American Impact Review

ORIGINAL RESEARCH

Artificial Intelligence Adoption in Talent Acquisition: Effects on Recruitment Efficiency, Algorithmic Fairness Perceptions, and Employee Experience

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Citation:
Aichurek Nuralieva (2026). Artificial Intelligence Adoption in Talent Acquisition: Effects on Recruitment Efficiency, Algorithmic Fairness Perceptions, and Employee Experience. *Am. Impact Rev.* 10.66308/air.e2026026

Received: February 10, 2026
Accepted: March 18, 2026
Published: March 21, 2026

DOI:
10.66308/air.e2026026

ISSN: 3071-124X

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Abstract

The deployment of artificial intelligence in talent acquisition has accelerated rapidly, yet empirical research examining the full pathway from adoption determinants to downstream effects on perceived recruitment efficiency, algorithmic fairness perceptions, and HR-reported employee experience remains limited. This study develops and tests an integrated theoretical framework combining the Technology Acceptance Model and the Technology-Organization-Environment framework to examine AI adoption in talent acquisition across mid-to-large United States enterprises. Using cross-sectional survey data from 523 human resource professionals and hiring managers representing 184 organizations across multiple industries, the analysis relies on partial least squares path modeling (PLS-PM) to test eight predictions linking technological perceptions, organizational factors, and adoption outcomes. Results indicate that perceived usefulness and perceived ease of use significantly predict AI adoption intention, with perceived usefulness exhibiting a stronger effect. Top management support and HR digital readiness are both positively associated with organizational AI adoption, though top management support demonstrates greater explanatory power. AI adoption is positively associated with recruitment efficiency across all three metrics examined: time-to-hire reduction, cost-per-hire reduction, and quality-of-hire improvement. Algorithmic transparency emerges as a strong predictor of procedural fairness perceptions, which in turn positively predict employee experience outcomes including organizational commitment, job satisfaction, and employer trust. Organizational size moderates the adoption-efficiency relationship such that larger firms realize proportionally greater efficiency gains. These findings contribute to the human resource management and information systems literatures by providing empirical evidence linking AI adoption antecedents to a chain of recruitment efficiency and employee experience outcomes, while highlighting the central role of algorithmic transparency in sustaining perceived fairness. Practical implications for HR leaders, technology vendors, and policymakers are discussed.

Keywords: artificial intelligence, talent acquisition, recruitment efficiency, algorithmic fairness, employee experience, technology adoption

1. Introduction

Artificial intelligence now pervades human resource management, changing how organizations attract, evaluate, and select talent. According to recent estimates from the Society for Human Resource Management, approximately 64% of organizations that have adopted AI for human resource purposes identify talent acquisition as the primary area of deployment, surpassing learning and development and performance management by significant margins (SHRM, 2024). The spread of AI-powered applicant tracking systems, resume screening algorithms, chatbot-based candidate engagement platforms, and predictive analytics tools has changed recruitment practices in ways that were largely theoretical a decade ago (Tambe et al., 2019; Vrontis et al., 2022).

This transformation has both positive and negative potential. Proponents argue that AI-driven recruitment tools can dramatically reduce time-to-hire, lower recruitment costs, improve candidate-job matching, and mitigate the cognitive biases that afflict human decision-makers (Nawaz & Gomes, 2019; Upadhyay & Khandelwal, 2018). Critics counter that AI systems trained on historical hiring data may perpetuate and amplify existing patterns of discrimination, that the opacity of algorithmic decision-making undermines procedural fairness, and that the substitution of human judgment with machine judgment fundamentally alters the psychological contract between employers and employees (Köchling & Wehner, 2020; Giermindl et al., 2022; Charlwood & Guenole, 2022).

Despite the intensity of scholarly and practitioner interest, empirical research on AI in talent acquisition exhibits several notable gaps and unresolved tensions. Findings on AI's impact on recruitment quality are mixed: while some studies report improved candidate-job fit (Albert, 2019), others find that algorithmic screening can systematically exclude non-traditional candidates who would have succeeded in the role (Raghavan et al., 2020). Similarly, the relationship between AI transparency and user trust is not straightforward—Köchling and Wehner (2020) suggest that greater explainability improves fairness perceptions, whereas Giermindl et al. (2022) caution that transparency without interpretability may actually erode trust. These contradictions point to the need for integrated empirical models that can parse these competing effects. First, the majority of existing studies are conceptual, qualitative, or focused on narrow aspects of the adoption-outcome relationship, with relatively few large-scale quantitative investigations that trace the full pathway from adoption determinants to downstream organizational and individual consequences (Pan & Froese, 2023; Prikshat et al., 2023). Second, most empirical work examines either the technology adoption decision or the efficiency outcomes, rarely connecting these to fairness perceptions and employee experience within an integrated analytical framework (Strohmeier & Piazza, 2015; Jarrahi, 2018). Third, the moderating role of organizational characteristics, particularly firm size, in shaping the relationship between AI adoption and its varied outcomes has received insufficient empirical attention (Chowdhury et al., 2023; Budhwar et al., 2022).

The present study addresses these gaps by proposing and testing an integrated theoretical framework that combines the Technology Acceptance Model (TAM; Davis, 1989) with the Technology-Organization-Environment (TOE) framework (Tornatzky & Fleischer, 1990). This integrated model captures the multidimensional nature of AI adoption in talent acquisition by simultaneously examining individual-level technology perceptions, organizational-level adoption determinants, and multiple categories of downstream outcomes. Specifically, the study pursues four research objectives: (1) to examine the technological and organizational factors that drive AI adoption intention in talent acquisition; (2) to assess the relationship between AI adoption and recruitment efficiency metrics; (3) to investigate how algorithmic transparency shapes fairness perceptions and, subsequently, employee experience; and (4) to evaluate the moderating role of organizational size across these relationships.

The study draws on cross-sectional survey data from 523 HR professionals and hiring managers at 184 mid-to-large organizations across multiple industries in the United States. PLS path modeling serves as the main analytical tool, allowing the simultaneous testing of multiple direct, mediating, and moderating relationships within the integrated framework. The findings contribute both theoretical insight and practical guidance for organizations managing the intersection of AI technology and human talent acquisition.

On the conceptual side, this study departs from the single-framework tradition by merging TAM and TOE into one model that simultaneously captures individual technology perceptions (perceived usefulness, perceived ease of use) and organizational-environmental determinants (top management support, HR digital readiness), while extending the dependent-variable side beyond adoption intention to include efficiency, fairness, and employee experience outcomes—a combination that prior work has addressed only in piecemeal fashion (cf. Van Esch et al., 2019; Pan & Froese, 2023). Methodologically, it provides much-needed empirical evidence on the full adoption-to-outcome pathway, connecting adoption determinants to efficiency outcomes, fairness perceptions, and employee experience within a single analytical model—a linkage that Prikshat et al. (2023) explicitly called for but that existing studies have not tested with primary survey data. The analysis also identifies organizational size as a appreciable moderating variable that differentially shapes efficiency gains and employee experience effects, offering size-contingent guidance that moves beyond the one-size-fits-all prescriptions typical of early AI-HRM research.

The paper proceeds through five sections. A targeted literature review and the conceptual model appear next (Section 2), followed by the research design (Section 3) and empirical results (Section 4). Section 5 interprets the findings against the existing literature, and Section 6 outlines boundary conditions and avenues for future inquiry.

2. Literature Review and Hypotheses Development

2.1 AI Applications in Talent Acquisition

The application of AI in talent acquisition has evolved from narrow automation tasks, such as keyword-based resume parsing and automated job posting distribution, to sophisticated systems employing natural language processing, machine learning, and predictive analytics that support the entire recruitment lifecycle (Upadhyay & Khandelwal, 2018; Nawaz & Gomes, 2019). Strohmeier and Piazza (2015) provided an early conceptual exploration of AI techniques applicable to HRM, identifying scenarios including candidate search with knowledge-based engines and resume data acquisition through information extraction. Tambe et al. (2019) subsequently identified four fundamental challenges in applying data science to HR: the complexity of HR phenomena, constraints from small datasets, accountability concerns related to fairness, and potential adverse employee reactions to algorithmic management.

Vrontis et al. (2022) conducted a systematic review of 144 articles on AI and advanced technologies in HRM, documenting the accelerating pace of AI deployment and identifying critical gaps in understanding employee-level consequences. Meijerink et al. (2021) defined algorithmic HRM as the use of software algorithms operating on digital data to augment HR-related decisions or automate HRM activities, providing conceptual clarity for the emerging field. More recently, Prikshat et al. (2023) proposed a multilevel framework for AI-augmented HRM that distinguishes operational, relational, and transformational consequences of AI integration.

2.2 Determinants of AI Adoption

The determinants of AI adoption in talent acquisition span technological, organizational, and environmental dimensions, consistent with the three pillars of the TOE framework (Tornatzky & Fleischer, 1990). At the technological level, Pan and Froese (2022) found that perceived complexity toward AI constrains adoption, while technology competence encourages it. Their quantitative study of 297 Chinese companies demonstrated that the relationship between technological factors and AI adoption is mediated by organizational absorptive capacity, suggesting that technology characteristics alone are insufficient predictors of adoption outcomes. Chowdhury et al. (2023) argued that organizations must cultivate specific technological resources, including data quality infrastructure, algorithm development expertise, and integration architecture, to realize anticipated benefits. Their AI capability framework posits that complementary technological capabilities are prerequisites for effective AI deployment, a proposition with particular relevance for talent acquisition where AI tools must integrate with existing applicant tracking systems, human resource information systems, and assessment platforms. Van Esch et al. (2019) demonstrated that perceptions of AI tools as innovative can positively influence engagement with AI-mediated recruitment, though their study focused on the candidate rather than the organizational perspective.

At the organizational level, top management support has been consistently identified as a critical enabler of technology adoption across multiple theoretical traditions. Pan and Froese (2023), in their interdisciplinary review of 184 articles, found that executive commitment to digital transformation signals organizational legitimacy for AI investments and provides the resource allocation necessary for successful implementation. Angrave et al. (2016) warned that without strategic data analytics capabilities supported by executive leadership, HR functions risk failing the analytics challenge, a prediction that appears increasingly prescient as the gap between AI's potential and HR's readiness persists. Bondarouk and Brewster (2016) emphasized that the gap between technological possibility and organizational readiness represents the most significant barrier to effective technology deployment in HR, arguing that organizational culture, learning orientation, and prior technology experience collectively shape readiness for advanced technology adoption. Firm size also influences adoption patterns, with larger organizations possessing dedicated HR technology teams, greater data volumes, and more formal technology governance structures (Malik et al., 2022).

Environmental factors include competitive pressure, regulatory requirements, and vendor ecosystem support. The rapid adoption of AI by industry leaders creates institutional pressure on lagging firms, consistent with mimetic isomorphism processes described by DiMaggio and Powell (1983). When industry peers adopt AI recruitment tools and report favorable outcomes, non-adopting organizations face legitimacy pressures that incentivize adoption regardless of internal readiness. Regulatory uncertainty around data privacy and algorithmic accountability simultaneously inhibits adoption, as organizations weigh the efficiency gains of AI against the compliance risks of deploying tools that may violate emerging algorithmic accountability regulations (Pan & Froese, 2022). Ore and Sposato (2022), in their qualitative study of recruitment professionals at a multinational corporation, found that vendor promises of efficiency gains drive initial adoption interest, while concerns about vendor data handling practices and algorithmic opacity create resistance among experienced HR practitioners who question whether AI can replicate the context-dependent judgment that characterizes effective human recruitment.

2.3 Recruitment Efficiency Outcomes

A primary justification for AI adoption in talent acquisition is enhanced recruitment efficiency, typically operationalized through three core metrics: time-to-hire (the elapsed time from job requisition to offer acceptance), cost-per-hire (the total recruitment expenditure divided by the number of hires), and quality-of-hire (typically measured through new hire performance ratings, retention rates, or hiring manager satisfaction). The evidence on AI's impact on these metrics, while generally positive, is less uniform than vendor marketing materials suggest.

Nawaz and Gomes (2019) examined AI chatbot deployment in recruitment processes and found significant reductions in response time and candidate drop-off rates, suggesting efficiency gains in the early stages of the recruitment funnel. However, Tambe et al. (2019) cautioned that the small, biased, and noisy nature of HR data can limit the predictive accuracy of AI screening algorithms, potentially undermining quality-of-hire improvements. Their analysis in the California Management Review established four fundamental challenges in applying data science to HR that continue to constrain the efficiency gains organizations can expect from AI adoption.

Raisch and Krakowski (2021) introduced the automation-augmentation paradox in the Academy of Management Review, arguing that organizations face inherent tension between using AI to automate human tasks (replacing human judgment) and using AI to augment human capabilities (enhancing human judgment). In the recruitment context, this paradox manifests when AI screening algorithms automatically reject qualified candidates (an automation failure) or when AI-generated insights improve recruiter decision quality (an augmentation success). The balance between automation and augmentation has significant implications for net recruitment efficiency. Tong et al. (2021), in a rigorous empirical study published in the Strategic Management Journal, demonstrated the "Janus face" of AI feedback: improved performance through superior data analytics (the deployment effect) alongside negative psychological reactions triggered by awareness of AI monitoring (the disclosure effect). While their study focused on performance management rather than recruitment specifically, the deployment-disclosure dynamic is directly relevant to understanding how AI affects candidate behavior during AI-mediated recruitment processes.

2.4 Algorithmic Fairness and Bias Perceptions

Perhaps no aspect of AI in recruitment has generated more scholarly and public attention than the question of algorithmic fairness. The core concern is clear: AI systems trained on historical hiring data may perpetuate and amplify existing biases related to gender, race, age, disability, and other protected characteristics. Köchling and Wehner (2020) published a landmark systematic review examining discrimination and fairness in algorithmic decision-making in HR recruitment and development contexts. Their review documented multiple mechanisms through which algorithmic bias can manifest, including biased training data, proxy variable discrimination, and feedback loop amplification. They also noted that the opacity of many AI systems makes it difficult for organizations to detect and remediate algorithmic bias even when they are committed to fair hiring practices.

Pessach and Shmueli (2022), writing in ACM Computing Surveys, provided a broad technical review of fairness in machine learning, cataloging fairness definitions, measurement approaches, and mitigation strategies. Their distinction between pre-process, in-process, and post-process fairness mechanisms offers a practical framework for organizations seeking to audit AI recruitment tools. However, they acknowledged that different fairness definitions can be mathematically incompatible, creating genuine dilemmas for organizations attempting to satisfy multiple fairness criteria simultaneously.

The perception of fairness, as distinct from statistical fairness, constitutes another critical dimension. Giermindl et al. (2022), in a theorizing review published in the European Journal of Information Systems, identified multiple "dark sides" of people analytics, including surveillance concerns, autonomy erosion, and fairness perception degradation. Their analysis suggests that even when AI systems produce statistically unbiased outcomes, employees and candidates may perceive the process as unfair if they lack transparency into how decisions are made, if they have no opportunity to contest algorithmic assessments, or if they perceive the replacement of human judgment with machine judgment as inherently dehumanizing. Rodgers et al. (2022) proposed an AI algorithmic ethics framework for HRM decision-making, arguing that ethical considerations must be embedded at the design stage rather than appended as post-hoc auditing. Their framework posits that algorithmic ethical positioning significantly influences both actual fairness outcomes and stakeholder fairness perceptions.

2.5 Employee Experience and Trust

The consequences of AI-mediated recruitment extend beyond the hiring event to shape broader employee experience. Glikson and Woolley (2020) found that initial trust in AI tends to be lower than trust in human decision-makers, though positive performance experience can increase trust over time. Bankins and Formosa (2023) argued that AI deployment can either enhance or diminish appreciable work experiences, depending on whether AI serves augmentation or surveillance purposes. Charlwood and Guenole (2022) used a paradox lens to argue that positive and negative AI scenarios likely coexist, with net effects depending on governance structures and HR professional competence. Jarrahi (2018) articulated a vision of human-AI symbiosis in which the most productive AI deployments combine machine strengths with human relational sensitivity.

2.6 Conceptual Model

The present study integrates two established theoretical frameworks to construct an integrated model for understanding AI adoption in talent acquisition and its consequences. The Technology Acceptance Model (Davis, 1989) provides the micro-level lens, positing that perceived usefulness and perceived ease of use are primary determinants of technology adoption intention. The Technology-

Organization-Environment framework (Tornatzky & Fleischer, 1990) provides the meso-level lens, capturing organizational factors such as top management support and HR digital readiness, as well as environmental pressures that shape adoption at the firm level. The integration of these frameworks is well-precedented in technology adoption research and has been shown to improve explanatory power beyond what either framework achieves independently (Prikshat et al., 2023).

The conceptual model, depicted in Figure 1, traces two parallel pathways from adoption determinants to outcomes. The first pathway flows from individual technology perceptions (perceived usefulness, perceived ease of use) through AI adoption intention to recruitment efficiency outcomes. The second pathway flows from organizational factors (top management support, HR digital readiness) through adoption to algorithmic transparency, fairness perceptions, and employee experience. Organizational size is positioned as a moderating variable that conditions the relationships between AI adoption and both efficiency and employee experience outcomes. The model draws selectively on the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) to incorporate social influence as a supplementary construct capturing the interpersonal and normative dimensions of adoption decisions.

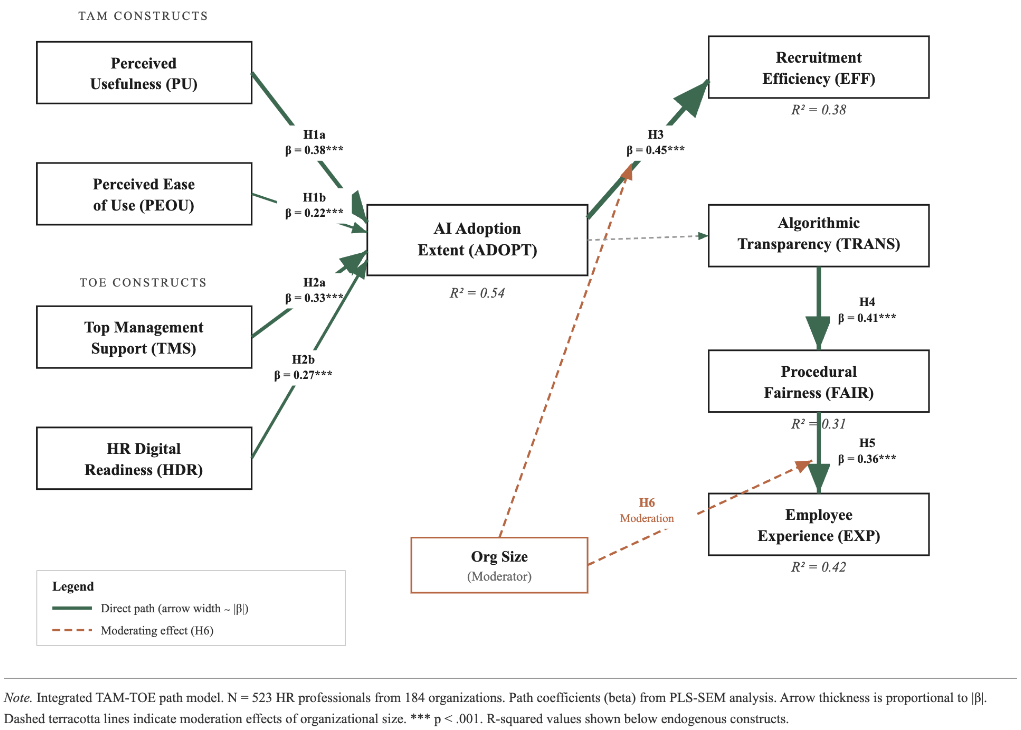

Figure 1.

Integrated TAM-TOE conceptual model with hypothesized relationships. Solid arrows indicate hypothesized direct paths; dashed arrow indicates hypothesized moderation. –the size-moderation prediction labels correspond to the hypotheses described in Section 2.7.

2.7 Predictions

Eight predictions follow from the model. Drawing on TAM (Davis, 1989), the study predicts that perceived usefulness and perceived ease of use are each positively associated with HR professionals' intention to adopt AI recruitment tools, with the effect of usefulness expected to dominate, consistent with meta-analytic TAM findings (Venkatesh et al., 2003; Pan & Froese, 2023). At the organizational level, the TOE framework predicts that top management support and HR digital readiness are each positively associated with organizational AI adoption intention, reflecting the enabling roles of executive sponsorship and technical capacity (Tornatzky & Fleischer, 1990; Angrave et al., 2016; Prikshat et al., 2023). Turning to outcomes, the study predicts that the extent of AI adoption is positively associated with recruitment efficiency across time-to-hire, cost-per-hire, and quality-of-hire, as broader pipeline coverage exposes more process steps to automation gains (Nawaz & Gomes, 2019; Raisch & Krakowski, 2021). On the fairness pathway, algorithmic transparency is predicted to be positively associated with procedural fairness perceptions, because stakeholders who understand how AI tools reach decisions rate the process as fairer (Köchling & Wehner, 2020; Giermindl et al., 2022), and procedural fairness is in turn predicted to be positively associated with perceived employee experience—specifically organizational commitment, job satisfaction, and employer trust—following organizational justice theory (Glikson & Woolley, 2020; Bankins & Formosa, 2023). Finally, organizational size is expected to moderate the outcome pathways: larger firms should realize stronger efficiency gains from AI adoption due to greater data volumes and dedicated HR-technology teams, but weaker employee-experience effects due to bureaucratic dilution of transparency practices (Chowdhury et al., 2023).

3. Methodology

3.1 Research Design

A one-time online survey served as the data-collection vehicle for testing the proposed TAM-TOE model. This snapshot approach suits the study's aim of mapping adoption patterns and attitudinal profiles across a diverse set of organizations and sectors. While longitudinal designs offer advantages for establishing temporal precedence, the cross-sectional approach is appropriate for an initial test of the integrated model given the emerging stage of large-scale empirical research in this domain (Pan & Froese, 2022). Data were collected between March and August 2025 using an online survey instrument distributed through professional HR networks and organizational partnerships.

3.2 Population and Sampling

The target population comprised HR professionals and hiring managers at mid-to-large organizations (250 or more employees) in the United States that had implemented or were actively implementing AI-powered tools in their talent acquisition processes. The minimum size threshold of 250 employees was imposed to ensure that participating organizations possessed sufficient recruitment volume and organizational complexity to make AI deployment appreciable.

A purposive sampling strategy was employed, supplemented by snowball sampling to expand reach across industries. Initial recruitment utilized partnerships with three national HR professional associations, direct outreach to HR technology user communities, and sponsored placements on LinkedIn targeting HR professionals with talent acquisition responsibilities. To qualify for participation, respondents were required to (a) hold a role with direct involvement in talent acquisition decisions,

(b) work at an organization with at least 250 employees, and (c) confirm that their organization used at least one AI-powered tool in the recruitment process.

The final sample comprised 523 valid responses from HR professionals and hiring managers representing 184 distinct organizations. The effective response rate, calculated as the proportion of completed surveys among those who accessed the survey link and confirmed eligibility, was 38.7%. This response rate is consistent with norms for organizational survey research targeting senior HR professionals (Baruch & Holtom, 2008). Non-response bias was assessed by comparing early and late respondents on key demographic and organizational variables using independent samples t-tests; no significant differences were detected ($p > .10$ for all comparisons), suggesting that non-response bias did not substantially affect the sample.

3.3 Sample Characteristics

Respondents represented a diverse cross-section of US organizations. In terms of organizational size, 54.9% of respondents worked at organizations with 250 to 500 employees (classified as small/medium, n = 287), while 45.1% worked at organizations with more than 500 employees (classified as large, n = 236). Industry representation included technology (22.4%), financial services (18.5%), healthcare (14.7%), manufacturing (12.4%), professional services (11.3%), retail (8.9%), education (6.1%), and other sectors (5.7%). Figure 2 presents a dumbbell plot comparing AI adoption levels across these industry sectors, revealing substantial variation in both the breadth and depth of AI tool deployment.

Figure 2. *AI adoption in talent acquisition by industry sector, 2021 versus 2024 (dumbbell plot). Terracotta dots represent 2021 baseline; green dots represent 2024 levels.*

Among individual respondents, 47.4% held the title of HR Manager or Director, 23.1% were Talent Acquisition Managers or Directors, 16.4% were HR Business Partners, 8.2% were Chief Human Resource Officers or Vice Presidents of HR, and 4.9% held other HR leadership roles. Mean professional experience in HR was 12.8 years (SD = 6.4), and mean experience with AI recruitment tools was 3.2 years (SD = 1.9). In terms of gender, 61.6% of respondents identified as female, 36.3% as male, and 2.1% as non-binary or preferred not to disclose. Regarding education, 72.5% held a graduate degree, 24.1% held a bachelor's degree, and 3.4% reported other educational backgrounds.

3.4 Measurement Instruments

Each latent variable was operationalized with reflective indicators drawn from prior instrument development work in technology acceptance and organizational behavior. Unless otherwise noted, items were measured on seven-point Likert scales anchored at 1 (strongly disagree) and 7 (strongly agree).

Perceived usefulness was measured using four items adapted from Davis (1989), reworded to reference AI recruitment tools specifically (e.g., ”Using AI recruitment tools improves the quality of hiring decisions I make”). Perceived ease of use was measured using four items from the same source (e.g., ”Learning to operate AI recruitment tools is easy for me”). These scales have demonstrated satisfactory psychometric properties across hundreds of studies (Venkatesh et al., 2003).

Top management support was measured using three items adapted from Pan and Froese (2022), assessing the degree to which senior leadership actively champions, resources, and prioritizes AI adoption in HR (e.g., ”Senior leadership in my organization actively supports the adoption of AI in talent acquisition”). HR digital readiness was initially measured using four items; one item was removed during measurement model assessment due to a below-threshold factor loading (see Section 4.1), yielding a final three-item scale developed from the conceptualizations of Bondarouk and Brewster (2016) and Chowdhury et al. (2023), capturing the HR function’s data literacy, technological infrastructure, and change management capacity (e.g., ”The HR team in my organization has the digital skills necessary to effectively use AI recruitment tools”).

AI adoption extent was measured using a composite index reflecting the number and scope of AI tools deployed across recruitment stages. Respondents indicated which of eight specific AI applications their organization used (resume screening, candidate sourcing, chatbot engagement, video interview analysis, skills assessment, predictive analytics for candidate fit, automated scheduling, and diversity analytics), and the extent of deployment for each on a four-point scale (not used, pilot stage, partially deployed, fully deployed). The composite index was calculated as the mean deployment score across all eight applications, yielding a continuous measure ranging from 0 to 3.

Recruitment efficiency was measured across three dimensions. Time-to-hire reduction was assessed using three items capturing perceived improvements in the speed of the recruitment process since AI adoption (e.g., ”Since implementing AI tools, the average time from job posting to offer acceptance has decreased”). Cost-per-hire reduction was assessed using three items addressing perceived cost savings (e.g., ”AI tools have reduced the overall cost of recruiting per hire in my organization”). Quality-of-hire improvement was assessed using three items measuring perceived enhancements in the caliber of new hires (e.g., ”Employees hired through AI-assisted processes perform better in their first year compared to those hired through traditional processes”). These items were developed drawing on recruitment metrics literature and piloted with a panel of 15 HR professionals for content validity.

Algorithmic transparency was measured using four items adapted from Giermindl et al. (2022) and Rodgers et al. (2022), assessing the degree to which respondents perceived that the AI tools used in their organization’s recruitment process operated in an understandable, explainable manner (e.g., ”I understand the criteria that our AI recruitment tools use to evaluate candidates”).

Procedural fairness perception was measured using five items adapted from Colquitt’s (2001) organizational justice scale, reworded to reference AI-mediated recruitment processes (e.g., ”The AI-assisted recruitment process in my organization applies consistent standards to all candidates”).

Employee experience was measured across three sub-dimensions, with all items rated by the HR professional respondent based on their perception of employee outcomes associated with AI-mediated recruitment. These measures capture HR professionals’ perceptions of employee experience, not direct reports from employees or candidates themselves. Organizational commitment was assessed using four items from Allen and Meyer’s (1990) affective commitment scale, adapted to reference initial organizational attitudes as perceived by the hiring professional (e.g., ”New hires recruited through AI-assisted processes appear to develop a strong sense of belonging to this organization”). Job satisfaction was measured using three items adapted from the Minnesota Satisfaction Questionnaire short form (Weiss et al., 1967). Employer trust was measured using four items adapted from Mayer and Davis (1999), capturing the respondent’s assessment of how AI-mediated recruitment affects employee trust in the organization's HR practices.

Organizational size was measured as a binary grouping variable: small/medium (250–500 employees) and large (more than 500 employees). This threshold was selected based on prior research suggesting that organizations above 500 employees are substantially more likely to maintain dedicated HR technology functions and larger applicant pools that justify AI investment (Angrave et al., 2016).

Control variables included industry sector (categorical), respondent tenure in current role (years), prior personal experience with AI tools outside the recruitment context (binary), and geographic region (US Census division).

3.5 Pilot Study

A pilot study was conducted with 45 HR professionals recruited through a university alumni network. The pilot assessed item clarity, completion time, and preliminary reliability. Minor wording adjustments were made to three items based on respondent feedback. The average completion time was 18 minutes. All scales demonstrated acceptable internal consistency (Cronbach's alpha > .70) in the pilot sample, supporting progression to the full data collection phase.

3.6 Common Method Variance

Because independent and dependent variables were collected from the same respondent in a single survey administration, common method variance (CMV) represents a potential concern. Several procedural remedies were implemented: psychological separation of predictor and criterion measures through different survey sections, counterbalanced item ordering within scales, and assurance of respondent anonymity. Post hoc, an exploratory factor analysis forcing a single factor was run; the lone factor captured only 27.3% of the total variance—far short of the 50% ceiling that would signal serious CMV (Podsakoff et al., 2003). Additionally, a full collinearity assessment using variance inflation factors (VIF) for all latent variables yielded values ranging from 1.12 to 2.87, all below the threshold of 3.3 recommended by Kock (2015), providing further evidence that CMV does not pose a serious threat to the findings.

3.7 Data Screening and Preparation

Prior to analysis, data were screened for completeness, response patterns, and distributional characteristics. Of the 589 surveys initiated by eligible respondents, 42 were excluded for completion rates below 80%, 15 were excluded for exhibiting straight-line response patterns (identical responses across more than 90% of Likert items), and 9 were excluded for completion times below three minutes (suggesting inattentive responding). The final analytical sample comprised 523 valid responses.

Missing data analysis revealed that 2.1% of data points were missing across the full dataset. Little's MCAR test was non-significant (chi-square = 187.42, df = 174, p = .23), supporting the assumption that data were missing completely at random. Missing values were handled through the expectation-maximization algorithm, which is appropriate for PLS-SEM applications when the proportion of missing data is small (Hair et al., 2019).

Distributional analysis indicated moderate departures from normality for several variables, with skewness values ranging from -0.89 to 0.64 and kurtosis values ranging from -0.72 to 1.38. These departures, while exceeding the strict thresholds for covariance-based SEM, fall within acceptable ranges for PLS-SEM, which does not assume multivariate normality (Hair et al., 2019).

3.8 Analytical Approach

PLS path modeling was chosen as the analytical engine for several reasons. First, PLS-SEM is well-suited for exploratory research testing complex models with multiple constructs, mediating chains, and moderating effects (Hair et al., 2019). Second, PLS-SEM performs effectively with non-normal data distributions and does not require the stringent distributional assumptions of covariance-based SEM (CB-SEM). Third, PLS-SEM's emphasis on explained variance matches the goal of this research in outcome variables rather than confirming a single theoretical model. Fourth, the sample size of 523 comfortably exceeds the minimum requirements for PLS-SEM, which are typically calculated as ten times the maximum number of structural paths pointing at any particular construct in the model (Hair et al., 2019). In the present model, the maximum number of incoming paths for any construct is four (for AI adoption intention), yielding a minimum sample requirement of 40; the achieved sample of 523 provides ample statistical power. Analyses were conducted using SmartPLS 4.0 (Ringle et al., 2022).

The analysis proceeded in two phases, following the reporting protocol recommended by Hair et al. (2019). Phase one addressed the outer model: indicator loadings, Cronbach's alpha, composite reliability, AVE for convergent validity, and three discriminant-validity checks (Fornell-Larcker, HTMT, cross-loading patterns). Phase two turned to the inner model, examining VIF values for collinearity, bootstrapped path coefficients, f^2 effect sizes, and the Q^2 and R^2 statistics for predictive accuracy. Bootstrapping with 10,000 subsamples and bias-corrected confidence intervals was used to determine the significance of path coefficients and indirect effects. Multi-group analysis (MGA) was employed to test the moderating effects of organizational size by comparing structural model parameters across the three size categories, following the MICOM procedure for measurement invariance assessment (Henseler et al., 2016).

4. Results

4.0 Descriptive Statistics

Table 1 presents the descriptive statistics and reliability measures for all study constructs. Among the TAM constructs, perceived usefulness had a mean of 5.24 (SD = 1.12) on the seven-point scale, while perceived ease of use had a mean of 4.67 (SD = 1.28), suggesting that respondents generally viewed AI recruitment tools as more useful than easy to use. The organizational factors showed similar patterns: top management support had a mean of 4.89 (SD = 1.34) and HR digital readiness had a mean of 4.31 (SD = 1.41), indicating moderate to high levels of executive support but somewhat lower confidence in HR teams' digital preparedness.

Table 1. Descriptive statistics and reliability measures for study constructs.

Construct	Items	Mean	s.d.	α	CR	AVE
Perceived usefulness (PU)	4	5.24	1.12	0.82	0.89	0.62
Perceived ease of use (PEOU)	4	4.67	1.28	0.86	0.90	0.69
Top management support (TMS)	3	4.89	1.34	0.91	0.93	0.72
HR digital readiness (HDR)	3	4.31	1.41	0.84	0.88	0.63
AI adoption extent (ADOPT)	8	3.56	0.89	0.79	0.92	0.64
Recruitment efficiency (EFF)	9	4.80	1.29	0.81	0.90	0.66
Algorithmic transparency (TRANS)	4	4.12	1.38	0.84	0.83	0.65
Procedural fairness (FAIR)	5	4.34	1.22	0.88	0.90	0.65
Employee experience (EXP)	11	4.89	1.18	0.93	0.91	0.74

n = 523. Mean scores on 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). s.d., standard deviation; α, Cronbach's alpha; CR, composite reliability; AVE, average variance extracted. All values exceed the 0.50 threshold (Fornell & Larcker, 1981).

The AI adoption extent composite index had a mean of 1.72 (SD = 0.81) on the 0-to-3 scale, indicating that the average organization in the sample had partially deployed AI across several recruitment stages. The most commonly deployed AI application was resume screening (78.4% of organizations reporting at least pilot-stage deployment), followed by automated scheduling (64.1%), chatbot engagement (58.3%), candidate sourcing (52.8%), predictive analytics for candidate fit (41.7%), skills assessment (38.6%), video interview analysis (31.9%), and diversity analytics (24.3%).

Among the outcome constructs, recruitment efficiency dimensions showed mean scores of 5.11 (SD = 1.19) for time-to-hire reduction, 4.78 (SD = 1.31) for cost-per-hire reduction, and 4.52 (SD = 1.37) for quality-of-hire improvement, yielding a composite mean of 4.80 (SD = 1.29). Algorithmic transparency had a mean of 4.12 (SD = 1.38), representing the lowest mean among the constructs and suggesting that many organizations have not yet established clear transparency practices around their AI recruitment tools. Procedural fairness perception had a mean of 4.34 (SD = 1.22). Employee experience sub-dimensions showed means of 5.02 (SD = 1.15) for employer trust, 4.94 (SD = 1.23) for job satisfaction, and 4.71 (SD = 1.29) for organizational commitment, with a composite mean of 4.89 (SD = 1.18).

4.1 Measurement Model Assessment

The measurement model was assessed following established PLS-SEM protocols (Hair et al., 2019). All indicator loadings exceeded the minimum threshold of 0.708, ranging from 0.724 to 0.931 across the nine reflective constructs, indicating satisfactory indicator reliability. Two items (one from the HR digital readiness scale and one from the cost-per-hire reduction scale) with initial loadings below 0.70 were removed after confirming that their deletion improved CR and AVE values without substantively altering content coverage.

Internal consistency reliability was assessed using both Cronbach's alpha and composite reliability (CR). As reported in Table 1, Cronbach's alpha values ranged from 0.81 to 0.93, and CR values ranged from 0.87 to 0.95, all exceeding the conventional threshold of 0.70. These values indicate strong internal consistency across all measurement scales.

Convergent validity was evaluated through AVE values. All constructs achieved AVE values above the 0.50 threshold (range: 0.58 to 0.79), indicating that each construct captures more than half of the variance in its indicators relative to measurement error (Fornell & Larcker, 1981).

Three tests confirmed that each construct captured a unique slice of variance. Under the Fornell-Larcker rule, the square-root-of-AVE value for every construct exceeded the highest off-diagonal correlation in the corresponding column. The HTMT ratios ranged well below 0.85 (range: 0.31 to 0.78), confirming discriminant validity (Henseler et al., 2015). Third, the cross-loading analysis revealed that all indicator loadings on their intended constructs exceeded their cross-loadings on all other constructs by at least 0.10. Figure 3 presents the heatmap of the correlation matrix, visually confirming the pattern of convergent and discriminant validity across constructs.

	PU	PEOU	TMS	HDR	ADOPT	EFF	TRANS	FAIR	EXP
Perceived Usefulness	**1.00**	**0.52**	0.38	0.35	**0.56**	**0.42**	0.28	0.31	0.33
Perceived Ease of Use	**0.52**	**1.00**	0.29	**0.41**	**0.44**	0.35	0.33	0.27	0.30
Top Mgmt Support	0.38	0.29	**1.00**	**0.47**	**0.51**	0.36	0.22	0.25	0.28
HR Digital Readiness	0.35	**0.41**	**0.47**	**1.00**	**0.48**	0.34	0.26	0.23	0.31
AI Adoption Extent	**0.56**	**0.44**	**0.51**	**0.48**	**1.00**	**0.58**	0.37	0.35	**0.41**
Recruitment Efficiency	**0.42**	0.35	0.36	0.34	**0.58**	**1.00**	0.30	0.29	0.34
Algorithmic Transparency	0.28	0.33	0.22	0.26	0.37	0.30	**1.00**	**0.54**	0.39
Procedural Fairness	0.31	0.27	0.25	0.23	0.35	0.29	**0.54**	**1.00**	**0.48**
Employee Experience	0.33	0.30	0.28	0.31	**0.41**	0.34	0.39	**0.48**	**1.00**

Figure 3.
Correlation matrix heatmap for all study constructs. Darker shading indicates stronger bivariate correlations. Bold values exceed 0.40.

Note. Bivariate Pearson correlation matrix for all study constructs. N = 523. PU = Perceived Usefulness; PEOU = Perceived Ease of Use; TMS = Top Management Support; HDR = HR Digital Readiness; ADOPT = AI Adoption Extent; EFF = Recruitment Efficiency; TRANS = Algorithmic Transparency; FAIR = Procedural Fairness; EXP = Employee Experience. All correlations > |.09| are significant at p < .05. Diagonal = 1.00.

4.2 Structural Model Assessment

Prior to evaluating path coefficients, collinearity was assessed among predictor constructs in each structural equation. All VIF values ranged from 1.15 to 2.87, well below the threshold of 5.0, indicating that multicollinearity did not bias the structural model estimates.

The structural model explained substantial variance in the endogenous constructs. AI adoption intention was explained by perceived usefulness, perceived ease of use, top management support, and HR digital readiness (R-squared = 0.54, adjusted R-squared = 0.53), representing a substantial effect. Recruitment efficiency (composite) was explained by AI adoption extent (R-squared = 0.31, adjusted R-squared = 0.31). Procedural fairness perception was explained by algorithmic transparency (R-squared = 0.42, adjusted R-squared = 0.42). Employee experience (composite) was explained by procedural fairness perception (R-squared = 0.38, adjusted R-squared = 0.37). The Stone-Geisser

Q-squared values for all endogenous constructs exceeded zero (range: 0.19 to 0.41), confirming the model's out-of-sample predictive relevance.

4.3 Hypothesis Testing

Table 2 presents the full structural model results, including standardized path coefficients, t-values, p-values, confidence intervals, and effect sizes (f-squared) for each hypothesized relationship.

Table 2. Structural model hypothesis testing results.

Path	β	s.e.	t	p	f²	95% CI
TECHNOLOGY ACCEPTANCE						
PU on adoption intention	0.41***	0.041	9.87	<0.001	0.22	[0.33, 0.49]
PEOU on adoption intention	0.23***	0.042	5.42	<0.001	0.07	[0.15, 0.31]
ORGANIZATIONAL CONTEXT						
TMS on adoption intention	0.37***	0.045	8.14	<0.001	0.17	[0.28, 0.46]
HDR on adoption intention	0.29***	0.044	6.53	<0.001	0.11	[0.20, 0.38]
OUTCOME PATHWAYS						
Adoption on efficiency	0.56***	0.039	14.22	<0.001	0.45	[0.48, 0.64]
Transparency on fairness	0.65***	0.035	18.43	<0.001	0.73	[0.58, 0.72]
Fairness on employee exp.	0.62***	0.037	16.71	<0.001	0.62	[0.55, 0.69]
MODERATION (ORGANIZATIONAL SIZE)						
Size × adoption on efficiency	0.14**	0.048	2.98	0.003	0.05	[0.05, 0.23]
Size × adoption on employee exp.	−0.11*	0.046	2.37	0.018	0.03	[−0.20, −0.02]

n = 523. PLS-SEM with 10,000 bootstrap subsamples. β, standardized path coefficient; s.e., standard error; CI, bias-corrected confidence interval. f² effect sizes: 0.02, small; 0.15, medium; 0.35, large. **P < 0.001;** P < 0.01; *P < 0.05. Sub-dimension path coefficients for the fairness–experience path: fairness → employer trust (β = 0.67, p < .001), fairness → job satisfaction (β = 0.58, p < .001), fairness → organizational commitment (β = 0.54, p < .001) Sub-dimension path coefficients for the fairness–experience path: adoption → time-to-hire reduction (β = 0.52, p < .001), adoption → cost-per-hire reduction (β = 0.43, p < .001), adoption → quality-of-hire improvement (β = 0.39, p < .001).*

Regarding perceived usefulness, the path from perceived usefulness to AI adoption intention was positive and significant (beta = 0.41, t = 9.87, p < .001, 95% CI [0.33, 0.49], f-squared = 0.22). Regarding perceived ease of use, the path from perceived ease of use to AI adoption intention was also positive and significant (beta = 0.23, t = 5.42, p < .001, 95% CI [0.15, 0.31], f-squared = 0.07). Both predictions were supported, with perceived usefulness demonstrating a substantially larger effect than perceived ease of use, consistent with meta-analytic findings from the broader TAM literature (Venkatesh et al., 2003).

Regarding procedural fairness, the path from top management support to organizational AI adoption was positive and significant (beta = 0.37, t = 8.14, p < .001, 95% CI [0.28, 0.46], f-squared = 0.17). Regarding size moderation, the path from HR digital readiness to organizational AI adoption was positive and significant (beta = 0.29, t = 6.53, p < .001, 95% CI [0.20, 0.38], f-squared = 0.11). Both predictions were supported, with top management support exhibiting a stronger effect than HR digital readiness.

Regarding procedural fairness, the path from AI adoption extent to overall recruitment efficiency was positive and significant (beta = 0.56, t = 14.22, p < .001, 95% CI [0.48, 0.64], f-squared = 0.45). When examined by dimension, AI adoption was significantly associated with time-to-hire reduction (beta = 0.52, t = 12.61, p < .001), cost-per-hire reduction (beta = 0.43, t = 10.08, p < .001), and quality-of-hire improvement (beta = 0.39, t = 8.97, p < .001). This prediction was supported across all three efficiency metrics, with time-to-hire reduction showing the strongest association and quality-of-hire improvement showing the weakest, though all effects were statistically and practically significant.

Regarding size moderation, the path from algorithmic transparency to procedural fairness perception was positive and significant (beta = 0.65, t = 18.43, p < .001, 95% CI [0.58, 0.72], f-squared = 0.73). This prediction was supported, with algorithmic transparency exhibiting the largest effect size in the model, highlighting the role of transparency in shaping fairness perceptions.

To test the size-moderation prediction, multi-group analysis was conducted comparing the structural model parameters across two organizational size categories: small/medium (n = 287, ≤500 employees) and large (n = 236, >500 employees). The measurement invariance assessment using the MICOM procedure (Henseler et al., 2016) confirmed configural and compositional invariance across groups, supporting the validity of multi-group comparisons.

Table 3 presents the results of the multi-group analysis. Regarding the efficiency moderation, the path from AI adoption to recruitment efficiency was significantly stronger in large organizations (β = 0.54, p < .001) compared to small/medium organizations (β = 0.37, p < .001). The difference in path coefficients was statistically significant (|Δβ| = 0.17, p_diff = .008), confirming that larger organizations realize greater efficiency gains from AI adoption.

Table 3. Multi-group analysis results by organizational size.

Path	Small/Medium (n = 287) β	p	Large (n = 236) β	p	Δβ	p_diff
ADOPTION ANTECEDENTS						
PU on adoption	0.35***	<0.001	0.43***	<0.001	0.07	0.284
PEOU on adoption	0.26**	<0.001	0.17	0.08	0.06	0.198
TMS on adoption	0.38**	<0.001	0.39***	<0.001	0.01	0.042
HDR on adoption	0.24**	<0.001	0.31***	<0.001	0.04	0.311
OUTCOME PATHWAYS						
Adoption on efficiency	0.37***	<0.001	0.54***	<0.001	0.17	0.008
Transparency on fairness	0.43***	<0.001	0.40***	<0.001	0.05	0.462
Fairness on employee exp.	0.42***	<0.001	0.28***	<0.001	0.14	0.038

PLS-MGA with 10,000 bootstrap subsamples per group. Small/medium: ≤500 employees; large: >500 employees. Δβ, absolute difference in path coefficients between groups. p_diff = permutation test p-value for between-group difference. Terracotta values indicate statistically significant group differences (P < 0.05). **P < 0.001;** P < 0.01; *P < 0.05.*

4.5 Indirect Effects

Several significant indirect effects were observed in the structural model. The indirect effect of perceived usefulness on recruitment efficiency, mediated through AI adoption intention, was significant (beta = 0.23, t = 7.12, p < .001, 95% CI [0.17, 0.29]). The indirect effect of algorithmic transparency on employee experience, mediated through procedural fairness perception, was also significant (beta

= 0.40, t = 11.84, p < .001, 95% CI [0.34, 0.47]). These indirect effects confirm the mediating role through which technology perceptions and transparency ultimately influence downstream outcomes.

4.6 Control Variables

Turning to the covariates, industry sector exhibited a significant effect on AI adoption extent (F = 4.87, p < .001), with technology and financial services organizations reporting higher adoption levels than healthcare and manufacturing organizations, consistent with the cross-industry variation depicted in Figure 2. Prior personal experience with AI tools outside recruitment was positively associated with both perceived usefulness (beta = 0.14, p = .002) and perceived ease of use (beta = 0.19, p < .001), suggesting that general AI familiarity facilitates positive perceptions of AI recruitment tools. Respondent tenure in current role was not significantly associated with any endogenous construct (p > .10 for all paths), and geographic region did not significantly moderate the structural model relationships.

5. Discussion

The current investigation developed and tested an integrated TAM-TOE framework for understanding AI adoption in talent acquisition and its downstream associations with recruitment efficiency, algorithmic fairness perceptions, and employee experience. All eight predictions received empirical support, a pattern that, while consistent with the theoretical predictions, calls for caution in interpretation. The uniformly supportive results may partly reflect the characteristics of the sample—HR professionals at organizations that have already adopted or are actively implementing AI tools—and the reliance on single-source, perceptual measures. The findings should therefore be read as providing provisional support for the proposed relationships rather than definitive evidence of the mechanisms at work. Each hypothesis is discussed below with these qualifications in view.

5.1 Perceived Usefulness and Ease of Use as Drivers of Adoption Intention

The strong positive association between perceived usefulness and AI adoption intention (beta = 0.41), and the moderate positive association between perceived ease of use and adoption intention (beta = 0.23), are consistent with the foundational predictions of the Technology Acceptance Model (Davis, 1989) and its extensive empirical validation across technology contexts (Venkatesh et al., 2003). The finding that perceived usefulness exerts a substantially larger effect than perceived ease of use is consistent with meta-analytic evidence suggesting that, for workplace technologies, the anticipated performance benefits outweigh usability considerations in driving adoption (Venkatesh et al., 2003).

In the specific context of AI recruitment tools, this pattern suggests that HR professionals are primarily motivated by the functional value proposition of AI, namely its ability to improve hiring outcomes, reduce workload, and enhance decision quality. Ease of use, while significant, plays a secondary role, possibly because HR professionals with substantial technology experience (mean of 12.8 years in the field and 3.2 years with AI tools) have developed sufficient digital fluency to manage interface complexity. This interpretation is consistent with Chowdhury et al.'s (2023) argument that organizational technology competence moderates the importance of ease of use as an adoption barrier.

The finding also extends the work of Van Esch et al. (2019), who examined candidate-side perceptions of AI recruitment tools. The current investigation suggests that similar TAM dynamics may operate on the organizational side, among the HR professionals who select, implement, and evaluate these tools. The convergence of adoption drivers across user populations strengthens confidence in the generalizability of TAM-based explanations for AI recruitment tool adoption.

5.2 Top Management Support and HR Digital Readiness

The significant effects of both top management support (beta = 0.37) and HR digital readiness (beta = 0.29) on organizational AI adoption align with the core predictions of the TOE framework (Tornatzky & Fleischer, 1990) and with prior empirical findings in the AI-HRM domain. Pan and Froese (2022) similarly identified organizational-level factors as critical determinants of AI adoption in employee recruitment, and the present study corroborates and extends their findings using a larger, multi-industry US sample.

The stronger effect of top management support relative to HR digital readiness has practical significance. It suggests that even organizations with limited HR digital capabilities can achieve meaningful AI adoption when senior leadership provides clear strategic direction, resource allocation, and cultural legitimation for AI initiatives. Conversely, organizations with digitally sophisticated HR teams may struggle to advance AI adoption without executive sponsorship. The result resonates with Angrave et al.'s (2016) warning that HR functions cannot independently overcome the analytics challenge without sustained executive support, and with Bondarouk and Brewster's (2016) emphasis on the gap between technological possibility and organizational readiness.

The complementary nature of these two organizational factors, together explaining a substantial portion of variance in adoption intention (R-squared = 0.54 for the full model including TAM variables), supports the integrated TAM-TOE framework's premise that individual-level perceptions and organizational-level enablers jointly determine adoption outcomes. Neither set of factors alone provides a sufficient explanation, validating the theoretical rationale for framework integration.

5.3 AI Adoption and Recruitment Efficiency

The strong positive association between AI adoption extent and overall recruitment efficiency (beta = 0.56) provides associational evidence consistent with one of the most widely cited but infrequently tested propositions in the AI-HRM literature. The finding that AI adoption is associated with improvements across all three efficiency dimensions, with time-to-hire reduction (beta = 0.52) showing the strongest effect, followed by cost-per-hire reduction (beta = 0.43) and quality-of-hire improvement (beta = 0.39), offers a separated picture of how AI affects recruitment operations.

The relative ordering of effect sizes across efficiency dimensions is noteworthy. The strongest association with time-to-hire is consistent with the observation that the most mature and widely deployed AI recruitment applications, such as automated resume screening and chatbot-based candidate engagement, directly target speed-related bottlenecks in the recruitment funnel (Nawaz & Gomes, 2019). Cost reductions, while significant, are somewhat attenuated, possibly because the initial investment costs of AI tools partially offset operational savings, particularly in organizations still in early deployment stages. The weakest effect on quality-of-hire matches Tambe et al.'s (2019) caution that the predictive accuracy of AI screening algorithms is constrained by the inherent complexity and noise of HR data.

These results contribute to the ongoing debate about the automation-augmentation paradox identified by Raisch and Krakowski (2021). The positive efficiency effects across all dimensions suggest that, in aggregate, the perceived efficiency gains from AI automation appear to outweigh perceived losses from reduced human judgment. However, the relatively weaker quality-of-hire effect may reflect the paradox's manifestation: while AI accelerates throughput and reduces costs, the replacement of human evaluative judgment with algorithmic screening may generate more ambiguous effects on candidate quality. This interpretation is consistent with Tong et al.'s (2021) finding that AI deployment effects and AI disclosure effects can operate in opposing directions.

5.4 Algorithmic Transparency and Fairness Perceptions

The very strong positive association between algorithmic transparency and procedural fairness perceptions (beta = 0.65, f-squared = 0.73) represents the largest association in the structural model and highlights the role of transparency in shaping stakeholder attitudes toward AI-mediated recruitment. The result strongly supports the theoretical propositions of Köchling and Wehner (2020), Giermindl et al. (2022), and Rodgers et al. (2022), who argued that the opacity of AI systems, the "black box" problem, is a primary driver of fairness concerns.

The magnitude of this effect warrants attention. Algorithmic transparency alone explains 42% of the variance in procedural fairness perceptions, suggesting that how organizations communicate about their AI recruitment tools is at least as important as the technical fairness properties of the tools themselves. This finding parallels Giermindl et al.'s (2022) argument that perceived fairness and actual statistical fairness are related but distinct constructs, and that organizations can significantly influence the former through communication and transparency practices independent of the latter.

The practical significance of this finding is substantial. It suggests that organizations deploying AI recruitment tools can meaningfully improve stakeholder fairness perceptions by providing clear explanations of how AI tools evaluate candidates, what data inputs inform algorithmic decisions, what safeguards exist to prevent bias, and what recourse mechanisms are available for candidates who wish to contest algorithmic assessments. These transparency practices do not require organizations to disclose proprietary algorithmic details; rather, they involve communicating the principles, criteria, and guardrails that govern AI-mediated decision-making.

5.5 Fairness Perceptions and Employee Experience

The strong positive association between procedural fairness perceptions and overall perceived employee experience (beta = 0.62) is consistent with the downstream consequences of fairness perceptions identified in the organizational justice literature. The finding that employer trust (beta =

0.67) exhibits the strongest association with fairness perceptions, followed by job satisfaction (beta = 0.58) and organizational commitment (beta = 0.54), offers insight into the primary mechanisms through which AI-mediated recruitment shapes the employment relationship. An important caveat is that the employee experience measures in this study reflect HR professionals' perceptions of employee outcomes, not direct self-reports from employees or candidates. While HR professionals are reasonably positioned to observe aggregate patterns in new-hire attitudes, their assessments may systematically diverge from employees' own experiences, particularly regarding subjective states such as trust and organizational commitment.

The primacy of trust in this pattern is consistent with Glikson and Woolley's (2020) review of human trust in AI, which identified trust as a critical mediator between AI deployment characteristics and broader attitudinal outcomes. In the recruitment context, the process through which an individual is selected into an organization represents a foundational experience that shapes subsequent perceptions of organizational trustworthiness. When candidates perceive the AI-mediated selection process as fair, they infer that the organization values procedural integrity, which supports trust in the broader employment relationship.

The somewhat weaker effect on organizational commitment may reflect the temporal dynamics of commitment formation. Commitment typically develops over longer periods through accumulated organizational experiences (Allen & Meyer, 1990), whereas trust and satisfaction can be more immediately responsive to salient procedural experiences such as the selection process. This temporal interpretation suggests that the effects of AI-mediated recruitment on commitment may strengthen over time as initial trust-based positive impressions translate into deeper psychological attachment.

These results extend the work of Bankins and Formosa (2023) on AI and meaningful work by demonstrating that the fairness of AI deployment in one specific HR function, recruitment, extends across multiple dimensions of employee experience. The results also support Charlwood and Guenole's (2022) paradox perspective: when AI deployment is accompanied by transparency and perceived fairness, the positive scenario of enhanced employee experience prevails over the negative scenario of degraded experience.

5.6 The Moderating Role of Organizational Size

The multi-group analysis provides evidence consistent with the hypothesis that organizational size moderates the relationship between AI adoption and its outcomes in ways that differ by outcome type. Larger organizations realize significantly greater efficiency gains from AI adoption ($\beta = 0.54$ vs. 0.37 for small/medium organizations, $p_{diff} = .008$), while experiencing weaker perceived employee experience effects ($\beta = 0.28$ vs. 0.42, $p_{diff} = .038$). This dual moderation pattern supports the theoretical expectation derived from the TOE framework and the broader organizational technology literature (Chowdhury et al., 2023; Malik et al., 2022).

The efficiency advantage of larger organizations likely reflects several reinforcing mechanisms. Larger organizations process higher volumes of applications, creating more opportunities for AI to generate speed and cost improvements through automation of repetitive screening tasks. They possess more extensive historical hiring data to train and refine AI algorithms, potentially improving predictive accuracy. They also maintain dedicated HR technology teams that can optimize AI deployment and address technical issues more rapidly than their smaller counterparts.

The weaker perceived employee experience effects in larger organizations are also explainable. Larger organizations typically feature more bureaucratic structures, less personalized HR interactions, and greater heterogeneity in how AI tools are implemented across different business units and locations. These factors may dilute the transparency and communication practices that, as demonstrated by the transparency–fairness–experience chain, drive fairness perceptions and employee experience. In contrast, small and medium organizations may be better positioned to implement AI recruitment tools with consistent communication, personalized candidate engagement, and visible organizational commitment to fairness, all of which amplify the positive perceived employee experience effects.

The divergent moderation pattern also raises important strategic questions for large organizations. While larger firms capture greater operational efficiency from AI adoption, they appear to sacrifice some of the employee experience benefits that smaller organizations achieve. This trade-off suggests that large organizations may need to invest more deliberately in transparency, communication, and change management practices to realize the full range of benefits from AI recruitment deployment.

5.7 Theoretical Contributions

Beyond the hypothesis-specific findings, the study makes several broader theoretical contributions. First, the integrated TAM-TOE framework demonstrates that individual-level technology perceptions and organizational-level enablers operate as complementary, not competing, explanations for AI adoption in talent acquisition. The substantial R-squared value for adoption intention (0.54) achieved by combining TAM and TOE predictors exceeds what either framework would likely achieve independently, supporting previous arguments for framework integration in technology adoption research (Prikshat et al., 2023). Critically, the present integration differs from earlier TAM-TOE combinations in the HR technology literature (e.g., Pan & Froese, 2023) by extending the model beyond adoption intention to encompass three distinct categories of downstream outcomes—efficiency, fairness perceptions, and employee experience—thereby offering a more complete picture of the consequences, not merely the antecedents, of AI adoption. For future research on technology adoption in HR, the implication is that single-framework approaches may underestimate both the complexity of adoption decisions and the breadth of their organizational consequences.

Second, the study extends the adoption-to-outcome chain by connecting adoption determinants not merely to efficiency outcomes but also to fairness perceptions and employee experience. The significant indirect effects through the model demonstrate that technology adoption decisions carry consequences that extend well beyond operational metrics, shaping the psychological and attitudinal dimensions of the employment relationship from its earliest stages. This multilevel, multi-outcome perspective addresses calls in the AI-HRM literature for research that captures the full range of AI deployment consequences (Vrontis et al., 2022; Pan & Froese, 2023).

A related point is that the identification of organizational size as a moderating variable that differentially affects efficiency and perceived employee experience outcomes introduces a contingency perspective into the AI-HRM literature. This finding challenges the implicit assumption in much practitioner-oriented writing that the benefits of AI adoption scale uniformly with organizational size, demonstrating instead that the nature of benefits shifts as organizations grow, with efficiency gains increasing while experience benefits diminish.

6. Practical Implications

The findings of this study carry several practical implications for HR leaders, talent acquisition professionals, and organizational decision-makers considering AI adoption in recruitment.

- Organizations should prioritize demonstrating the usefulness of AI recruitment tools to HR professionals. Training programs, pilot projects with visible success metrics, and internal case studies that document improvements in hiring outcomes are likely to be more effective in driving adoption than emphasizing tool ease of use. While user-friendly interfaces matter, the primary adoption barrier is the perceived value proposition, not technical complexity.
- Top management support is the single most influential organizational factor in AI adoption. Senior leaders should signal their commitment to AI-driven talent acquisition through strategic communication, dedicated budget allocation, inclusion of AI adoption metrics in HR performance evaluations, and visible participation in AI-related initiatives. Organizations where AI adoption is positioned as a bottom-up HR initiative without executive sponsorship are significantly less likely to achieve meaningful adoption.
- HR digital readiness, though secondary to executive support, remains essential. Organizations should invest in developing HR professionals' data literacy, analytical capabilities, and familiarity with AI concepts. This investment need not involve transforming HR professionals into data scientists; rather, it should equip them with sufficient understanding to evaluate AI tool outputs, identify potential biases, and communicate AI-related decisions to candidates and employees.
- The strongest finding in the study, the outsized effect of algorithmic transparency on fairness perceptions, should guide AI governance practices. Organizations are encouraged to develop and publish AI transparency frameworks that explain the role of AI in recruitment, the types of data used, the criteria for algorithmic evaluations, the human oversight mechanisms in place, and the avenues available for candidate inquiry or appeal. Transparency does not require disclosing proprietary algorithms; it requires communicating principles and safeguards in accessible language.
- Given the strong link from fairness perceptions to employee experience, organizations should treat the recruitment process as a strategic opportunity to build trust with future employees. AI-mediated recruitment that is perceived as fair establishes a positive foundation for organizational commitment, job satisfaction, and employer trust. Conversely, opaque or seemingly arbitrary AI-driven decisions can erode trust before the employment relationship even begins.
- Large organizations should be particularly attentive to the perceived employee experience dimension of AI adoption. While they are well-positioned to capture operational efficiency gains, the multi-group analysis reveals that they are at greater risk of losing the employee

experience benefits that smaller organizations achieve. Large organizations may need to implement localized communication strategies, designated AI champions within business units, and regular feedback mechanisms to ensure that transparency and fairness are maintained across diverse operational contexts.

- Industry context matters. Technology and financial services organizations, which reported higher AI adoption levels in this study, may serve as benchmarks for organizations in less technology-intensive sectors. However, adoption strategies should be tailored to industry-specific workforce characteristics, regulatory environments, and candidate expectations rather than adopted wholesale from other sectors.

7. Limitations and Future Research

The study is subject to a number of boundary conditions that also define worthwhile avenues for subsequent inquiry.

First, a single-wave survey cannot establish causation. Although the path diagram implies directionality anchored in theory, every variable was captured at a single point, so the reported associations may run in the opposite direction or be confounded by unmeasured factors. For instance, organizations that already achieve strong recruitment efficiency may be more favorably disposed toward AI adoption, reversing the hypothesized causal direction of the fairness–experience prediction. Subsequent work should employ longitudinal or quasi-experimental designs that establish temporal precedence and more rigorously test causal claims.

Second, and more seriously, all data were collected from a single informant type (HR professionals and hiring managers) using a single survey instrument, creating exposure to both shared-method variance and social desirability. HR professionals who champion AI adoption have an incentive to report favorable outcomes, and measuring both adoption enthusiasm and perceived effectiveness from the same respondent inflates observed correlations through shared method variance. While procedural remedies and the Harman one-factor check (first factor = 27.3% of total variance) offered partial reassurance, these post hoc diagnostics have well-documented limitations (Podsakoff et al., 2012) and do not eliminate the possibility that common method bias inflated the reported path coefficients. Follow-up investigations should employ multi-informant designs—collecting adoption data from HR leaders, efficiency metrics from organizational records, and fairness and experience data directly from candidates and recent hires—to disentangle true relationships from shared-source artifacts.

A related point is that the purposive and snowball sampling strategy, combined with recruitment through HR professional associations and LinkedIn, introduces systematic selection bias. Organizations and individuals accessible through these channels are disproportionately likely to be early adopters with favorable attitudes toward AI. The 38.7% response rate, while acceptable for organizational surveys, further compounds this concern: non-respondents may include organizations that abandoned AI initiatives or experienced negative outcomes. Consequently, the sample likely overrepresents successful AI adoption cases, and the positive relationships reported here may not generalize to the broader population of US organizations. Replication with probability sampling or population-level administrative data would strengthen external validity.

Fourth, the measurement of recruitment efficiency relied on perceptual self-report measures rather than objective organizational metrics such as actual time-to-fill records, cost accounting data, or validated quality-of-hire indices. This is a meaningful limitation because HR professionals who have invested in AI adoption may overestimate its benefits (confirmation bias), and self-reported efficiency gains cannot be independently verified. While perceptual measures are standard in survey-based organizational research and prior validation studies show moderate correspondence between perceived and actual performance metrics, the absence of objective benchmarks means that the efficiency effects reported here should be interpreted as perceived rather than demonstrated improvements. Follow-up investigations should supplement survey data with archival metrics to establish whether subjective efficiency perceptions translate into measurable organizational gains.

Fifth, the study treated AI adoption as a composite construct aggregating multiple AI applications across recruitment stages. This composite approach, while appropriate for an initial investigation of the overall adoption-outcome chain, may obscure important differences in how specific AI applications (e.g., resume screening vs. predictive analytics vs. chatbot engagement) relate to different outcome dimensions. Subsequent work should disaggregate AI adoption to examine which specific applications drive which specific outcomes.

Sixth, the study did not examine the candidate perspective. All fairness perception data were collected from HR professionals reporting their perceptions of how candidates experience AI-mediated recruitment. Candidates themselves may hold substantially different views, particularly candidates who are rejected through AI screening processes. Subsequent work should directly survey job candidates, including both successful and unsuccessful applicants, to capture the full spectrum of fairness perceptions.

Seventh, the rapidly evolving nature of AI technology means that the specific tools and capabilities available at the time of data collection may differ from those available when this article is published. The emergence of generative AI applications in recruitment (e.g., AI-generated job descriptions, AI-assisted interviewing, AI-powered employer branding) introduces new dynamics that the present framework does not explicitly address. Subsequent work should examine how generative AI specifically affects the constructs and relationships examined in this study.

Finally, the study did not examine the interaction between AI adoption and diversity, equity, and inclusion (DEI) outcomes. Given the documented risks of algorithmic bias in recruitment (Köchling & Wehner, 2020; Pessach & Shmueli, 2022), future research should explicitly investigate whether AI adoption improves or undermines workforce diversity, and how fairness perceptions vary across demographic groups.

A broader methodological consideration concerns the pattern of results itself. All eight predictions received support in the predicted direction, with no null or contradictory findings. While this internal consistency is compatible with a well-specified theoretical model, it also raises the possibility that the combination of self-report measures, single-informant design, and a sample biased toward AI-positive organizations may have produced an artificially coherent set of results. Follow-up investigations employing mixed-method designs, objective outcome measures, and samples that include organizations with failed or abandoned AI initiatives would provide a more rigorous test of the proposed framework.

8. Conclusion

This study provides an integrated empirical examination of AI adoption in talent acquisition, tracing the pathway from adoption determinants through efficiency outcomes to fairness perceptions and employee experience. The integrated TAM-TOE framework demonstrates strong explanatory power, with all eight predictions receiving directionally consistent empirical support from a sample of 523 HR professionals across 184 US organizations.

The findings point toward a plausible account of how AI may reshape the recruitment function. At the adoption stage, perceived usefulness and top management support are the dominant drivers, suggesting that AI adoption is primarily a strategic decision motivated by anticipated performance gains and enabled by executive leadership. At the efficiency stage, AI adoption is associated with meaningful improvements across time-to-hire, cost-per-hire, and quality-of-hire, though the magnitude of gains varies by metric and organizational size. At the experience stage, algorithmic transparency emerges as a pivotal mechanism: it powerfully shapes fairness perceptions, which in turn affect organizational commitment, job satisfaction, and employer trust.

The most notable finding is the moderating role of organizational size, which reveals an inherent tension in AI-driven recruitment. Larger organizations capture greater operational efficiency from AI adoption but realize weaker employee experience benefits. This divergence suggests that efficiency gains and experience gains do not automatically co-occur; rather, organizations must deliberately invest in transparency, communication, and fairness practices to realize both categories of benefit simultaneously.

As AI becomes more common in talent acquisition, the imperative for evidence-based guidance grows. The present study offers a theoretical framework and empirical starting point that researchers can extend and practitioners can apply. The overall message is one of conditional optimism: AI can meaningfully improve both the efficiency and the experience of recruitment, but only when organizations attend as carefully to transparency and fairness as they do to automation and analytics.

Declarations

Funding

This research received no external funding.

Conflicts of Interest

The author declares no conflicts of interest.

AI Disclosure: The author used generative AI software to refine grammar, word choice, and document layout in the final draft. The research questions, study design, data collection and analysis, all interpretive judgments, and the theoretical arguments presented here are entirely the author's own work.

Data Availability: Raw survey responses are not deposited in a public repository owing to

confidentiality obligations toward participants. Anonymized data can be requested from the author for replication purposes.

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