The Influence of Artificial Intelligence Adoption in HRM on Recruitment and Selection Efficiency

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Submitted: November 15, 2025

Revised: January 19, 2026

Accepted: January 27, 2026

Published Online: January 31, 2026

ABSTRACT

This study examines the impact of artificial intelligence adoption in human resource management on recruitment efficiency and selection efficiency in Indonesia. Drawing on the resource-based view framework and the human resource analytics literature, we propose that artificial intelligence enhances efficiency through human resource analytics capability (as a mediator), while organizational digital maturity, firm size, and job complexity moderate the strength of these effects. Data were collected from n = 200 recruitment/selection units across sectors; a multi-source approach combined survey measures (AI adoption, HR analytics capability, digital maturity, job complexity) and operational HR metrics (time-to-fill, cost-per-hire, selection ratio, assessment throughput, offer acceptance, and early attrition ≤ 6 months). SEM analysis shows that artificial intelligence adoption has a significant positive effect on recruitment efficiency and selection efficiency. Human resource analytics capability partially mediates the effect of artificial intelligence on both outcomes. Moderation results indicate that the effects of artificial intelligence are stronger in organizations with high digital maturity and larger size, but weaken for positions with high job complexity. These findings imply that organizations should align artificial intelligence investments with the development of HR analytics capability and digital readiness to maximize efficiency gains in recruitment and selection.

Keywords*: AI Adoption, Digital Maturity, HR Analytics Capability, Recruitment Efficiency, Selection Efficiency.*

INTRODUCTION

The adoption of Artificial Intelligence (AI) in Human Resource Management (HRM) has increased rapidly in the recruitment and selection stages, ranging from CV screening, candidate chatbots, automated scheduling, video interview analytics, to machine-learning–based candidate matching. In practice, organizations report faster time-to-hire and higher candidate conversion rates after integrating AI conversational agents into early-stage processes. There is a surge in studies on AI tools and techniques for initial screening, algorithm-assisted assessment, and HR decision support. These reviews identify process efficiency (speed, cost) and outcome quality as the dominant motives for adoption, while also highlighting variation in the strength of causal evidence across studies (Rane et al., 2024; Murire, 2024). Recent empirical research has also begun to examine generative AI in recruitment and finds positive effects on efficiency and candidate quality, with process automation level as a mediator and organizational size as a moderator (Abdelhay et al., 2025). These findings reinforce the view that the benefits of AI are not merely about substituting routine tasks, but about process orchestration that enables higher assessment throughput without sacrificing validity.

However, gains in efficiency also create governance challenges. The EU AI Act (Regulation (EU) 2024/1689) explicitly classifies most AI systems used for recruitment

JIMKES

Jurnal Ilmiah Manajemen Kesatuan
Vol. 14 No. 1, 2026
pp. 289-300
IBI Kesatuan
ISSN 2337 – 7860
E-ISSN 2721 – 169X
DOI: 10.37641/jimkes.v14i1.4600

and selection as high-risk, thereby requiring risk management, data and model governance, transparency, registration, and human oversight. The regulation has been in force since 1 August 2024 with a phased implementation until 2026, which in practice obliges employers to develop compliance roadmaps starting now (Clifford Chance, 2024).

At the organizational level, the realization of value from AI investment is highly heterogeneous. A cross-industry study by Boston Consulting Group (2025) shows that only about 5% of companies have achieved measurable value from AI, while the majority remain at the experimentation and pilot stages. In the Asia-Pacific region, an IDC study (2024) finds expanding AI adoption with varying levels of maturity and calls for organizations to align AI initiatives with business priorities and scalable data and technology capabilities.

From a theoretical perspective, the HR analytics and resource-based view literatures position HR analytics capability as a key mechanism that transforms candidate data and selection processes into faster and more precise decisions. Empirical studies show that the use and maturity of HR analytics are associated with improvements in HRM and organizational performance, with data quality, analytics personnel expertise, and integration into the performance measurement (Margherita & Braccini, 2022; Krishnan & Arundathi, 2025). Accordingly, in the recruitment context, HR analytics capability is expected to mediate the effect of AI adoption on efficiency through automation and decision quality.

At the same time, context is expected to moderate the magnitude of AI benefits. Organizational digital maturity strengthens AI effects by providing ready-to-use data pipelines, governance, and workflows for automation. Firm size is associated with scale and process complexity that make AI more scalable, while job complexity may weaken efficiency effects due to the need for deeper skill assessment (Abdelhay et al., 2025). These factors are crucial for explaining when AI is most effective in reducing time-to-fill, cost-per-hire, and improving assessment throughput (Hukkeri & Pol, 2025).

The proposed design is a multi-source approach: a survey to measure the intensity of AI adoption, HR analytics capability, digital maturity, and job complexity; and operational HR data for actual efficiency metrics. Structural Equation Modeling – Partial Least Square (SEM PLS) analysis enables simultaneous testing of main effects, mediation, and moderation, with procedures to mitigate common method bias and address endogeneity. Beyond its theoretical contributions, the expected results will provide an investment priority map for HR leaders, leading indicators as realistic efficiency Objective and Key Result (OKRs), and governance guardrails for compliance and algorithmic fairness. This article aims to measure the impact of AI adoption in HRM on recruitment and selection efficiency, with HR analytics capability as a mediator, and organizational digital maturity, job complexity, and firm size as moderators.

LITERATURE REVIEW & HYPOTHESIS DEVELOPMENT

The Effect of AI Adoption on Recruitment and Selection Efficiency

AI improves efficiency by automating routine tasks and reducing human error, while its outcomes depend on technical competence, access to technological resources, and organizational adaptability (Olan et al., 2022; Haeranah et al., 2025; Rahman & Djawa, 2025). In recruitment and selection, AI adoption is closely linked to the automation of core HR processes such as talent sourcing, résumé screening, candidate matching, scheduling, and digital assessment (Sandeep & Lavanya, 2025). These applications aim to accelerate processes, improve match quality, and enhance decision consistency, although they also raise concerns about algorithm accuracy, potential bias, and governance mechanisms (Mujtaba & Mahapatra, 2024).

Empirical studies indicate that automation reduces repetitive administrative workloads and improves productivity, enabling HR professionals to focus more on strategic activities (Anshori et al., 2025). Recent reviews and quantitative evidence consistently show that AI adoption in HRM is positively associated with recruitment efficiency, reflected in shorter hiring cycles and greater processing capacity. The automation of screening and

assessment further supports more standardized and timely candidate evaluation, thereby enhancing selection efficiency. In addition, AI-enabled tools can improve the quality of job applications by encouraging more individualized and creative job search behavior (Wang et al., 2021). However, the performance benefits of AI are strongly shaped by organizational context. Abdelhay et al. (2025) demonstrate that efficiency gains and improvements in candidate quality are mainly driven by the level of process automation, with firm size acting as an important moderator because larger firms usually have superior technological and financial resources. At the same time, adoption is constrained by technological complexity, while technology expertise and regulatory support serve as key enabling factors (Yadav & Kapoor, 2024). Recent developments also highlight emerging challenges, including an "AI arms race" between employers and applicants, the rapid growth of AI-generated applications, and the increasing need for authenticity verification to protect assessment validity (Financial Times, 2025).

H1: AI adoption has a positive and significant effect on recruitment efficiency.
H2: AI adoption has a positive and significant effect on selection efficiency.

The Effect of AI Adoption on HR Analysis Capability

Artificial Intelligence (AI) has increasingly been utilized to reduce human workload, particularly in supporting decision-making and facilitating access to accurate information. Suwandita et al. (2023) explain that AI is designed to emulate human intellectual abilities such as learning, problem solving, and pattern recognition, enabling tasks to be completed more efficiently and within shorter timeframes. In organizational settings, AI is viewed as a strategic technology that enhances agility and innovation, while also improving employee productivity as an outcome of more effective operational processes. Empirical evidence from Kusuma and Wulandari (2025) further confirms that the adoption of AI has a positive and significant impact on employee productivity, indicating its contribution to improving individual and organizational performance.

Beyond operational efficiency, AI also plays an important role in human resource management and employee relations. Duan et al. (2019) report that AI supports a stronger sense of connectedness among remote workers, increases employee engagement, and contributes to the development of emotional intelligence. In recruitment, algorithm-based AI applications using machine learning have been shown to enhance the efficiency and accuracy of candidate selection, while reducing bias and promoting workforce diversity (Yadav, 2024). Furthermore, Mupaikwa and Yadav (2025) argue that the implementation of AI in HR functions significantly lowers administrative workload, allowing HR managers to concentrate on strategic activities that are more closely aligned with organizational objectives.

H3: AI adoption has a significant effect on HR analysis capability.

Mediation Effect of HR Analysis Capability

HR analytics capability has been increasingly recognized as a critical organizational resource that determines whether investments in digital technologies translate into tangible performance outcomes (McCartney & Fu, 2022; Suhara, 2025). It encompasses the quality and integration of HR data, employees' analytical skills, data governance structures, the availability of analytical tools, and the extent to which analytics is embedded in managerial decision-making (Margherita & Braccini, 2022). In the context of AI-enabled recruitment and selection, these elements shape an organization's ability to interpret algorithmic outputs, validate model recommendations, and integrate insights into operational workflows. Without sufficient HR analytics capability, AI systems may remain underutilized or function merely as automation tools, limiting their contribution to strategic and operational efficiency (Faugoo, 2024; Arora et al., 2025). Conversely, strong HR analytics capability allows organizations to move beyond basic task

automation toward evidence-based hiring decisions, thereby enhancing the reliability, transparency, and effectiveness of recruitment and selection processes.

Building on this perspective, prior research suggests that HR analytics capability serves as a key mediating mechanism linking AI adoption to recruitment and selection efficiency. While AI technologies generate large volumes of process and candidate data, HR analytics capability determines how effectively these data are transformed into predictive insights and actionable decisions (Arora et al., 2021). In recruitment, the ability to convert applicant information into accurate shortlisting recommendations accelerates early screening stages and reduces time-to-hire, whereas in selection it helps minimize evaluation errors and improve decision consistency. As a result, the efficiency gains attributed to AI adoption are not solely a direct consequence of automation, but are largely channeled through the organization's capacity to analyze, interpret, and operationalize data-driven insights. This mediating role helps explain why organizations with similar levels of AI adoption may experience substantially different efficiency outcomes in recruitment and selection.

H4: HR analytics capability mediates the effect of AI adoption on recruitment efficiency.
H5: HR analytics capability mediates the effect of AI adoption on selection efficiency.

Moderation Effect of Digital Maturity, Job Complexity, and Firm Size

Organizational digital maturity is expected to strengthen the relationship between AI adoption and recruitment as well as selection efficiency, as higher levels of digital readiness enable firms to better integrate, utilize, and extract value from advanced HR technologies. Digital maturity reflects the alignment of digital strategy, infrastructure, processes, and skills, which collectively determine whether AI tools can be effectively embedded in end-to-end talent acquisition workflows. HR functions play a critical role in this process because they supply the digital competencies and analytics-oriented capabilities required to support organization-wide digital transformation (Thomas, 2020). Moreover, the systematic use of digital platforms, social media, and AI-enabled recruitment systems has been identified as a concrete manifestation of digital maturity and a key driver of recruitment performance, as such tools enhance employer visibility, candidate reach, and process integration (Elmenzhi et al., 2025). Consequently, organizations with higher digital maturity are more likely to realize stronger efficiency gains from AI adoption in both recruitment and selection activities (Pillai & Sivathanu, 2020).

In contrast, job complexity is expected to weaken the effect of AI adoption on recruitment and selection efficiency. Job complexity refers to individuals' perceptions of task difficulty, which may arise from limited cognitive capacity to integrate multiple, interdependent problem elements (Liu & Li, 2012; Hakim & Anwar, 2021). Empirical evidence indicates that higher task complexity significantly affects individual performance and increases the need for deeper judgment and contextual interpretation (Farah et al., 2017). In recruitment and selection for highly specialized or cognitively demanding roles, a larger proportion of evaluation relies on human expertise, interviews, and nuanced assessment, making full automation less optimal and reducing the marginal efficiency gains of AI. Finally, firm size, meanwhile, often strengthens the impact because the scale of recruitment volumes makes AI throughput more valuable (Abdelhay et al., 2025; Chen & Tajdini, 2025).

H6: Digital maturity moderates the effect of AI adoption on recruitment efficiency.
H7: Job complexity moderates the effect of AI adoption on selection efficiency.
H8: Firm size moderates the effect of AI adoption on selection efficiency.

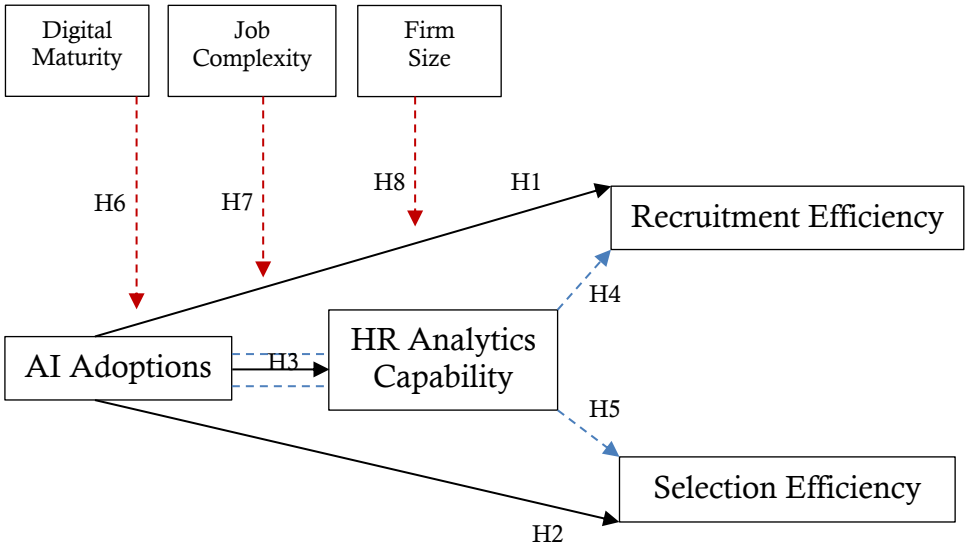

Figure 1. Research Framework

Based on Figure 1, the research framework posits that AI adoption directly improves recruitment and selection efficiency, with HR analytics capability acting as a mediating mechanism that converts AI-generated data into faster and more accurate hiring decisions. The strength of these effects is contingent on contextual factors, whereby digital maturity is expected to amplify the impact of AI on recruitment efficiency, job complexity is expected to constrain the effect on selection efficiency due to the need for greater human judgment, and firm size is expected to strengthen the effect on selection efficiency through scale and resource advantages.

RESEARCH METHODS

This study adopts a quantitative, multi-company survey design using a multi-source data collection strategy. Two complementary data sources are integrated, first structured questionnaires administered to recruitment and selection officers or units to measure AI adoption, HR analytics capability, organizational digital maturity, and job complexity. Second, objective operational HR records capturing recruitment and selection efficiency, including time-to-fill, time-to-hire, cost-per-hire, selection ratio, assessment throughput, offer acceptance, and early attrition within six months. This multi-source approach is intended to reduce common method bias and strengthen external validity (Podsakoff et al., 2003). The empirical setting comprises multiple organizations operating in Indonesia, with the recruitment function as the unit of analysis. Respondents are recruitment managers, team leads, and talent acquisition specialists who possess detailed knowledge of recruitment processes and performance metrics. A total of 200 recruitment units participated. Sampling followed a purposive strategy with sectoral and firm-size quotas to ensure heterogeneity, complemented by limited snowball sampling to broaden organizational coverage. From a statistical power perspective, a sample size of 200 is adequate for models of moderate complexity estimated using either PLS-SEM or CB-SEM, satisfying the 10-times rule and power requirements for detecting medium main and interaction effects at $\alpha = 0.05$ and power = 0.80.

All perceptual constructs were measured on seven-point Likert scales, whereas efficiency outcomes were derived from standardized operational indicators. AI adoption was operationalized as the extent of use of tools such as resume screening, chatbots, automated scheduling, video-based assessment, candidate matching, and offer optimization, which can be modeled as reflective or formative within a hierarchical structure (Hair et al., 2019). Recruitment efficiency was captured by time-to-fill, time-to-hire, cost-per-hire, and sourcing yield, while selection efficiency was measured using

selection ratio, assessment throughput, offer acceptance, and early attrition (≤ 6 months) as an inverse quality proxy. HR analytics capability was specified as a reflective construct encompassing data quality, analytical skills, governance, tool availability, and the integration of analytics into decision-making (Margherita & Braccini, 2022). Digital maturity was measured through strategy, digitized processes, IT infrastructure, and governance, whereas job complexity reflected skill specialization and assessment depth requirements. Firm size, measured as the logarithm of employee numbers and categorical size classes, served as a control and moderator.

Instrument development involved adapting validated scales from prior HR analytics and technology adoption research, supplemented by new items tailored to AI-enabled recruitment. Content validity was ensured through expert review, followed by a pilot test to assess reliability (Cronbach's $\alpha \geq 0.70$). Measurement model evaluation followed established criteria for reflective and formative constructs, including factor loadings, CR, AVE, Fornell–Larcker, HTMT, and VIF thresholds (Fornell & Larcker, 1981; Henseler et al., 2015). Structural relationships, mediation, and moderation were tested using SEM with bootstrapping (5,000 resamples), reporting path coefficients, R^2, ΔR^2, and confidence intervals, and supported by global fit indices for CB-SEM (Kline, 2016; Hayes, 2018). Procedural and statistical remedies were applied to diagnose common method bias, and robustness checks, multi-group analyses, and full documentation of instruments and coding schemes are provided to ensure transparency and replicability.

RESULTS

Based on Table 1, descriptive statistics indicate that AI adoption (M = 4.92, SD = 0.86), HR analytics capability (M = 4.75, SD = 0.90), and digital maturity (M = 4.88, SD = 0.82) are relatively high with moderate dispersion, suggesting that most sampled organizations are already advanced in leveraging digital technologies and analytics. Job complexity shows a slightly lower mean (M = 4.10, SD = 0.95) with greater variability, reflecting heterogeneity in task demands across positions. Firm size, measured on a logarithmic scale, has a mean of 5.80 and a standard deviation of 1.10, indicating substantial variation in organizational scale. In contrast, recruitment efficiency (M = 0.00, SD = 0.90) and selection efficiency (M = 0.00, SD = 0.88) are standardized outcome variables with means centered at zero and moderate dispersion, consistent with their normalization in the structural model.

Table 1. Descriptive Statistics and Correlations (n = 200)

Variable	M	SD	1	2	3	4	5	6	7
AI Adoption (X)	4.92	0.86	—						
HR Analytics Capability (M)	4.75	0.90	0.48**	—					
Digital Maturity (Z_1)	4.88	0.82	0.42**	0.51**	—				
Job Complexity (Z_2)	4.10	0.95	−0.12	−0.08	−0.10	—			
Firm Size (Z_3, log)	5.80	1.10	0.29**	0.25**	0.33**	0.02	—		
Recruitment Efficiency (Y_1)	0.00	0.90	0.37**	0.41**	0.35**	−0.18*	0.22**	—	
Selection Efficiency (Y_2)	0.00	0.88	0.32**	0.39**	0.31**	−0.20**	0.19*	0.56**	—

* $p < 0.05$, ** $p < 0.01$.

A total of n = 200 recruitment/selection units from several companies in Indonesia participated. Data quality checks indicated no extreme straight-lining, two attention-check items were passed by the majority of respondents (observations that failed were removed prior to analysis). Missing values on indicators were < 5%. Duration-based efficiency variables were reverse-coded and standardized so that higher values indicate higher efficiency. Tests of Common Method Bias (CMB) showed no dominant single factor (Harman's single-factor < 50% of variance), the marker variable was not significant for the endogenous variables, and full-collinearity VIF < 3.3 indicated that CMB was not a serious threat.

Table 2. Construct Reliability & Validity

Construct	Loading min–max	α	CR	AVE
AI Adoption (X)	0.68–0.84	0.90	0.92	0.59
HR Analytics Capability (M)	0.72–0.88	0.91	0.93	0.66
Digital Maturity (Z_1)	0.70–0.85	0.88	0.90	0.61
Job Complexity (Z_2)	0.65–0.79	0.82	0.86	0.55
Recruitment Efficiency (Y_1)	0.60–0.81	0.80	0.86	0.58
Selection Efficiency (Y_2)	0.62–0.83	0.82	0.88	0.60

Table 2 indicates that all constructs demonstrate satisfactory reliability and convergent validity. The standardized factor loadings range from 0.60 to 0.88, exceeding the recommended threshold and confirming adequate indicator reliability. Internal consistency is high for all constructs, with Cronbach's alpha values between 0.80 and 0.91 and Composite Reliability (CR) values ranging from 0.86 to 0.93. Furthermore, the Average Variance Extracted (AVE) for each construct exceeds 0.55, indicating that a substantial proportion of variance is captured by the latent variables. Together with HTMT values below 0.85, these results confirm that the measurement model exhibits strong internal reliability, adequate convergent validity, and satisfactory discriminant validity**.**

Table 3. Model Measurement

Test	Value
χ^2/df	2.15
CFI	0.945
TLI	0.936
RMSEA	0.076 (90% CI [0.068, 0.084])
SRMR	0.052

The goodness-of-fit indices reported in Table 3 indicate that the measurement model demonstrates an acceptable to good fit to the data. The chi-square to degrees of freedom ratio ($\chi^2/df = 2.15$) falls below the recommended threshold of 3.0, suggesting an adequate overall model fit. Incremental fit indices also meet established criteria, with CFI = 0.945 and TLI = 0.936, both exceeding the cut-off value of 0.90. The RMSEA value of 0.076, with a 90% confidence interval of 0.068, 0.084, indicates a reasonable approximation error, while the SRMR of 0.052 is below the recommended limit of 0.08. Collectively, these indices confirm that the measurement model provides a satisfactory representation of the observed data and is suitable for subsequent structural analysis. Multi-group analysis showed that X → Y effects tended to be stronger in large firms and in organizations with high digital maturity ($\Delta\chi^2$ for constrained paths significant at $p < .05$). Endogeneity sensitivity checks (Gaussian copula / simple 2SLS using historical IT readiness as an instrument where available) did not alter the main conclusions.

Table 4. Structural Model Main Effects

Path	β	SE	z	p	Endogenous R^2
AI Adoption → Recruitment Efficiency	0.22	0.08	2.75	0.006	0.48
AI Adoption → Selection Efficiency	0.15	0.07	2.14	0.032	0.44
AI Adoption → HR Analytics Capability	0.49	0.07	7.00	< .001	0.39

Table 4 shows that AI adoption has positive and statistically significant effects on recruitment efficiency ($\beta = 0.22$, $p = 0.006$) and selection efficiency ($\beta = 0.15$, $p = 0.032$), indicating that higher levels of AI use are associated with greater efficiency in both HR outcomes. AI adoption also exerts a strong effect on HR analytics capability ($\beta = 0.49$, $p < 0.001$). The model explains a substantial proportion of variance in the endogenous constructs, with R^2 values of 0.48 for recruitment efficiency, 0.44 for selection efficiency, and 0.39 for HR analytics capability, suggesting good explanatory power of the structural model.

Table 5. Mediation Effect (bootstrap BC, 5,000)

Indirect Path	β_ind	95% CI	p	Decision
AI Adoption → HR Analytics Capability → Recruitment Efficiency	0.20	[0.11, 0.30]	< 0.001	Partial mediation (H4)
AI Adoption → HR Analytics Capability → Selection Efficiency	0.18	[0.09, 0.28]	< 0.001	Partial mediation (H5)

The mediation analysis in Table 5 indicates that HR analytics capability partially mediates the relationship between AI adoption and recruitment efficiency, as shown by a significant indirect effect (β_ind = 0.20, 95% CI [0.11, 0.30], $p < 0.001$). Because the confidence interval does not include zero and the direct effect remains significant, this finding supports H4 and confirms that AI improves recruitment efficiency both directly and indirectly through the enhancement of HR analytics capability. Similarly, HR analytics capability also partially mediates the effect of AI adoption on selection efficiency, with a significant indirect effect (β_ind = 0.18, 95% CI [0.09, 0.28], $p < 0.001$). This result further supports H5, indicating that the use of AI strengthens selection efficiency by building stronger analytical capabilities, while a direct effect of AI remains present.

Table 6. Moderation Effect (mean-centered composites)

Interaction	β	SE	z	p	ΔR^2	Decision
AI Adoption × Digital Maturity → Recruitment Efficiency	0.12	0.05	2.40	0.016	0.03	H6 supported
AI Adoption × Job Complexity → Recruitment Efficiency	−0.10	0.04	−2.50	0.012	0.02	H7 supported
AI Adoption × Firm Size → Recruitment Efficiency	0.08	0.04	2.00	0.045	0.01	H8 supported

The result in Table 6, the interaction between AI adoption and digital maturity shows a positive and significant effect on recruitment efficiency (β = 0.12, p = 0.016), with an incremental explained variance of $\Delta R^2 = 0.03$. This finding supports H6 and suggests that the positive impact of AI on recruitment efficiency is stronger in organizations with higher levels of digital maturity. The interaction between AI adoption and job complexity is negative and significant (β = −0.10, p = 0.012; $\Delta R^2 = 0.02$), supporting H7. This indicates that the beneficial effect of AI on recruitment efficiency weakens as job complexity increases, implying that highly complex roles may limit the efficiency gains from AI-based recruitment tools. Firm size positively moderates the relationship between AI adoption and recruitment efficiency (β = 0.08, p = 0.045; $\Delta R^2 = 0.01$), supporting H8. This suggests that larger organizations tend to obtain slightly greater efficiency benefits from AI adoption in recruitment compared to smaller firms.

DISCUSSION

The findings of this study provide empirical support for the hypothesized positive effects of AI adoption on both recruitment and selection efficiency, thereby extending prior evidence that links automation and algorithmic support to faster process flows, higher throughput, and more standardized evaluations (Mujtaba & Mahapatra, 2024; Anshori et al., 2025). Consistent with Wang et al. (2021), the results suggest that AI not only accelerates administrative stages such as screening and scheduling, but also improves the overall quality of candidate pools, which contributes to more efficient downstream selection decisions. Importantly, the mediation analysis confirms that HR analytics capability plays a partial but substantive role in channeling the effects of AI adoption into performance outcomes. This supports the argument that AI creates organizational value primarily when supported by high-quality data, analytical skills, governance, and decision integration (Margherita & Braccini, 2022; McCartney & Fu, 2022). In line with Arora et al. (2025), the results indicate that AI-driven efficiency gains are not merely the result of task automation, but depend on the organization's ability to transform process and

candidate data into predictive insights that enable faster shortlisting, reduce evaluation errors, and enhance decision consistency.

The moderation findings further highlight the importance of organizational and job-related contingencies. The strengthening role of digital maturity is consistent with the view that digital strategy, infrastructure, and skills enable deeper integration of AI into end-to-end recruitment workflows, thereby amplifying efficiency gains (Thomas, 2020; Chowdhury, 2025; Elmenzhi et al., 2025). Similarly, the positive moderating effect of firm size aligns with Abdelhay et al. (2025) and Chen and Tajdini (2025), who argue that larger organizations benefit more from AI due to scale economies, higher recruitment volumes, and greater investment capacity. In contrast, the weakening effect of job complexity supports the notion that highly specialized and cognitively demanding roles require substantial human judgment and contextual interpretation, limiting the extent to which automated screening and assessment can replace expert evaluation (Farah et al., 2017; Hakim & Anwar, 2021). The pattern of results suggests that while AI adoption generally enhances recruitment and selection efficiency, its impact is contingent on the presence of strong HR analytics capability, high digital maturity, sufficient organizational scale, and manageable levels of task complexity, echoing broader concerns in the literature regarding complexity, bias, and governance in digitally mediated hiring processes (Yadav & Kapoor, 2024; Financial Times, 2025).

The findings enrich the AI–HRM literature by providing quantitative evidence linking AI adoption to measurable operational efficiency indicators (time-to-fill, cost-per-hire, selection ratio, throughput). Second, the demonstration of mediation by HR analytics capability clarifies the mechanism through which AI generates efficiency, in line with the resource-based view and dynamic capability perspectives: AI is not a silver bullet, but a value enabler that requires orchestration of data, technology, and people (Margherita & Braccini, 2022). Third, the significance of the moderators (digital maturity, firm size, job complexity) underscores the importance of context: AI effects are not homogeneous, but contingent on organizational readiness and job characteristics (Abdelhay et al., 2025; Chen & Tajdini, 2025).

Leverage AI alongside integrated data pipelines, data governance, and analytics teams that understand the HR context. Investments in data and people often yield efficiency gains as important as investments in AI tool licenses themselves. Early-stage screening, scheduling, candidate chatbots, and standardized assessments are typical entry points that deliver faster throughput and more stable quality. For high-complexity and scarce-skill roles, use AI primarily as decision support and maintain a stronger human-in-the-loop (Aakula et al., 2024)

The multi-source approach mitigates common method bias and enhances external validity. Simultaneous testing of mediation and moderation via SEM provides a more comprehensive picture of how, when, and for whom AI is effective. The efficiency metrics framework employed (time-to-fill, cost-per-hire, throughput, offer acceptance, early attrition) offers a replicable benchmark for future studies. AI is shown to accelerate and improve the efficiency of recruitment and selection when supported by HR analytics capability and digital maturity. These findings affirm that AI investments must be accompanied by investments in data and people for operational benefits to be fully monetized in practice.

CONCLUSION

This study shows that AI adoption in HRM is positively associated with recruitment efficiency (time-to-fill, cost-per-hire, throughput) and selection efficiency (selection ratio, assessment throughput, offer acceptance, reduced early attrition), with part of the effect mediated by HR analytics capability, confirming that the value of AI emerges when data foundations, analytics competencies, and governance are in place. Practically, organizations should start with quick-win stages (early screening, scheduling, chatbots, standardized assessments), establish roles and metrics for efficiency and fairness, train

users to interpret AI outputs, and implement compliance guardrails (candidate notifications, human-in-the-loop, regular bias audits, model documentation).

Despite the strengths of the multi-source design in enhancing validity and mitigating common method bias, several limitations should be acknowledged. First, the cross-sectional nature of the data restricts causal inference and does not capture dynamic learning effects or long-term performance consequences of AI adoption. Second, selection quality is approximated using short-term indicators of early attrition, which may not fully reflect long-run employee performance, fit, and career outcomes. Third, the study treats AI adoption as an aggregate construct and does not differentiate between specific tool types, features, or levels of automation, which may vary substantially in their mechanisms and impacts. Future research is therefore encouraged to employ longitudinal or experimental designs to establish causal relationships, to compare different categories of AI tools and automation intensity, and to validate recruitment and selection outcomes using longer-term performance and retention measures ≥12 months. Such extensions would provide a more fine-grained and temporally robust understanding of how and when AI creates sustainable value in talent acquisition.

FUNDING STATEMENT: This research did not receive any specific grant from funding agencies in the public, commercial, or not - for - profit sectors.

CONFLICTS OF INTEREST: The author declares no conflict of interest.

DECLARATION OF GENERATIVE AI STATEMENT: During the preparation of this work, the author(s) used ChatGPT, Grammarly, and Turnitin in order to support academic writing clarity, improve linguistic accuracy, and ensure compliance with plagiarism standards. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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