

Artificial Intelligence in Talent Acquisition: An Empirical Assessment of Recruitment Outcomes and Responsible Use

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Abstract: Artificial intelligence (AI) is increasingly used to source applicants, display screening packages, match candidates, communicate with applicants, and analyse workforce data. Processing speed alone does not indicate whether it is AI-powered. Recruitment outcomes also include shortlist relevance, applicant delight, recruiter productivity, and high-quality decisions. This study examines the relationship between AI adoption and five perceived skill-acquisition outcomes, drawing on questionnaire responses from 70 individuals. The analysis uses descriptive statistics, Cronbach's alpha, Pearson correlation, and separate simple linear regression. AI adoption undoubtedly improves recruitment performance ($\beta = 0.546$, $R^2 = 0.282$), recruitment effectiveness ($\beta = 0.514$, $R^2 = 0.295$), perceived candidate experience ($\beta = 0.569$, $R^2 = 0.363$), recruiter productivity ($\beta = 0.498$, $R^2 = 0.329$) and overall performance of talent acquisition ($\beta = 0.341$, $R^2 = 0.120$). All five regression relationships are statistically significant at the 5% level. Candidate experience has the highest R^2 among the five factors, while specific skill acquisition performance has the lowest. Additionally, respondents who report greater AI adoption tend to report more favourable recruiting outcomes, but the study does not establish causality or confirm changes in overall objective hiring performance. The article discusses these findings in relation to fairness, transparency, confidentiality, and human oversight. It recommends that firms assess the use of multiple end-result markers in AI-enabled hiring and conduct meaningful human assessment of the resulting options.

Keywords: Artificial Intelligence; Talent Acquisition; Recruitment Efficiency; Candidate Experience; Recruiter Productivity; Algorithmic Fairness; Human Oversight

1. Introduction

Recruitment is often viewed as a sequence of operational tasks: advertising a vacancy, collecting applications, screening candidates, scheduling interviews, and deciding on candidates. In practice, these processes shape corporate skill acquisition and affect how applicants evaluate the organisation's capability. Delays can cause qualified candidates to withdraw, while poor testing can also exclude candidates who no longer fit the profile defined by a narrow set of keywords. Recruitment is therefore both an operational method and a resulting control trait. Digital recruitment platforms have expanded the records available to recruiters. Applicant tracking systems package and organise workflow statistics, while expert web and online job portals develop pools of potential applicants. AI tools add efficiency through resume parsing, semantic matching, automated negotiation, predictive assessment, and generative drafting. Such structures can help recruiters manage large volumes of data, but the suggestions they produce are based on the information, criteria and techniques they are built on (Black & van Esch, 2020; Tambe et al., 2019). A.I. Enables Faster testing, helping maintain awareness of useful, suitable candidates. Automated communications can also increase response times, but candidates can still avoid impersonal or difficult appointments. The algorithm can consistently observe the rule, but consistency does not establish whether the rule is valid or fair. Therefore, research on algorithmic hiring has examined the benefits of automation and its implications for differentiation and transparency, and agrees with Köchling & Wehner (2020), Raghavan et al. (2020), and Lavanchy et al. (2023).

2. Literature Review and Conceptual Background

2.1 AI as recruitment support

AI in recruitment is not a single technology; it's a set of tools. Natural language processing extracts information from résumés and job descriptions, and matching systems compare candidate profiles to stated requirements. Chatbots handle routine queries, and scheduling tools minimise coordination work. Generative systems can help write job advertisements, interview questions, and messages to candidates. Each app's significance depends on the task and how well it integrates with the recruitment process. "HR decisions are complicated by complex human behaviour and imperfect data, making uncritical reliance on predictions risky," warn Tambe et al. (2019). The efficiency and effectiveness should be distinguished. Efficiency is how long something takes and how many resources it uses. Effectiveness is whether we do the right thing. AI tool can quickly screen applications, but may still miss candidates whose skills are described in unfamiliar language. A matching system may replicate assumptions built into previous recruitment decisions. Cappelli et al. (2019) thus propose that using AI in HR requires attention to data limitations and the organisational context in which predictions are applied.

2.2 Candidate experience and recruiter work

Candidate experience includes convenience, responsiveness, communication, perceived fairness and the opportunity to understand the process. Van Esch et al. (2019) found that AI

recruitment can influence applicants' behaviour in their responses to the technology. Acceptance of highly automated interviews was found to be partly conditional on the stakes of the decision (Langer et al., 2019). More explanation and human contact are expected when a system impacts a selection. Applicants might accept automation for scheduling or routine updates.

AI can also reshape recruiters' work. When repetitive tasks are removed from their plate, recruiters can consult with hiring managers, engage with candidates and perform complex evaluations. But the change will require new skills. Recruiters need to interpret the system's outputs, identify recommendations that are unlikely to be accurate, and understand the information the system used. Ore and Sposato (2022) showed that recruiters saw opportunities in artificial intelligence but also felt concern and mistrust. Adoption is therefore a managerial and human process as well as a technical one.

2.3 Fairness, privacy and accountability

Employment processes can determine who gets a job, so fairness and accountability are critical. But existing data will likely mirror unequal opportunities or the organisation's previous biases, and models trained on it may become biased themselves. Simply eliminating explicit demographic data won't solve this problem: other data can serve as proxies. Removing demographic variables may not address the problem. Köchling and Wehner (2020) and Fabris et al. (2024) explain why claims of algorithmic objectivity should be examined rather than assessed subjectively.

Transparency (is there information about AI use and the results generated that are decision-relevant?); privacy (how candidate data is observed, stored, and shared for legitimate reasons in an open and transparent manner, and with appropriate levels of control); human in the loop (recruiters having enough information and power to challenge recommendations, add additional information, report problems, alter outcomes, and escalate as appropriate (Autio et al., 2024). The NIST Generative AI Profile identifies risks of privacy, harmful bias, confabulation, and information security, all of which are relevant to using generative technology for recruiting.

2.4 Research gap and conceptual model

The research literature describes many possible HR applications of AI and their potential advantages; however, it offers no insight into how perceived adoption relates to specific recruitment outcomes. Using a single recruitment performance score obscures distinctions in speed, decision support, candidate experience, and value. Our research fills this gap by analysing five outcomes individually. The conceptual model treats AI adoption as the independent variable and each perceived outcome as a separate dependent variable. Fairness, transparency, privacy, and human oversight are governance dimensions, not outcomes determined by the regression models.

3. Objectives and Hypotheses

The study has three objectives:

- To examine respondents' awareness of AI and their perceptions of AI adoption in talent acquisition;
- To assess the relationships between AI adoption and recruitment efficiency, recruitment effectiveness, candidate experience, recruiter productivity, and overall talent acquisition performance; and
- To draw practical implications for the responsible implementation of AI-enabled recruitment.

The five tested relationships are as follows:

- H1, AI adoption is positively related to recruitment efficiency;
- H2, AI adoption is positively related to recruitment effectiveness;
- H3, AI adoption is positively related to perceived candidate experience;
- H4, AI adoption is positively related to recruiter productivity; and
- H5, AI adoption is positively related to overall talent acquisition performance.

The corresponding null hypotheses state that there is no significant relationship between AI adoption and each outcome.

4. Research Methodology

The study is descriptive, analytical and quantitative. Primary data were collected through a structured questionnaire using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The survey included questions on respondent characteristics, AI awareness and adoption, AI-enabled recruitment practices, the five outcome constructs, and governance dimensions. Construct scores were calculated as the mean of responses to the respective items. Higher scores reflected a greater agreement with the construct statement.

The dataset includes 70 respondents. The profile variables are age, gender, educational qualification, designation, work experience, industry, organisational tenure and AI awareness. The sample is described using frequencies and percentages, construct scores are summarised using means and standard deviations, internal consistency is reported using Cronbach's alpha, bivariate associations are examined using Pearson's correlation, and the five hypotheses are tested using separate simple linear regression models.

In all of the regression models, AI adoption is the independent variable, and one recruitment outcome is the dependent variable. In each model, the coefficient (β), standard error, t-statistic, R^2 , adjusted R^2 , and p-value are reported. At the 5% significance level, the null hypothesis is rejected. Given the cross-sectional design and the respondents' perceptions, the regression results should be interpreted as associations within the sample. They do not show that AI adoption led to better hiring outcomes.

5. Results and Analysis

5.1 Respondent profile

The sample includes respondents of different age groups and work backgrounds. The 25–34 and 35–44-year-old age groups each make up 30.0% of the sample. The 45–54 age group comprises 20.0% of respondents, while the under-25 and 55+ age groups each comprise 10.0%. 55.7% of respondents are male, 41.4% are female, and 2.9% did not disclose their gender. Half the sample are postgraduates. The largest designation group is HR or recruitment professionals (34.3%), followed by executives or officers (30.0%) and managers or supervisors (27.1%).

The highest representation by industry is IT/ITeS (25.7%), manufacturing (17.1%) and retail (15.7%). 75.7% report awareness of AI, 17.1% are not sure, and 7.1% report no awareness. This profile shows that the responses represent participants from a range of organisational backgrounds, making them representative of the wider workforce.

Table 1: Selected characteristics of respondents.

Percentages are reported as given in the study dataset

Profile indicator	Category	N	%
Age	25–34 years	21	30.0
	35–44 years	21	30.0
	45–54 years	14	20.0
	Below 25 years	7	10.0
	55 years and above	7	10.0
Gender	Male	39	55.7
	Female	29	41.4
	Prefer not to say	2	2.9
AI awareness	Yes	53	75.7
	Not sure	12	17.1
	No	5	7.1

5.2 Descriptive statistics and reliability

The construct means fall close to the midpoint of the five-point scale. AI adoption has a mean of 2.93 (SD = 0.91),

recruitment efficiency 2.97 (SD = 0.93), recruitment effectiveness 2.95 (SD = 0.86), perceived candidate experience 2.85, and overall talent acquisition performance 2.98. Agreement is not high overall. Respondents hold moderate or mixed perceptions of AI-enabled recruitment, which qualifies the positive regression relationships below.

Cronbach's alpha exceeds .70 for the principal constructs, ranging from .907 for perceived candidate experience to .921 for AI adoption. Alpha is also above .70 for every other measured construct, including the governance dimensions. The item sets therefore show internal consistency. Reliability alone does not demonstrate construct validity, show that the items capture the intended concept completely, or establish the accuracy of AI tools in practice.

Table 2: Selected descriptive and reliability results. Constructs not listed are omitted

Construct	Mean	SD	Cronbach's α
AI adoption	2.93	0.91	0.921
Recruitment efficiency	2.97	0.93	0.919
Recruitment effectiveness	2.95	0.86	0.913
Perceived candidate experience	2.85	0.89	0.907
Overall talent acquisition performance	2.98	0.79	0.902
Privacy	3.00	0.72	0.816

5.3 Correlation and regression findings

Pearson correlations are positive for all five pairs of AI adoption and the hypothesised outcomes. The correlation is strongest for perceived candidate experience ($r = 0.602$) and weakest for overall talent acquisition performance ($r = 0.346$). These coefficients indicate that higher AI adoption scores tend to occur alongside more favourable outcome scores in the sample. Correlation alone does not establish direction of influence or rule out other explanations, such as organisational resources, management support or the maturity of recruitment processes.

Table 3: Summary of simple linear regression results.

Hypothesis / outcome	β	SE	t	R^2	Adjusted R^2	p-value	Decision
H1 Recruitment efficiency	0.546	0.106	5.170	0.282	0.272	< 0.001	Supported
H2 Recruitment effectiveness	0.514	0.096	5.333	0.295	0.285	< 0.001	Supported
H3 Candidate experience	0.569	0.091	6.221	0.363	0.353	< 0.001	Supported
H4 Recruiter productivity	0.498	0.086	5.780	0.329	0.320	< 0.001	Supported
H5 Overall TA performance	0.341	0.112	3.046	0.120	0.107	0.0033	Supported

For H1, $\beta = 0.546$ and $R^2 = 0.282$, so AI adoption accounts for 28.2% of the variance in perceived recruitment efficiency in the fitted model. The result is statistically significant ($p < 0.001$). This is consistent with the possibility that automated screening, sourcing, and scheduling reduce repetitive work, although the survey does not directly measure time saved.

For H2, AI adoption has a positive coefficient of 0.514 and the model R^2 is 0.295. The result is statistically significant ($p < 0.001$). Respondents reporting greater adoption also tend to rate recruitment effectiveness more favourably. This should not be read as proof that the system selects better employees. Objective evidence would require measures such

as job-related assessment validity, quality of hire, retention or hiring-manager evaluations.

H3 produces the largest coefficient ($\beta = 0.569$) and the highest R^2 (0.363) among the five models. The result is statistically significant ($p < 0.001$). Within this sample, perceived candidate experience has the strongest model-level association with AI adoption. One possible interpretation is that respondents notice the visible effects of AI through faster communication, easier application processes or more timely updates. However, the questionnaire records perceptions rather than direct feedback from applicants, so the result should be described as perceived candidate experience.

For H4, the coefficient is 0.498, and R^2 is 0.329 ($p < 0.001$). This is consistent with the view that AI can help recruiters organise information and manage repetitive tasks. It does not mean that recruiter roles become unnecessary. The organisational benefit depends on whether time released from administration is redirected toward candidate engagement, consultation with hiring managers and careful evaluation.

H5 is also supported, with $\beta = 0.341$, $R^2 = 0.120$ and $p = .0033$. The relationship is positive, but its explanatory value is lower than that of the other four models. Overall talent acquisition performance likely depends on much more than AI adoption: workforce planning, employer reputation, compensation, leadership decisions, labour-market conditions, organisational readiness and the quality of the recruitment process. The low R^2 therefore matters, because it cautions against treating AI as a complete solution to recruitment challenges.

6. Discussion

The results support a positive relationship between AI adoption and the five perceived recruitment outcomes. This aligns with the literature recognising automation and data processing as sources of efficiency and support for recruiters (Black & van Esch, 2020; Vrontis et al., 2022). It also lets you see the results for yourself. The strongest model is candidate experience, and the weakest is overall talent acquisition performance. A technology may fix some touchpoints, but it won't fix the larger organisational issues that define recruitment quality.

Moderate construction moderates the positive regression results. Respondents have a positive relationship with AI, which does not mean they agree with AI or think the systems work. This implies that higher AI adoption scores are correlated with higher outcome measures. This distinction matters for both researchers and managers. The results should not be interpreted as suggesting that AI necessarily improves recruitment for all employers, job families, or groups of candidates.

The findings also need to be read in conjunction with the ethical literature. A system can improve throughput while systematically disadvantaging those whose backgrounds differ from the historical data. As Raghavan et al. (2020) argue, it is important to study the development, validation, and use of algorithmic hiring tools, not just vendor claims. Lavanchy et al. (2023) show how algorithmic procedures can influence applicants' perceptions of fairness. Therefore, organisations need to monitor both efficiency and fairness simultaneously. An organisation should ask whether the system produces a shortlist faster and, if so, who is being excluded; whether the criteria relate to the job; and whether a candidate can request human review.

The relatively low R^2 for overall talent acquisition performance suggests that AI is just one component of a larger operating system. Other factors, beyond technology, could influence the results, including data quality, recruitment policy, management capacity, job design, and the labour market. AI in strategic HRM research is also

viewed as a source of organisational capability and implementation, not an independent source of value (Malik et al., 2023).

7. Managerial Implications and Recommendations

Before selecting an AI tool, organisations need to determine the recruitment problem they are trying to solve. If scheduling is the main bottleneck, then a scheduling system might be better than an automated assessment product. If candidate matching is the problem, the organisation should first ensure that the job requirements are clear and that the skills are represented in a way that does not unduly restrict the candidate pool.

In addition, performance evaluations should be based on a well-balanced set of indicators. Measures such as shortlist relevance, offer acceptance, candidate withdrawal, candidate feedback and quality-of-hire give a broader view. Efficiency is measured by the time it takes to fill a position and the amount of work produced during the screening process. Document baseline measurements at the start of implementation and compare them continuously after adoption. Distinguish between verified operational changes and perceived improvements to avoid confusion.

The third recommendation is that human supervision must be part of the workflow. Recruiters need to understand the system's purpose and its limitations. Moreover, they need to retain the ability to veto inappropriate outputs and assess strange suggestions. The ultimate hiring decision should not be delegated to a score that is not transparent and not supported by documented justification. The organisation should clearly identify who is responsible for investigating complaints, correcting errors, and monitoring performance.

Privacy and fairness tests should be applied continuously. Organisations should decide not only whether selection rates or error patterns vary among relevant candidate groups, but also whether the variables relate to the job, restrict access to candidate data, and establish retention periods. Explain the use of artificial intelligence in a large part of the process in notices addressed to candidates. If generative artificial intelligence is used to draft messages or summarise information about candidates, a human should review the output for accuracy and remove any claims not backed up by evidence before using the AI. Implementation will require investment in recruiters' capabilities. Training should cover interpreting AI outputs, data protection, bias awareness, candidate communication, and escalation procedures. Employees should be able to report mistakes and not be forced to accept a system recommendation simply because it is automated. Adopting these procedures will help transform artificial intelligence into a tool that supports professional judgment rather than a substitute for accountability.

8. Limitations and Future Research

The study has several limitations. First, the sample contains 70 respondents, and its composition and sampling context limit generalisation. Second, the measures are self-reported perceptions. They do not directly establish the technical

accuracy of AI systems, actual time saved, hiring quality or candidate satisfaction. Third, using separate simple linear regression models does not control for other organisational factors and cannot establish causal effects. Fourth, the analysis covers five principal outcomes and does not test the proposed role of human oversight as a moderator. The governance dimensions are described separately and should not be presented as statistically verified moderators.

Future studies could recruit larger samples across multiple organisations and sectors, and compare HR professionals with candidates who have directly experienced AI-supported recruitment. Researchers could combine survey responses with objective indicators such as time-to-fill, application-to-interview ratios, offer acceptance, candidate withdrawal and post-hire performance. Longitudinal or before-and-after designs would help determine whether outcomes change after implementation. Further work could also test organisational readiness, data quality and governance practices in a multivariable model, provided the sample size and measurement quality are adequate.

9. Conclusion

This study examined the relationship between AI adoption and the 5 perceived talent acquisition outcomes of 70 respondents. The analysis reveals positive, statistically significant relationships between AI adoption and the five outcomes. Candidate experience has the highest R^2 , while overall talent acquisition performance has the lowest. The perceived value of AI differs by recruitment dimension, and the findings do not show a general enhancement across all areas of talent acquisition.

The study considers operational outcomes and the circumstances under which AI ought to be used. Recruitment decisions affect people's access to work, and the benefits of automation do not absolve us of obligations around fairness, privacy, transparency and accountability. Organisations must measure outcomes against clear baselines, validate systems for job-related use, protect candidate information and preserve meaningful human review. The findings should be interpreted as evidence of association in the observed sample. Further studies with larger samples and objective recruitment data are required to draw more general conclusions on the effect of AI on hiring performance.

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