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FROM DECISION-MAKERS TO ALGORITHM INTERPRETERS: HOW ARTIFICIAL INTELLIGENCE IS RESHAPING THE HR MANAGER'S ROLE

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ABSTRACT

Artificial intelligence is revolutionising employee selection, helping firms scan applications, rank prospects and make faster hiring decisions. Nevertheless, the application of AI in recruitment also raises questions about algorithmic bias, transparency, regulatory compliance and the ongoing relevance of human judgment. Automated hiring has been studied in terms of its technical and ethical implications, but little is known about how recruiters really work with human-AI partnership. The objective of this study was to explore how U.S. business recruiters incorporate AI recommendations with human judgement and to understand the elements that influence their trust, acceptance and use of AI-supported hiring tools. A phenomenological qualitative design was employed Primary data was acquired through semi-structured interviews with 25 HR professionals working in technology, finance, healthcare and education businesses, identified using purposive and snowball sampling. The study is based on the technology acceptance model, human-automation interaction theory and socio-technical systems theory. Thematic analysis of interview transcripts was conducted using iterative coding and NVivo, assisted by member verification and peer debriefing. Three themes emerged: AI enhanced screening speed but required human verification; algorithmic fairness, transparency, and legal compliance influenced recruiter trust; and human–AI partnership transitioned recruiters to strategic and supervision positions. This implies that AI-enabled recruitment is seen as a decision assistant rather than a replacement of recruiters. The report suggests training for recruiters, explainable AI, bias audits, and human-in-the-loop governance. It is cross-sectional, self-reported, and U.S.-focused which restricts its generalizability. Future research should investigate the long-term implications on quality of selection, workforce diversity, and candidate experience.

1 INTRODUCTION

The use of artificial intelligence (AI) in recruitment has become widespread and has altered talent acquisition in recent years. Industry data indicate that over half of U.S. organisations were regularly employing AI solutions for HR functions such as resume screening and candidate evaluation by 2025 (Heymans, 2025). Proponents say artificial intelligence may vastly enhance hiring efficiency and applicant matching by processing massive amounts of applications faster and with fewer routine errors. For instance, AI-enabled applicant tracking systems automatically analyse resumes and evaluate candidates based on learning criteria, which may reduce time-to-hire by swiftly finding top talent (Chen, 2023a; Kumari et al., 2025). Big vendors are also marketing AI-powered interviewing chatbots and predictive analytics as strategies to increase candidate pools and improve decision quality. Organisations define AI deployment as a strategic move in the "global war for talent" (Heymans, 2025). Talent consultants indicate that an increasing percentage of HR teams think

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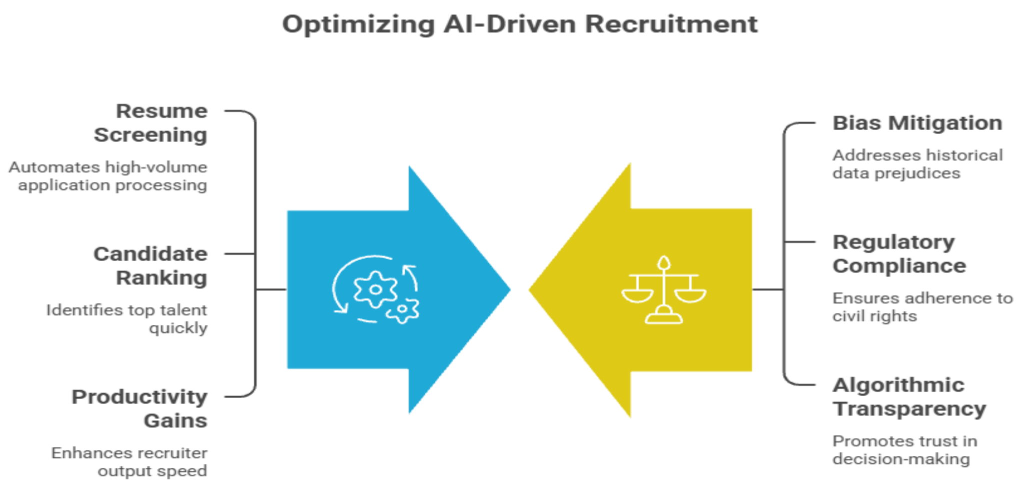
Figure 1. Optimizing AI-Driven Recruitment



AI technologies boost recruiter productivity (LinkedIn, 2018; Heymans, 2025).

But the change in technology is not without its controversy. Critics caution that opaque algorithms may embed biases that lead to biased employment decisions (Sony et al., 2025; Chen, 2023b). For example, research on AI recruiting has demonstrated gender and racial biases when algorithms are trained on historical data (Barocas & Selbst, 2016; Kumar et al., 2024). Regulators and employers have been driven by legal and ethical concerns to stress accountability: In 2023, for example, the U.S. EEOC issued guidance emphasising that civil rights laws apply equally to AI-based employment tools. Therefore, organisations find themselves in a challenging position to reconcile the advancement of AI with the principles of justice, transparency, and trust (Kumari et al., 2025; Barocas & Selbst, 2016). This is a two-sided story, according to scholars: industry sources emphasise efficiency and innovation, while academic and policy voices stress prejudice, legal risk, and the need for monitoring (Kumari et al., 2025; Sony et al., 2025).

Yet, empirical research on how these interactions unfold in practice is limited. In particular, the views of recruiters — the human specialists who operate and oversee these systems – remain underexplored. Much of the research is theoretical or based on quantitative trials; few studies reflect the firsthand experiences of recruiters. Yet these practitioners control the final employment decisions and can choose to believe or override AI outputs. It is consequently important to understand their opinions.

This study tries expressly to fill that gap. We explore the experience of U.S. HR professionals as they negotiate the intersection between human judgement and AI in hiring. From a socio-technical perspective (Trist & Bamforth, 1951), we consider both technical elements (AI design) and social factors (organisational setting). We use theories of human–automation interaction (Parasuraman et al., 2000) and technological acceptability (Davis, 1989) to interpret our findings. The rest of the paper is organised as follows: a review of relevant literature and theory, explanation of our approach, followed by findings, recommendations and conclusions.

1.1 Employee Selection Process in the United States: Traditional and AI-Assisted Approaches

The selection of employees is a systematic procedure by which firms find and choose the best individuals for the available jobs. Traditional employee selection process in the United States typically consists of multiple steps: job analysis, recruitment, collecting of applications, resume screening, interviews, assessment tests, background checks and final hiring decisions. Recruiters first look at the candidate's qualifications, education, professional experience, and skills. Candidates that are shortlisted are usually interviewed by recruiters and hiring managers, and human judgement is important in these interviews in assessing communication skills, cultural fit, motivation and other

personal qualities.
Traditional selection techniques can be time-consuming and occasionally impacted by unconscious human biases. As Artificial Intelligence (AI) is developing, several companies have developed AI-supported recruitment methods to increase productivity. AI solutions are widely used for resume screening, candidate ranking, talent matching and interview scheduling. Such technologies can sift through many applications in a short time and assist recruiters to spot promising prospects.
However, AI is unable to totally substitute human judgement since many critical elements of employee selection such as emotional intelligence, leadership potential, ethical principles, and organizational fit require human assessment. Thus, the most effective strategy is to combine the efficiency of AI and the decision-making of humans. AI should be a support tool, but ultimate employment decisions should be kept under human supervision to ensure fairness, accuracy and ethical considerations.

2 LITERATURE REVIEW

The AI in recruitment literature covers topics such technology development, fairness problems, and organisational acceptance. A lot of attention has been paid to the capabilities and risks of AI-powered hiring tools. For example, IBM and others' industry reports show that modern AI systems (natural language processing, computer vision, etc.) are increasingly being utilised for resume parsing, candidate ranking, and even video interview analysis. These papers highlight that AI can improve the efficiency of talent acquisition by automating operations such as resume screening, which may decrease time-to-hire and uncover applicants that best suit competency profiles. Empirical surveys support great interest. LinkedIn (2018) revealed that most recruiters expected AI to dramatically impact recruiting in a few years. IDC (2020) projected a soaring of corporate AI spending for HR as firms seek competitive advantage.

In contrast, academic research has raised issues regarding prejudice and fairness in AI hiring systems. Chen (2023b) and Sony et al. (2025) evaluate evidence of algorithmic models that may perpetuate or increase bias against women, minorities or old candidates, due to unbalanced training data or opaque feature selection. Google, for example, famously found that its large-language-model screen preferred male-dominated profiles, reflecting the asymmetry of previous data. Broad theoretical critiques (Barocas & Selbst, 2016; Diakopoulos & Koliska, 2017) stress that "invisible" decision rules might create uneven impact. This has resulted in recommendations for fairness-oriented design: techniques such as de-biasing training sets, imposing transparency, and employing oversight mechanisms (Mujtaba & Mahapatra, 2021; Raghavan et al., 2020). Recent assessments categorise these solutions as transparency, accountability and inclusive governance initiatives.

Another branch of the literature looks at the organisational and psychological elements of AI adoption. Research on the Technology Acceptance Model (TAM) reveals that the acceptance by users of new systems is based on perceived usefulness and simplicity of use (Davis, 1989). Almeida et al. (2025) used TAM with recruiters and found that perceptions about efficiency advantages and system quality influenced intentions to employ AI solutions. Similarly, Roppelt et al. (2025) interviewed 42 talent experts and presented elements (technology features, management support, training) that impact detrimental practices (filter failures and bias). Research on human-automation interaction has shown that users' trust in automated decisions is a function of system performance and feedback (Lee & See, 2004). Research on "algorithm aversion" shows that managers may undervalue even the best AI suggestions once the first mistakes are made (Dietvorst et al., 2015). In HR settings, early research suggests that recruiters are more likely to favour human judgements over AI judgements in situations that are not clear-cut.

Some scholars additionally point to the socio-technical dimension, meaning that technology must fit into human and organisational context (Trist & Bamforth, 1951; Orlikowski, 1996). The use of AI in HR is expected to change the function of the recruiter (calibration of automation). For example, Tambe et al. (2019) showed that companies with large candidate pools used AI for screening but still relied on human knowledge for interviews. Others point out that AI adoption can flatten or rearrange HR structures (Gill et al., 2018). The general take-away from policy and empirical research is that AI in recruiting is a double-edged sword: it offers

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potential for more efficiency and data-driven insights, but also ethical and legal issues (Chen, 2023a; Kumari et al., 2025).

But these conversations typically miss the expertise of day-to-day practice. Few studies have involved real recruiters. A qualitative analysis (Chen, 2022) provides evidence that recruiters are often sceptical about recommendations made by AI, particularly where diversity is an issue. Another poll (Franz et al., 2020) indicated that recruiters are more inclined to consult colleagues than AI when recommendations clash. To address this gap, we focus on the lived experiences of recruiters: how they integrate AI outputs, when they trust them, and how concerns about bias or candidate experience impact use. We seek to contribute to the literature on algorithmic hiring with frontline perspectives by integrating technology research and social science perspectives.

3 ADVANTAGES AND LIMITATIONS OF AI IN EMPLOYEE SELECTION

Artificial Intelligence offers various benefits in personnel selection. First, artificial intelligence may make the recruitment process more efficient by automating repetitive processes such as screening resumes and sifting candidates. It enables firms to assess thousands of applications in a short span of time and eases the burden on recruiters. Second, artificial intelligence can improve candidate matching by comparing candidates' talents and experiences to job criteria. Third, AI-supported solutions may provide uniform evaluation standards and eliminate certain types of human bias in the initial screening.

Besides these benefits, AI has a few drawbacks. Artificial intelligence systems are based on historical data, and biased training data might lead to biased recommendations. If earlier hiring judgments were discriminatory, artificial intelligence algorithms may replicate similar tendencies. Furthermore, AI may not possess a full understanding of human attributes including creativity, leadership, personality, and cultural fit. Overreliance on artificial intelligence may harm the quality and fairness of personnel selection.

For these reasons, firms should embrace a human-in-the-loop approach, where artificial intelligence can aid recruiters, but final decisions are made through human appraisal and ethical approval.

4 THEORETICAL FRAMEWORK

We examine recruiters' viewpoints through four theoretical lenses. The theory of human–AI collaboration emphasises the fact that artificial intelligence systems and humans can work together as teams with different capabilities (Parasuraman et al., 2000; Rashidi & Cook, 2020). This indicates that, in recruiting, AI might be used for pattern identification, and humans might provide context and empathy. We thus seek indications of such synergy or conflict in the language recruiters use to talk about 'working with' AI.

The Technology Acceptance Model (TAM) suggests that the adoption of a new technology is affected by the perceived usefulness and simplicity of use (Davis, 1989; Venkatesh & Davis, 2000). We utilise TAM to understand the attitudes of the recruiters. For example, if recruiters see AI helpful in their activities of sifting the resumes (perceived usefulness) and easy to use, then they are more likely to employ it. However, if the AI tool is complicated or the results are not trusted, then acceptance may lag.

How individuals respond to recommendations offered by artificial intelligence systems is explained by algorithmic decision-making and human judgment theory. Research on algorithm aversion (Dietvorst et al., 2015) suggests that people can lose trust in AI once it makes mistakes. In contrast, algorithm appreciation (Logg et al., 2019) posits that individuals may rely on AI, especially for simple or low-risk decisions. People tend to trust greater AI judgments that are visible, intelligible, and accountable, according to the notion of trust in automation (Lee & See, 2004; Langer et al., 2021). These ideas will assist this study to assess whether recruiters exhibit trust, uncertainty, or overconfidence when employing AI in employment selection.

Technology is at its best when it is well matched to the organisation's structure, work processes and culture (Trist & Bamforth, 1951; Mumford, 2006) according to the socio-technical systems theory. The introduction of AI in recruitment can impact the hiring process, job functions, and organizational processes. The study will also examine the broader organisational and regulatory environment in which recruiters operate, including business policy and employment regulations, which may affect their use of AI. As an example, the recruiters of organizations with official AI-based screening rules may be obliged to employ AI, whereas the recruiters of organizations without such policies may still heavily depend on traditional hiring methods. Together, these ideas give a wide framework for understanding how recruiters encounter and use AI in conjunction with human judgment in personnel selection.

5 OBJECTIVES OF THE STUDY

To explore how HR recruiters in U.S. organizations use AI and human judgment during employee selection, focusing on the factors that affect their trust, acceptance and use of AI hiring tools.

Specific Objectives:

i. Examine recruiters' views on AI's role in streamlining tasks (e.g. resume screening) and how they validate or override AI outputs.
ii. Identify how concerns about bias, legal compliance, and candidate experience affect recruiters' trust in and reliance on AI.

These objectives guided the interview design and data analysis, drawing on TAM and human–automation theory (Davis, 1989; Parasuraman et al., 2000) as interpretive anchors.

6 METHODOLOGY

6.1 Research Design

We utilised a qualitative phenomenological design to explore the lived experiences of recruiters. Phenomenology uses the participants' own words to get depth of insight (Merriam & Tisdell, 2016). Semi-structured interviews were used to facilitate frank discussion of AI experiences. This approach is appropriate for studying complex attitudes and discovering unexpected themes (Creswell & Poth, 2017).

6.2 Data Collection

Individuals: We recruited around 27 individuals via purposive and snowball sampling in the U.S. across varied industries. The eligible participants were HR professionals who had at least two years of recruiting experience and exposure to AI or algorithmic technologies in hiring. We contacted HR associations and the LinkedIn network. Respondents were from tech, finance, healthcare and education sectors, from large corporations and small firms. In total, 25 (of 27 initially contacted) recruiters completed interviews. Demographics (gender, role level, sector) were balanced to ensure various perspectives.

Interview Schedule: We carried out one-hour semi-structured interviews (via video call). Questions explored how recruiters use certain AI tools (e.g. ATS filters, chatbots), their trust in output, experiences of bias or legal difficulties, and changes to their role. Sample prompts ranged from: "Describe a time you disagreed with an AI recommendation," to "How do you check AI decisions?" Interviews were captured on audiotape and transcribed verbatim. We received informed consent and guaranteed anonymity (Creswell & Creswell, 2018).

6.3 Data Analysis

Transcripts were analysed using theme analysis (Braun & Clarke, 2006). We undertook a four-stage process: (1) first open coding by the first author to find basic notions; (2) construction of a coding schema iteratively by frequent comparison; (3) theme production by grouping related codes; and (4) evaluation and refinement of themes by both researchers. Codes were organised using NVivo software. Member checking (sharing summaries with participants) and peer debriefing with an HR professional were used to increase trustworthiness. We continued coding until topic saturation was achieved (Guest et al., 2006). We kept memos and discussed coding decisions to minimise bias (Lincoln & Guba, 1985) throughout. Our study was informed by TAM and socio-technical theory, but we stayed open to emergent patterns derived from the data.

7 CONTEXTUAL ANALYSIS

7.1 Efficiency and productivity gains in AI-assisted screening

The article frames AI adoption in recruitment as a response mainly to scale and speed pressures: organisations employ applicant tracking systems and predictive analytics to handle big candidate pools and reduce time-to-hire (LinkedIn, 2018; Kumari et al., 2025). According to empirical and industrial sources

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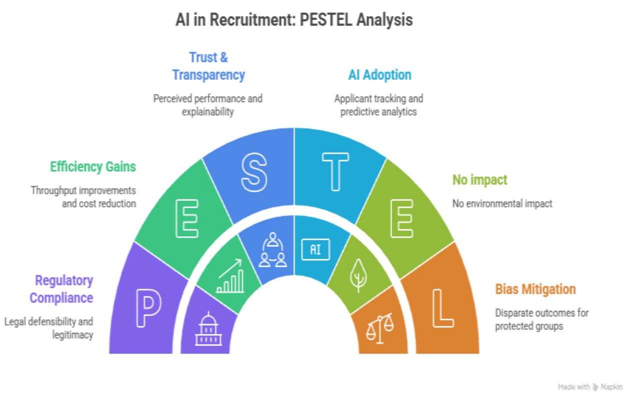
included in the paper, artificial intelligence can "automatically parse resumes and rank candidates on learned criteria," resulting in large throughput gains (Campion et al., 2016; Chamorro-Premuzic et al., 2016). The study's recruiters cited tangible productivity gains—AI "highlights top candidates" and reduces big applicant sets—but also outlined routine verification measures that curb uncritical faith in automated outputs (Almeida et al., 2025; Tambe et al., 2019). This dichotomy suggests a pragmatic adoption pattern where AI takes over repetitive, low ambiguities activities, while human practitioners are still responsible for the complex judgements (Parasuraman, Sheridan, & Wickens, 2000; Logg, Minson, & Moore, 2019).

Figure 2. AI in Recruitment: PESTEL Analysis



7.2 Fairness, bias, and legal risk as adoption constraints

A common theme throughout the piece is concern about algorithmic bias and regulatory compliance. Repeatedly, the research and participants connect biased training data and opaque decision procedures with unequal outcomes for protected groups (Barocas & Selbst, 2016; Chen, 2023a). The study is consistent with previous concerns that artificial intelligence systems trained on historical hiring patterns may perpetuate gender and racial disparities (Sony et al., 2025; Raghavan et al., 2020). Recruiters conditionally trust tools more when they are transparent and legally validated, emphasising how fairness and compliance serve as preconditions for wider acceptance (EEOC, 2024; Kumari et al., 2025). This means that organisations must combine technological mitigation (e.g., de-biasing datasets) with governance measures (audits, reporting) to retain both legal defensibility and public legitimacy (Barocas & Selbst, 2016; Raghavan et al., 2020).

7.3 Trust, transparency, and human oversight

Trust is a significant determinant of recruiters' acceptance and use of AI for employment selection. In this study, trust is defined as a function of three factors: the performance of the AI system, the transparency of the decision-making process of the AI system, and who is responsible for the AI system's decision making (Lee & See, 2004; Mayer, Davis, & Schoorman, 1995). Many recruiters said they lost faith in AI when it made mistakes, a finding consistent with prior study on algorithm aversion (Dietvorst, Simmons, & Massey, 2015). But recruiters were more comfortable using AI if they were provided with detailed explanations of how the system worked and if the system's judgments were verified by vendors or internal specialists. These techniques are in line with the principles of explainable AI (XAI) and human-in-the-loop decision-making, where humans remain in control of AI recommendations (Lee & See, 2004; Logg et al., 2019). Thus, the study reveals that openness is critical for establishing confidence, supporting the correct use of AI, and ensuring recruiters remain responsible for the final recruiting decisions (Lincoln & Guba, 1985; Guest, Bunce, & Johnson, 2006).

7.4 Role evolution, skills, and socio-technical fit

Beyond discrete tool effects, the research points to how AI reshapes the work content and necessary competencies of recruiters. Participants reported a move away from screening and administrative tasks toward strategic activities, such as candidate engagement, employer branding, and interpretive oversight. This reflects socio-technical accounts that emphasise the alignment of technology and organisational roles (Trist & Bamforth, cited in the article; Mumford, 2006). This role change created both opportunity and friction: some recruiters welcomed liberated capacity for higher-value work, while others reported worry and a need for new literacies to comprehend AI results (Miles & Huberman, 1994; Creswell & Poth, 2017). The study consequently suggests investment in AI literacy and changes management so that human expertise and automated skills create a complimentary system rather than a cause of role displacement (Almeida et al., 2025; Raisch & Krakowski, 2021).

7.5 Methodological and governance implications for practice

Methodologically, the article's qualitative, phenomenological method (Braun & Clarke, 2006; Creswell & Poth, 2017) highlights real recruiting behaviours that quantitative surveys often miss—such as routine manual overrides and ad hoc audits. These findings suggest that organisations should institutionalise monitoring (disparate impact analyses, periodic audits) and formalise human review thresholds to maintain fairness and traceability (Barocas & Selbst, 2016; Raghavan et al., 2020). The study's use of member checking and iterative coding (Guest et al., 2006; Lincoln & Guba, 1985) strengthens the credibility of these practitioner-oriented recommendations and suggests a model for future evaluative research that combines technical metrics with qualitative process indicators (Miles & Huberman, 1994; Braun & Clarke, 2006).

7.6 Integrative perspective and future research directions

Thematic threads in combination point to a balanced, socio-technical view: AI provides measurable efficiency but cannot replace human judgement for fairness, context and candidate experience (Chamorro-Premuzic et al, 2016; Tambe et al, 2019). The essay thus positions AI as an enhancing technology whose successful implementation hinges on explainability, governance, and recruitment training (Lee & See, 2004; EEOC, 2024). Future research should longitudinally assess the effects of human–AI collaborations on selection validity and workforce diversity, and experimentally test governance interventions (e.g., mandated human review, transparency disclosures) to determine which practices best maintain both efficiency and equity (Raghavan et al., 2020; Kumari et al., 2025).

7.7 Examples of AI and Human Collaboration in Corporate Recruitment

Some companies are using AI assistance in recruitment, but with human input in final selection decisions. Take for instance organizations like IBM, Unilever and Amazon which have deployed AI-backed recruitment technology for duties such as resume screening, candidate assessment, and interview help. These firms employ AI tools for efficiency, but the ultimate assessment and recruiting choices are left to recruiters and managers.

In this strategy AI carries out data-intensive activities such as finding eligible candidates in vast pools of applicants, while human recruiters assess more judgemental aspects such as communication skills, motivation, leadership potential and fit with the firm. It illustrates that AI functions most successfully as a decision-support tool, rather as a substitute for human recruiters.

8 FINDINGS AND DISCUSSION

8.1 Efficiency and Verification

Most recruiters agreed that AI tools improve efficiency in early-stage screening. "Running 2,000 resumes through an ATS takes 5 minutes instead of 5 hours," noted one recruiter. They valued AI for quickly identifying keyword matches or flagging gaps (e.g. experience mismatches). Several cited figures: one said AI reduced resume throughput by 70%. However, recruiters did not blindly trust these outputs. Many described a verification step: they "double-check" or sample AI shortlists. One talent acquisition manager said, "The AI highlights top candidates, but I still review their files. If something seems off, I dig deeper." This aligns with our first objective and reflects TAM's "perceived usefulness" tempered by caution. Recruiters often had domain knowledge (e.g. industry jargon, company culture nuances) that the AI lacked, so they would override "perfect AI scores" if human expertise suggested otherwise. For example, an IT recruiter noted that AI missed a developer with unconventional career paths, whom the recruiter identified through manual review.

This theme mirrors other findings that AI is most effective for routine tasks (Almeida et al., 2025; Chen, 2023a) but that human judgment remains critical for higher-level decisions. Our participants appreciated AI's speed but saw accuracy and nuance as human responsibilities. Thus, AI was "trusted to narrow the field" but final decisions were human-driven. This combined process fits a human–AI collaboration model: AI augments efficiency, while recruiters verify for fairness and fit. As one said, "AI is a first-pass filter, but I'm ultimately accountable, so I treat AI outputs as advice, not the final say." This dynamic suggests that

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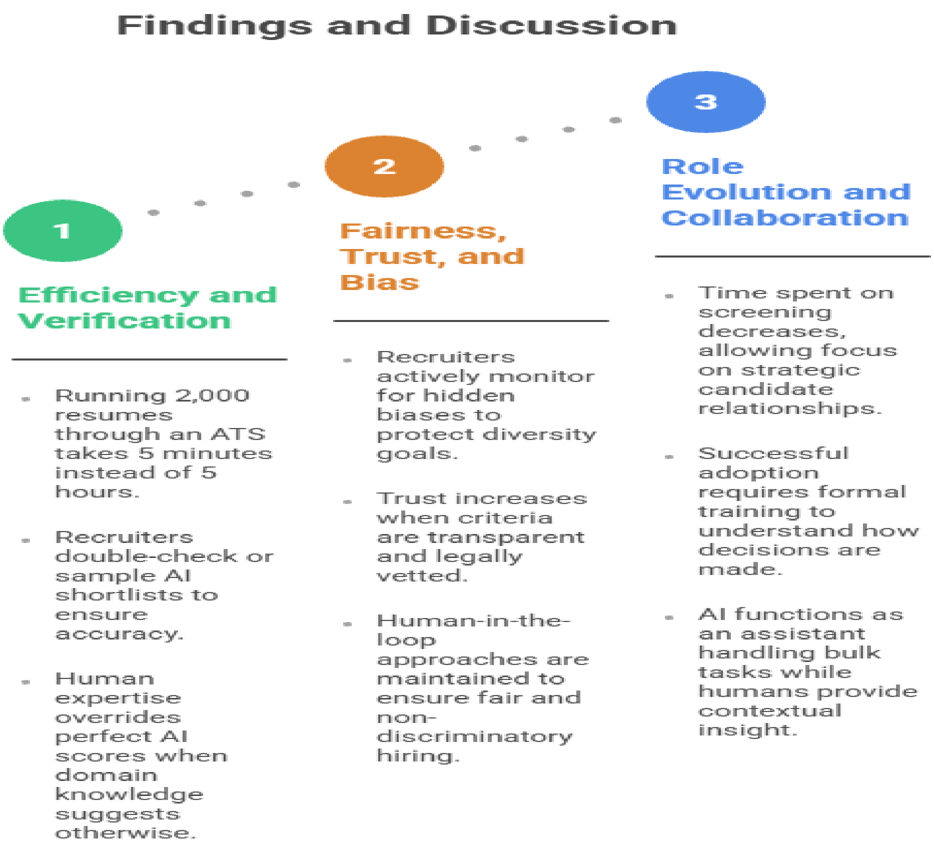
Figure 3. Findings and Discussion



perceived usefulness (efficiency gain) was high, but perceived risk of error led to deliberate reliance on personal expertise.

8.2 Fairness, Trust, and Bias

Fairness concerns were raised as a prevalent theme (related to our second purpose). Recruiters knew algorithms could be biased. Many said they were expressly tasked with safeguarding diversity goals. "We train our AI to ignore demographics, but I still watch out for hidden biases," one responder said. Several provided personal anecdotes, such discovering that an ATS was down-ranking women for IT roles because of historical data patterns. Such stories mirror well-documented occurrences of gender bias (Sony et al., 2025; Barocas & Selbst, 2016). Trust in AI was consequently conditional, with most participants stating that they trusted AI more when it was transparent and law compliant. For instance, an HR director said: "If the AI's criteria were visible and legally vetted, I'd have more faith. "I get nervous around secret formulas." This points out the necessity of disclosure (Parasuraman et al., 2000) and regulation (EEOC, 2024). Companies with formal compliance checks had recruiters who reported fewer problems with trust.

Interviewees also tied fairness concerns to the applicant's experience. They were concerned about how applicants would view it: Would AI rejections feel impersonal? Would biases leak out, making prospects think the organization was unfair? Recruiters said they felt responsible for protecting the company's reputation. "A bad auto-screening could really tick off applicants," said one. So even if AI was technically efficient, mistrust or backlash could occur. This implies that an adoption is influenced by emotional and ethical aspects (beyond TAM's "usefulness"), which is consistent with theory (Crawford & Paglen, 2019). The issues also impacted acceptance: Some recruiters elected not to use AI screening for key posts, preferring manual assessment despite the added labour. This suggests a gap between procedural justice and efficiency.

In general, confidence was stronger when recruiters were able to intervene. The "human-in-the-loop" method was mentioned many times. As one corporate recruiter summarised: "We use AI for scalability, but we'll never leave it completely alone." This finding is in line with recent studies (Chen, 2023b; Dietvorst et al., 2015) suggesting that supervision by humans tends to be re-established when stakes are high. The opinions of our participants suggest a cautious approach: they value data-driven screening, but require inspections to ensure fair, non-discriminatory employment.

8.3 Role, Evolution and Collaboration

Beyond efficiency and fairness, a bigger topic was how AI transformed recruiters' duties. Many described a move away from data input to more strategic work (consistent with socio-technical theory). "I used to spend 80% of my time screening; now it's 30%," claimed one senior recruiter. This meant they could focus on the qualitative side of things: candidate interactions, employer branding and fine-tuning hiring criteria. In this sense, AI was viewed to make work more human-centric. But this transformation demanded new talents. Some participants were unprepared at first, such as an HR manager who remarked, "I had to learn how the AI makes decisions before I could trust it." Training and changing management have become key. Those at firms with formal AI training said it was a smoother transition, and others were left "figuring it out myself."

At the same time, other recruiters said they were anxious about job security or the usefulness of their role. A junior recruiter quipped that she was afraid of the "AI overlord," though she stressed the AI was more of a "assistant than a replacement." But senior personnel thought their experience was still irreplaceable: "AI doesn't understand team dynamics or unforeseen fit," remarked a director. Thus, the findings imply that AI adoption can redistribute duties, but it does not eliminate human involvement. Recruiters tended to see successful adoption as a partnership: AI conducts bulk jobs, and humans provide oversight and contextual knowledge. This collaborative approach is consistent with current conceptions of human–AI teaming (Raisch & Krakowski, 2021). For instance, one respondent described a workflow in which AI performs initial screening, recruitment professionals undertake personalised outreach, and management make final picks - an example of an integrated process flow. (See Fig. 1.)

In conclusion, the recruiters' experiences point to a balanced perspective: AI is helpful, but human judgement is still at the heart of everything. Technology was often embraced when it was perceived to complement rather than conflict with their skills. Because of concerns about prejudice, compliance and empathy, AI is rarely entrusted with final choices. Findings These findings add to our knowledge of technology acceptance in recruiting. The decision to trust or override AI is influenced by instrumental (efficiency) and normative (fairness, accountability) concerns.

9 CONCLUSION

The study investigated the use of artificial intelligence and human judgement in the personnel selection process by recruiters in U.S. businesses. The findings show that AI increases recruiting efficiency by speeding up the screening of résumés, ranking of candidates and other repetitive duties, but recruiters do not consider automated recommendations a replacement for professional judgement. Instead, they often review, interpret or override AI-generated outcomes, especially when judgments concern fairness, legal compliance, applicant experience and organisational fit. Hence, the adoption of AI by recruiters is driven not only by its usefulness but also by transparency, explainability, accountability and trust in the fairness of its conclusions. The survey also demonstrates that AI is transforming the roles of recruiters by lowering administrative work and boosting their involvement in candidate engagement, strategic decision-making and technology oversight. The findings theoretically support the Technology Acceptance Model, human-automation interaction theory and socio-technical systems theory. They show that successful AI adoption depends on the alignment of technology capabilities with human expertise, ethical expectations and organisational practices. In practice, businesses should invest in training for recruiters, explainable AI tools, regular bias audits, clear governance procedures and mandated human review of high-stakes hiring decisions. Policymakers should also create clear and legally accountable criteria for recruitment using AI. However, the study is constrained in that it is qualitative and cross-sectional, uses self-reported experiences, and has a very small sample and a concentration on US companies that may limit the transferability of the findings. Future study should use longitudinal, quantitative, and cross-national methods to examine the effect of human–AI collaboration on

JOURNAL OF MACHINE LEARNING, DATA ENGINEERING AND DATA SCIENCE
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selection accuracy, workforce diversity, applicant perceptions, and long-term organisational outcomes. Ultimately, responsible recruitment is not about unbridled automation nor the rejection of technology progress, but a carefully managed collaboration where AI drives efficiency and human judgement protects fairness, context and accountability.

10 RECOMMENDATIONS

Based on the essay, we recommend several organizational actions:

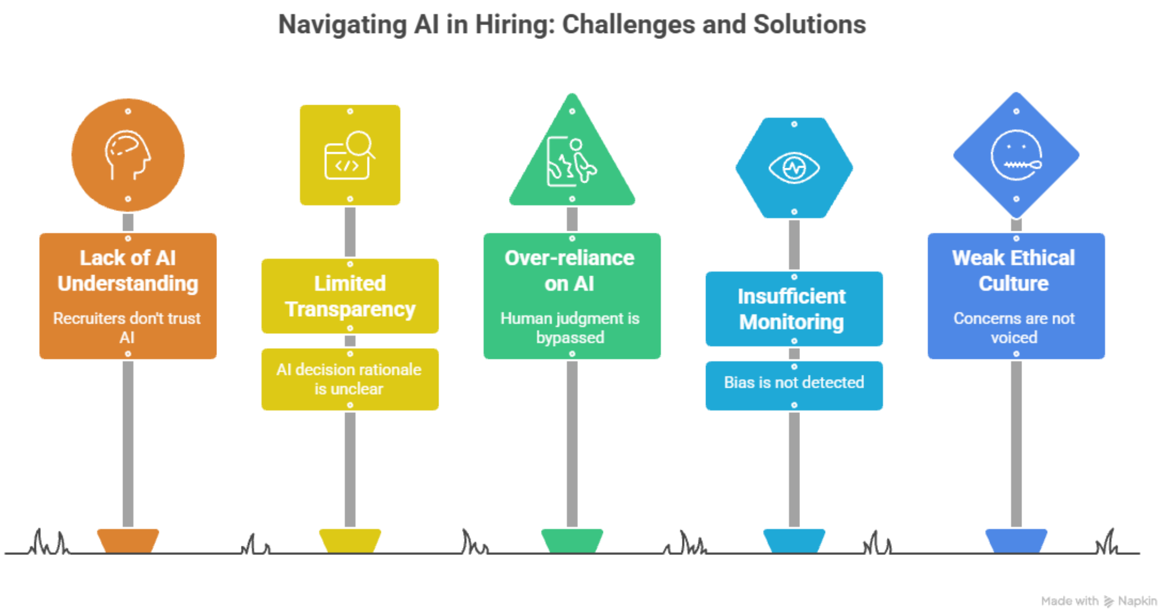
a. Invest in Recruiter Training and AI Literacy: Train HR staff on how AI tools work and can go wrong (Sony et al., 2025; Lee & See, 2004). Interviewees said knowing the AI's criteria fosters trust. Training should include bias awareness and legal rules (EEOC, 2024). One HR director, for example, created workshops where recruiters went over examples of AI screening, which helped them feel more confident utilising the system.

b. Enhance Transparency and Oversight: Encourage the adoption of explainable AI (XAI) methods to provide recruiters with transparency into the reasons behind rankings. This can include the vendor providing model summaries or employing open-source technologies. Participants advised periodic assessments of AI outputs for disparate impact, in line with legal compliance (Barocas & Selbst, 2016). Organisations should establish governance policies (like Kumar et al., 2025) that mandate human validation before high-stakes choices.

c. Maintain Human-in-the-Loop Decision Authority: Even with the best AI in the world, top recruiters should still have the option to refuse suspect recommendations. Companies can formalise this by requiring a dual signature process or demanding human assessment of flagged circumstances. One practical approach is to create explicit criteria for when human review is mandatory (e.g. all diversity-short-short-short-short-shortlisted applicants). This ensures that AI supports rather than replaces human judgement, echoing the participants' attitude.

d. Monitor and Evaluate Fairness Outcomes: Set up ongoing monitoring of employment outcomes to detect any bias in the AI screening. For example, monitor demographic distributions of AI vs. human advised shortlists. Regular reporting to an ethical or compliance committee helps keep the accountable high. Participants said that data-driven checks (e.g., disparate impact analysis) helped to assuage their concerns about fairness.

Figure 4. Navigating AI in Hiring: Challenges and Solutions



JOURNAL OF MACHINE LEARNING, DATA ENGINEERING AND DATA SCIENCE
Vol. 02, No. 02, September, 2026, **Page**: 1-12

e. **Foster a Culture of Ethical AI Use**: Encourage recruits to discuss their fears of AI. Establish feedback loops between HR and AI developers. One recruiter said: "We should hold AI to our standards of fairness. Creating a culture that embraces innovation and ethics can assist ensure responsible AI adoption.

These actions are consistent with broader guidelines (EEOC, 2024; Kumar et al., 2025) and were expressly recommended by the respondents. They try to balance the efficiency improvements with the trust and fairness recruiters and society require.

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