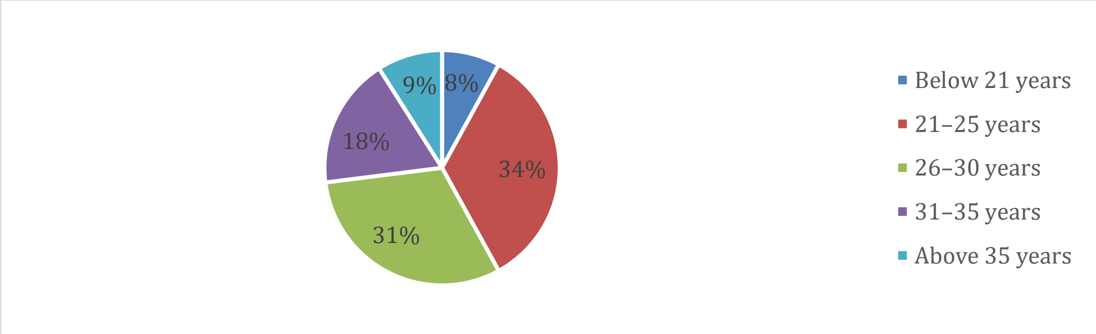
Gender	Frequency	Percent	Valid Percent	Cumulative Percent
Male	115	57.5	57.5	57.5
Female	81	40.5	40.5	98.0
Prefer not to say	4	2.0	2.0	100.0
Total	200	100.0	100.0	—



Most of the respondents are male, 57.5 per cent, while 40 per cent of the respondents are female. Both groups are adequately represented and only 2 per cent did not indicate their gender.

Table 11.2: Age Group of Respondents

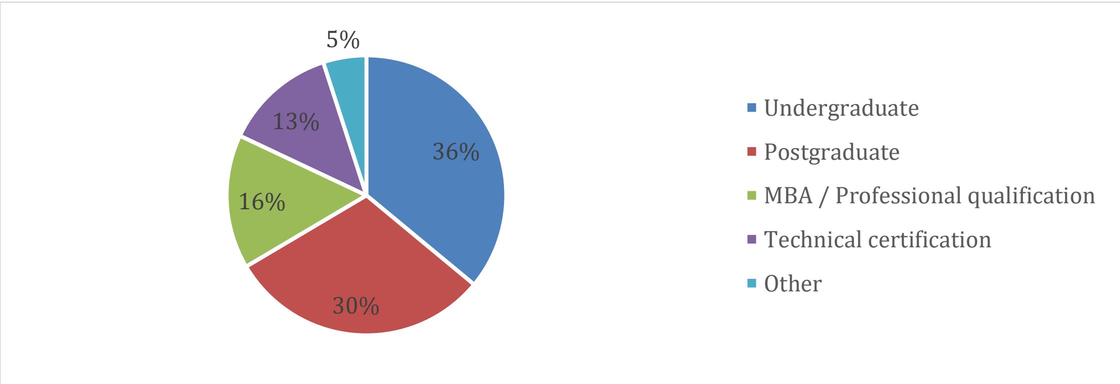
Age Group	Frequency	Percent	Valid Percent	Cumulative Percent
Below 21 years	16	8.0	8.0	8.0
21–25 years	68	34.0	34.0	42.0
26–30 years	62	31.0	31.0	73.0
31–35 years	36	18.0	18.0	91.0
Above 35 years	18	9.0	9.0	100.0
Total	200	100.0	100.0	—



The largest group of respondents is aged 21-25 years (34 per cent), while 26-30 years olds follow (31 per cent). The sample thus primarily consists of young applicants and early-career professionals who are likely to experience digital recruitment systems.

Table 11.3: Educational Qualification

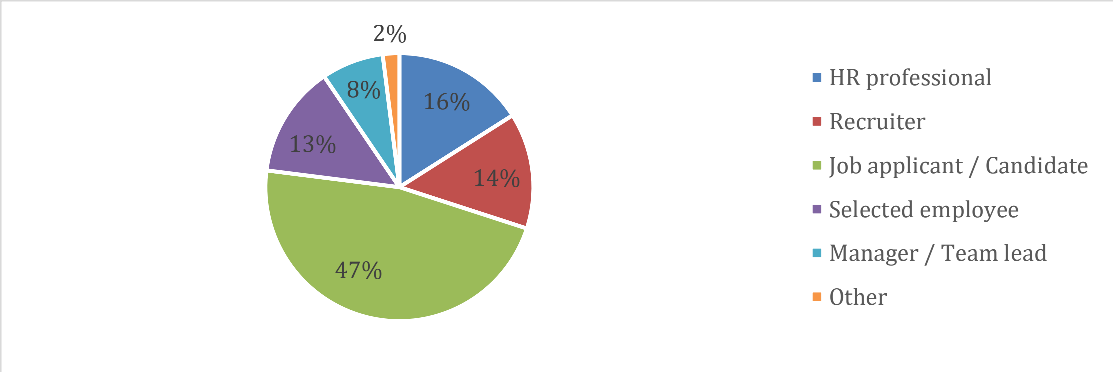
Educational Qualification	Frequency	Percent	Valid Percent	Cumulative Percent
Undergraduate	72	36.0	36.0	36.0
Postgraduate	61	30.5	30.5	66.5
MBA / Professional qualification	31	15.5	15.5	82.0
Technical certification	26	13.0	13.0	95.0
Other	10	5.0	5.0	100.0
Total	200	100.0	100.0	—



36 percent are undergraduates and 30.5 percent are postgraduates. Most of the respondents would be capable of understanding the questionnaire due to their educational profile and have experience with technology-facilitated recruitment.

Table 11.4: Respondent Category

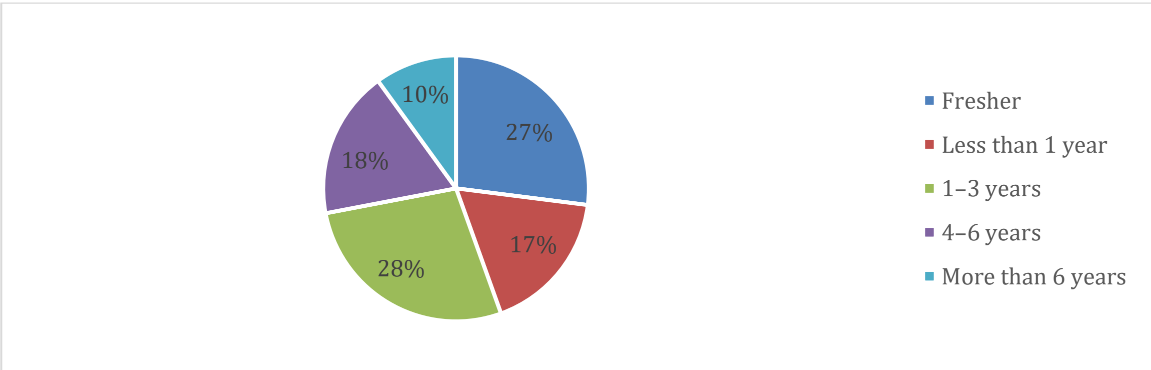
Respondent Category	Frequency	Percent	Valid Percent	Cumulative Percent
HR professional	32	16.0	16.0	16.0
Recruiter	28	14.0	14.0	30.0
Job applicant / Candidate	94	47.0	47.0	77.0
Selected employee	27	13.5	13.5	90.5
Manager / Team lead	15	7.5	7.5	98.0
Other	4	2.0	2.0	100.0
Total	200	100.0	100.0	—



The biggest chunk or largest category of respondents at 47 per cent are job applicants or job candidates. Including both candidate-side and recruitment-side perspectives, the 30 per cent allocation to HR professionals and recruiters is inclusive.

Table 11.5: Work Experience

Work Experience	Frequency	Percent	Valid Percent	Cumulative Percent
Fresher	54	27.0	27.0	27.0
Less than 1 year	35	17.5	17.5	44.5
1–3 years	55	27.5	27.5	72.0
4–6 years	36	18.0	18.0	90.0
More than 6 years	20	10.0	10.0	100.0
Total	200	100.0	100.0	—



The biggest work-experience group is 1-3 years (27.5 per cent), and freshers follow closely (27 per cent). The profile is relevant because those who are early in their careers are likely to have participated in online applications or automated screening or digital interview processes more recently.

11.2 Descriptive Statistics

Table 11.6: Descriptive Statistics for Perception Variables

Question	SPSS Variable Name	N	Minimum	Maximum	Mean	Std. Deviation
Q6	AI_Useful_Score	200	1	5	4.020	.924
Q7	Resume_Screening_Score	200	1	5	4.135	.855
Q8	Candidate_Match_Score	200	1	5	3.955	.963
Q9	HR_Workload_Score	200	1	5	4.015	.927
Q10	Shortlisting_Speed_Score	200	1	5	4.100	.868
Q11	Matching_Accuracy_Score	200	1	5	3.910	.968
Q12	Recruitment_Error_Reduction_Score	200	1	5	3.740	1.038
Q13	Application_Management_Score	200	1	5	4.120	.871
Q14	Interview_Scheduling_Score	200	1	5	4.195	.861
Q15	Fair_Opportunity_Score	200	1	5	3.470	1.102
Q16	Transparency_Score	200	1	5	3.240	1.148
Q17	Candidate_Experience_Score	200	1	5	3.705	1.060

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Q18	Lack_Human_Interaction_Score*	200	1	5	2.105	1.014
Q19	Data_Privacy_Concern_Score*	200	1	5	1.920	.932
Q21	Human_Support_Decision_Score	200	1	5	4.245	.877
Q22	Overall_Impact_Code	200	1	5	3.960	.934

**Coding note: The exact wording supplied in the description is used in questions 18 and 19. The raw response frequencies are reversed for means and are thus treated as reversed coded limitation/concern indicators. The frequency distributions indicate that most respondents agreed that lack of human interaction is a limitation and data privacy concerns is an important issue.*

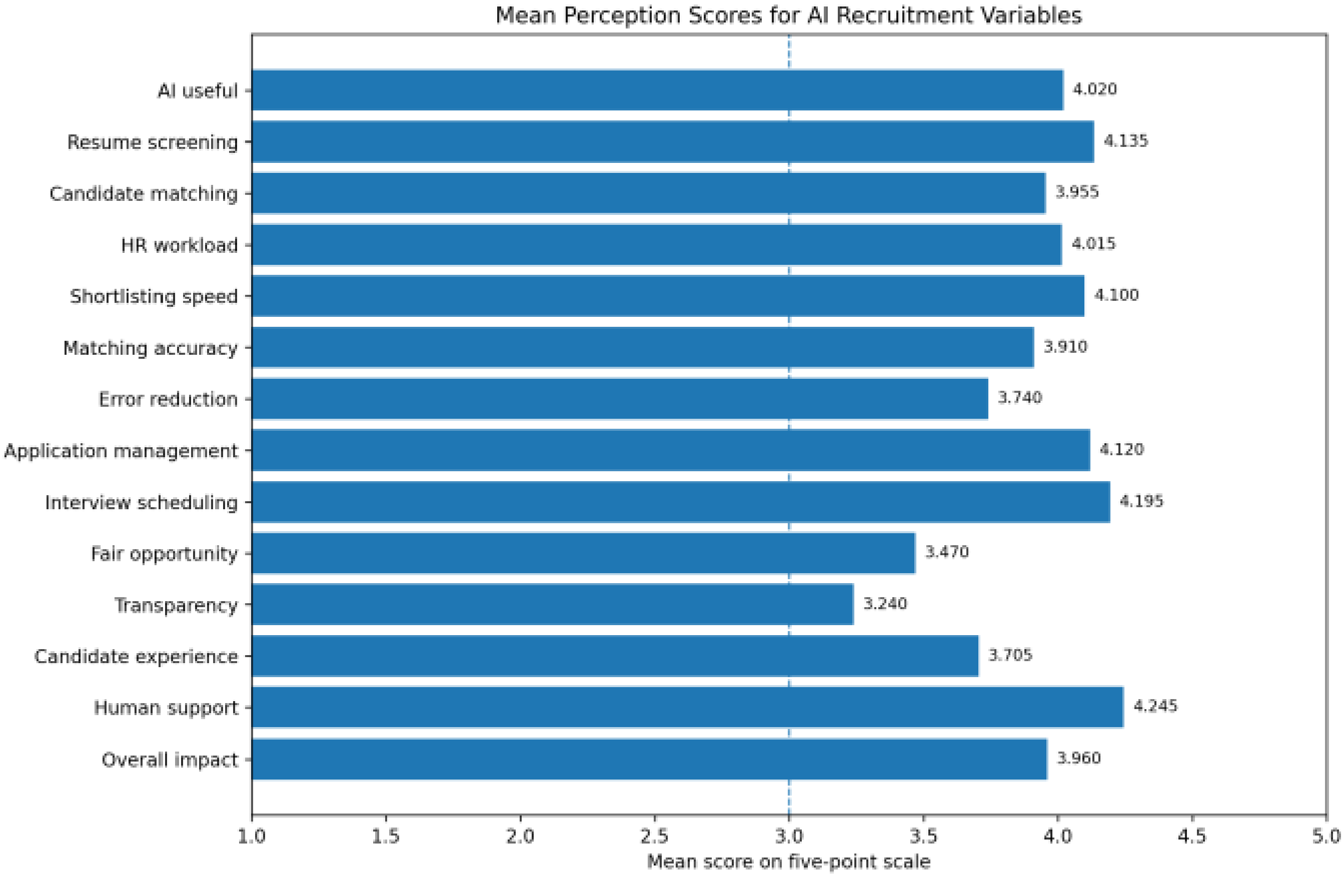

Figure 11.1: Mean Perception Scores (Selected Directly Coded Variables)

The descriptive findings demonstrate a positive overall attitude towards AI recruitment. Human support in decision making was the highest direct mean (4.245) and respondents strongly agree that AI should help recruiters, not replace them. The scores recorded for interview scheduling (4.195), a faster resume screening (4.135), application management (4.120) and shortlisting speed (4.100). These findings indicate that respondents see AI as a tool for efficiency and administration. Acceptance is less certain when respondents think about explainability and fairness: both fair opportunity (3.470) and transparency (3.240) are lower. Candidate experience is pleasant but moderate (3.705), which indicates that technology may not efficient by itself create a good hiring experience.

Table 11.7: Suggested Measure for Effective Use of AI

Improvement Measure	Frequency	Percent
HR training on AI tools	23	11.5
Clear explanation of AI screening criteria	25	12.5
Human involvement in final selection	28	14.0
Strong data privacy protection	30	15.0
Regular checking of AI bias	24	12.0
All of the above	70	35.0
Total	200	100.0

The highest single answer is "all of the above" (35 per cent). The respondents want a balance of HR training, transparent selection requirements, humans, robust privacy safeguards and regular bias assessments. None of the measures seems to be satisfactory alone.

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11.3 Test 1: One-Sample t-Test

Objective covered: To study the role of Artificial Intelligence in recruitment and selection processes.

H_0: The mean opinion score regarding the usefulness of AI in recruitment and selection is not significantly above the neutral level (test value = 3).

H_1: The mean opinion score regarding the usefulness of AI in recruitment and selection is significantly above the neutral level.

Table 11.8: One-Sample Statistics

Variable	N	Mean	Std. Deviation	Std. Error Mean
AI_Useful_Score	200	4.020	.924	.065

Table 11.9: One-Sample Test (Test Value = 3)

Variable	t	df	Sig. (2-tailed)	Mean Difference	95% CI Lower	95% CI Upper
AI_Useful_Score	15.611	199	.000	1.020	.891	1.149

Formula: $t = (\bar{X} - \mu) / (s / \sqrt{n})$, where $\bar{X}$ is the sample mean, μ is the test value, s is the sample standard deviation, and n is the sample size.

The significance value reported is .000, which is less than .05. Thus, we reject H_0. The average usefulness rating of 4.020 is considerably above the neutral score of 3. Respondents believe that AI has a useful use in recruitment and selection. The findings of this study are in line with the literature that describes AI as a tool used to automate repetitive HR activities and support faster information processing (Murugesan et al., 2023; Meshram, 2023). This result does not imply that every AI decision is correct or fair; it shows that the overall usefulness perception about the sample is clearly positive.

11.4 Test 2: Multiple Regression Analysis

Objective covered: To analyse the impact of AI on recruitment efficiency, candidate screening, and selection accuracy.

Dependent variable: Q22, Overall_Impact_Code.

Independent variables: Q10 shortlisting speed, Q11 matching accuracy, Q12 recruitment error reduction, Q13 application management efficiency, and Q14 interview scheduling time saving.

- H_0: AI-related recruitment efficiency factors do not significantly influence the overall impact of AI on recruitment and selection.
- H_1: AI-related recruitment efficiency factors significantly influence the overall impact of AI on recruitment and selection.

Table 11.10: Regression Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of Estimate	Durbin–Watson
1	.882	.777	.772	.446	2.088

Table 11.11: Regression ANOVA

Model	Source	Sum of Squares	df	Mean Square	F	Sig.
1	Regression	135.010	5	27.002	135.462	.000
	Residual	38.670	194	.199		
	Total	173.680	199			

Table 11.12: Regression Coefficients

Predictor	B	Std. Error	Beta	t	Sig.
Constant	-.114	.175	—	-.649	.517
Shortlisting speed	.194	.058	.181	3.375	.001
Matching accuracy	.313	.063	.325	4.976	.000
Recruitment error reduction	.099	.055	.110	1.797	.074
Application management	.068	.066	.064	1.033	.303
Interview scheduling	.334	.064	.307	5.186	.000

Regression equation: The regression equation is $Y = -0.114 + 0.194X_1 + 0.313X_2 + 0.099X_3 + 0.068X_4 + 0.334X_5$, *in which Y shows overall AI impact,* X_1 *is speed of shortlisting,* X_2 *is matching accuracy,* X_3 *is error mitigation,* X_4 *is application management, and* X_5 *interview scheduling.*

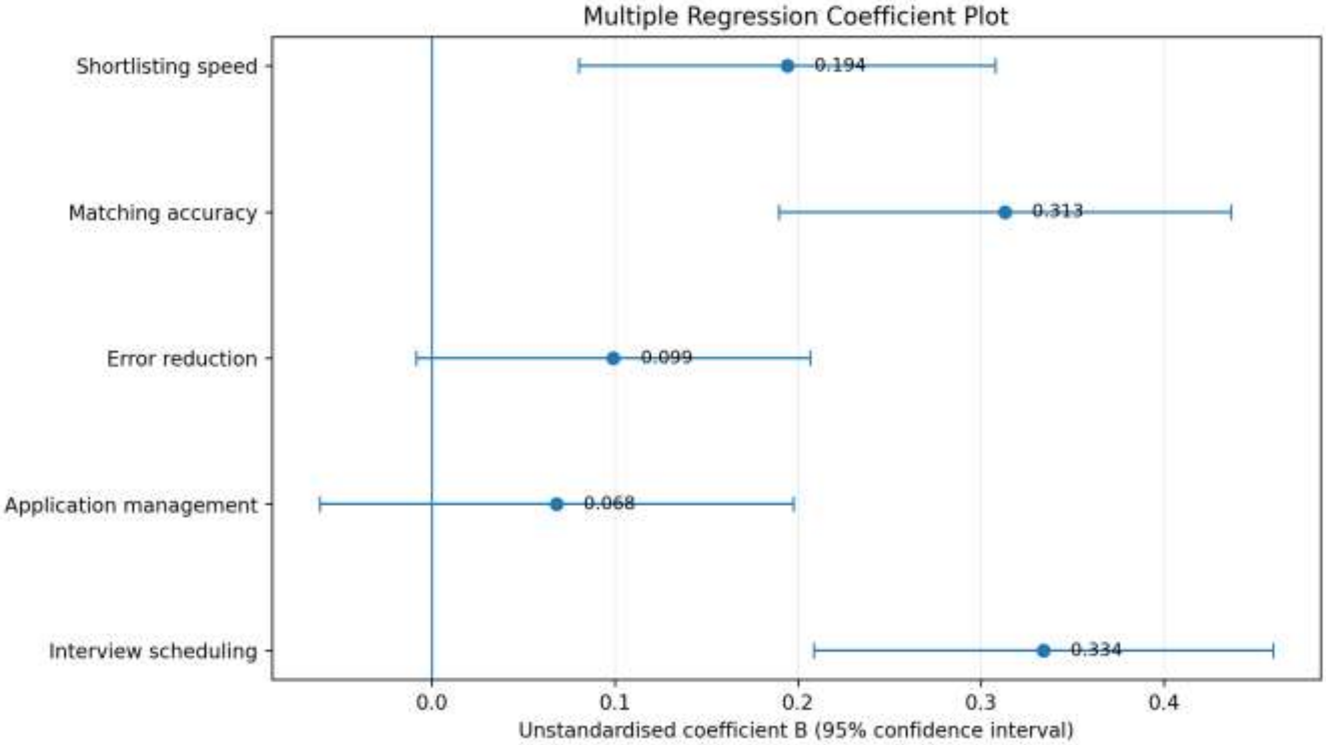

Figure 11.2: Regression Coefficient Plot Based on Supplied SPSS Output

Decision and interpretation: Since the p-value is less than 0.05, we can conclude that. The model accounts for 77.7 per cent (R^2 = .777) of the variance in overall AI impact, and the adjusted R^2 of .772 shows only a small reduction given the number of predictors. The study reveals that matching accuracy (B = .313, p < .001), interview scheduling (B = .334, p < .001), and shortlisting speed (B = .194, p = .001) are significant positive predictors. When the other predictors are held constant, error reduction (p = .074) and application management (p = .303) are not significant individually. This indicates that visual improvements in matching, speed, and coordination primarily shape the overall opinion of respondents. The value of the Durbin Watson statistic is 2.088 which is close to 2 indicating that there is no serious first order autocorrelation in the model output provided. Due to lack of raw case level residuals, the figure shows coefficient and 95 per cent confidence interval, not invented residual histogram.

11.5 Test 3: Pearson Correlation Analysis

Objective covered: To examine perceptions of fairness, transparency, and candidate experience in AI-based recruitment.

H_0: There is no significant relationship between transparency of AI recruitment decisions and candidate experience.
H_1: There is a significant relationship between transparency of AI recruitment decisions and candidate experience.

Table 11.13: Correlation between Transparency and Candidate Experience

Variables	N	Pearson Correlation	Sig. (2-tailed)
Transparency_Score and Candidate_Experience_Score	200	.504	.000

Formula: $r = \Sigma[(X - \bar{X})(Y - \bar{Y})] / \sqrt{[\Sigma(X - \bar{X})^2 \Sigma(Y - \bar{Y})^2]}$.

The decision and conclusion made on this analysis is to reject 10 the null hypothesis H_0 because p = .000. a .504 correlation coefficient implies moderate positive correlation More transparency leads to better candidate experience. Candidate experience generally has a positive relationship with applicant outcomes. However, candidate experience is likely to depend on a range of factors, including communication, response time, opportunity for human contact, perceived relevance of assessments and treatment received. The relationship is not perfect, so any one aspect of candidate experience will not determine outcome success or failure. Nonetheless, transparency is a significant element. This literature is consistent with what is known about ethics and candidate perceptions (Hunkenschroer & Luetge, 2022; Horodyski, 2023b; Rukadikar & Khandelwal, 2025b), which shows that candidates are more accepting when the procedure is clear and contestable.

11.6 Test 4: Chi-Square Test of Independence

Objective covered: To provide suitable suggestions for improving the effective use of AI in recruitment and selection.

H_0: There is no significant relationship between suggested improvement measures and overall opinion about AI impact.
H_1: There is a significant relationship between suggested improvement measures and overall opinion about AI impact.

Table 11.14: Improvement Measure × Overall AI Impact Crosstabulation

Improvement Measure	Count Type	Very Negative	Negative	Neutral	Positive	Very Positive	Total
HR training on AI tools	Observed	0	1	3	8	11	23
	Expected	.46	1.27	3.91	10.47	6.90	23.00
Clear explanation of AI screening criteria	Observed	2	1	4	16	2	25
	Expected	.50	1.38	4.25	11.38	7.50	25.00
Human involvement in final selection	Observed	0	1	4	12	11	28
	Expected	.56	1.54	4.76	12.74	8.40	28.00
Strong data privacy protection	Observed	0	2	4	15	9	30
	Expected	.60	1.65	5.10	13.65	9.00	30.00
Regular checking of AI bias	Observed	0	3	8	11	2	24
	Expected	.48	1.32	4.08	10.92	7.20	24.00
All of the above	Observed	2	3	11	29	25	70
	Expected	1.40	3.85	11.90	31.85	21.00	70.00
Total	Observed	4	11	34	91	60	200

Table 11.15: Chi-Square Tests

Test	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	32.873	20	.035
Likelihood Ratio	35.934	20	.016
N of Valid Cases	200	—	—

Formula: $\chi^2 = \Sigma(O - E)^2 / E$, where E = (row total × column total) / grand total. For example, the expected frequency for HR training × very negative impact is (23 × 4) / 200 = 0.46.

Decision and interpretation: It is concluded that there is a significant relationship between the social media advertising expenditure and brand image at a 5 per cent level of significance. The preference for suggested improvement was found to have overall AI opinion in this sample. Individuals who chose "All of the above" are concentrated in positive and very positive categories. Therefore, it is evident that they support a combined safeguards strategy. The expected count for 16 individual cells (53.3 per cent) is lower than five. The minimum expected count is .46. This does not conform to large-sample expectation for standard Chi-square approximation. As a result, the association should be addressed cautiously. An exact significance procedure or a Monte Carlo significance procedure may be utilized in the next study along with sparse combinations of categories that are justified conceptually.

11.7 Overall Discussion

The results taken together indicate that AI is viewed positively when it entails clear observable functions. More respondents are interested in quicker resume screening and application handling shortlisting and matching. These tasks can be repetitive and time-based and are amenable to technological support. The strong t-test results displays that usefulness is an opinion that is not marginal and above neutrality. The argument in AI-augmented HRM literature that technology can enhance the capacity of HR processes, freeing up the professionals for judgment, communication and strategic tasks, is supported (Budhwar et al., 2022; Prikshat et al., 2023a).

Analysis of regression provides insight into impacts on the operation. The highest standardized coefficient was obtained for matching accuracy (β = .325), while the interview scheduling (β = .307) and shortlisting speed (β = .181) showed relatively lower standardized coefficient values. This indicates that respondents are not only focused on the speed of the AI, but also on the relevance of the match between a candidate and a job. Just because the model of the two together doesn't signify error reduction and application managing is useless, it doesn't mean they don't have value. These can interact with the more powerful predictors or the respondents may not experience them directly. Applicants can easily see an accelerated timetable or a job relevance but not how many internal errors are being avoided.

Fairness and transparency ratings are lower than the efficiency ratings. It is very significant. It means that trust is not an automatic by-product of automation. Transparency moderately correlates with candidate experience – providing details on the use of AI, the type of information being utilized, the timing when it is reviewed by a human, and the avenue available for clarification should help to boost acceptance rates. This is in line with fairness research, which considers explanation and accountability as part of a valid job application process instead of an optional technical component (Rigotti and Fosch-Villaronga, 2024).

The strong average for human-supported decision making, and the high level of want for "all of the above" improvements, is a hybrid expectation. Individuals embrace AI, but they want to control it. Complementary safeguards include final selection by people, privacy protection, bias-checking and clear criteria and HR training. The basic counts of raw frequencies for Q18 and Q19 indicative of lack of human interaction and data privacy are also well recognised although the provided descriptive table reverse codes these questions. This can lead to the organization appearing to have a purely automated process where an applicant receives an automated decision, but without a meaningful explanation or chance of further input.

The demographic profile also affect decipher. Almost two-thirds of participants belong to the 21–30-year-age category and 47 percent are candidates. As a result, while the findings are particularly relevant to early career digitally exposed job seekers, they may not speak fully to senior executives, older employees or highly specialised hiring. The diversity of HR professionals, recruiters, candidates, selected employees and managers is a strength because it allows for several views to be captured within one study.

12. FINDINGS

1. 57.5% of the sample are male respondents, while 40.5% are female respondents.
2. The sample consists of 21-30 year olds (65 per cent), meaning the study is mostly relevant to young applicants and junior professionals.
3. Job seekers make up 47 per cent of the survey respondents while H.R. professionals and recruiters together are 30 per cent.
4. The average usefulness score of AI was 4.020, which is significantly greater than the neutral score; $t = 15.611$, $p < .001$.
5. Respondents believe that AI must assist recruiters but cannot entirely replace human input in decision-making. (mean = 4.245)
6. Some of the most highly-rated operational functions include interview scheduling (mean = 4.195), resume screening (mean = 4.135), application management (mean = 4.120), and shortlisting speed (mean = 4.100).
7. With a mean of 3.470, Fair opportunity and a mean of 3.240 for Transparency EU citizens demonstrate a lower average score suggesting continuing concerns regarding procedural fairness and explainability.
8. The multiple regression model is significant and explains 77.7% of the variance in overall AI impact ($R^2 = .777$).
9. Matching accuracy, interview scheduling, and shortlisting speed are important individual predictors of overall impact of AI.
10. There is some evidence that being more transparent in throughout the hiring process improves candidate experience, although it turns out HRM practitioners don't find transparency very important.
11. The most preferred improvement response is a combined approach covering training, clear criteria, human involvement, privacy, and bias checking (35 per cent).
12. The chi square test indicates that the improvement measures and overall opinion of AI are significantly associated ($\chi^2 = 32.873$, $p = .035$), but cell counts are sparse and should thus be interpreted carefully.
13. The raw response frequencies suggest that an absence of human connection and data privacy was taken as important even though these were reverse coded in the provided descriptive output.

13. RECOMMENDATIONS AND SUGGESTIONS

1. Use AI to make decisions, not make them for you. Automating resume screening, ranking, scheduling and application management may be possible, but it cannot be the final decision, since it will be the responsibility of a being to review the applications.
2. Provide candidates with a brief summary of the application of AI, the information that has been taken into account, and how they can get clarification and/or correction if needed.
3. Critically review selection rates and patterns of errors and conduct periodic bias audits across relevant applicant groups, using neither protected variables nor inappropriate proxy variables.
4. Compare similar models with job related criteria. The suitability of candidates is not judged based on the keywords alone but also skills, experience, transferable capability and contextual evidence.

5. Increasing awareness of HR professionals of limitations of AI models for them to question unusual recommendations and document reasons for final recommendations.
6. Privacy by design: Collect only necessary information, define the length of time it will be held, restrict access, secure the stored information and communicate the consent explicitly.
7. The process must have a significant human interaction at sensitive stages namely, rejection review, interview, accommodation request, salary discussion, and final selection.
8. Monitor the candidate experience by sending brief feedback surveys on clarity, response time, fairness, ease of use and contact with someone.
9. Provide an appeals or reconsideration process for candidates whose application was deemed to have been ineligible or incomplete based on automated screening because they believe that the information was inaccurate or that their qualifications were not considered.
10. Use example data and double human check to analyze AI servers before full adoption. Organisations have to evaluate accuracy, consistency, adverse impact and time saving.
11. If the question is complex or personal, then it is recommended to let the conversation flow smoothly into the human recruiter.
12. Carefully review vendors. Ownership of data, updates to models, access rights to audit trails, security requirements and liability in the case of errors or mistakes should be defined.
13. Develop innovative implementation guidance for campus recruitment, lateral recruitment, high volume hiring and senior level hiring based on different levels of acceptable automation.
14. Log decisions made for recruitment. Document the AI recommendation and human review, final decision and override reason. This can help in holding someone accountable and learning.

14. LIMITATIONS

1. The research used convenience sampling techniques and the findings of the study cannot be statistically generalised across all organisations and across all applicants for jobs.
2. The large proportion of young respondents and candidates in the sample may lead to an under-representation of senior managers and specialised recruiters.
3. The data is based on perceptions and self-report and is not a reflection of actual time to hire, cost of hire, accuracy or adverse impact.
4. The research is a “cross-sectional study” where opinions are measured at one point in time and does not measure changes in perceptions after multiple AI recruitment experiences.
5. The material presented is in the aggregate SPSS format rather than case by case. Because it was not possible to independently replicate testing of reliability analysis, residual diagnostics, multicollinearity statistics or alternative model checks, these tests were not reported.
6. Questions 18 and 19 seem to be reverse coded in the descriptive table but have been presented in the original direction of the agreement in this table. This is an issue addressed in this paper but coding should be verified against the SPSS original file prior to final submission.
7. Caution needs to be taken in interpreting the asymptotic p-value; there are some expected counts on the Chi-square table that are less than 5.
8. Does not compare candidates, recruiters, HR professionals, Managers with sub-groups; combines different respondents' categories.

15. CONCLUSION

According to research, the perception of the role of AI in recruitment and selection is quite positive. The feature that respondents believe makes AI valuable in real-world use is its resume screening, resume shortlisting, resume matching, application management and interview scheduling capabilities. Results of one sample t-test indicate that perceived usefulness is significantly higher than neutral. The overall impact of AI on recruitment efficiency as determined through the multiple regression analysis, covers a significant portion of the total recruitment efficiency. Factors that are observed to be significant predictors include matching accuracy, interview scheduling and shortlisting speed.

At the same time, the repercussions are not sufficient to justify a free-for-all model of automation. The scores for variables related to fairness and transparency are lower than those for variables related to efficiency, and transparency scores have a positive and meaningful relationship with candidate experience. The survey results show that respondents are very supportive of the use of AI as a support tool and not a replacement. They would want HR personnel to be trained, standards to be established to screen applicants, have a standard human final review, privacy protection, and regular bias checks.

In short, success is achieved when AI is technically effective and procedurally valid. A rapid, but vague, system can damage candidate trust while an accurate system that lacks transparency can also fail. For this reason, organisations need to look for a balanced approach that puts the human in the loop as the main decision maker: processes, evidence and tasks are to be supplemented by AI; but judgement, communication, exceptions and final accountability are to be left to trained humans. This sort of approach can quicken the recruitment process without compromising with fairness, dignity, and privacy.

16. FUTURE SCOPE

1. Future studies can use probability sampling and larger multi-industry sample improve generalisability.
2. Separate analyses can compare candidates, recruiters, HR professionals, managers, freshers and experienced respondents.
3. Longitudinal studies will be able to assess perceptions both prior to and after actual use.
4. Case-level data can be used to test reliability, conduct factor analysis, test mediation or structural equation modelling, diagnose multicollinearity and test residuals.
5. Field studies may compare the AI-assisted selection against the traditional selection on parameters like time-to-hire, cost-per-hire, quality-of-hire, retention, applicant drop-off and adverse impact.
6. Future studies may consider usage of generative AI in writing job-descriptions, communicating with candidates, support in interviews, and summaries of recruiter decisions.
7. Research may test whether the enhancement of fairness perception and trustworthiness of the candidates takes place via explanation formats, human-review notices, or appeal mechanisms.
8. Examining multi-axes: A Cross-cultural and legal comparison of AI recruitment governance across Indian states, industries and the world.
9. A follow-up study should confirm the coding direction of the negatively itemized concerns; and use exact or Monte Carlo tests of sparsely filled categorical tables.

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