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Generative AI Adoption in Human Resource Management: Effects on Recruitment Quality and Decision-Making

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Abstract - The development of generative artificial intelligence (GenAI) has seen a swift transition from a novel HR pilot study to an operational application, with a dramatic increase in GenAI adoption in human resources management in less than one year. This paper will review how the adoption of GenAI is transforming the quality of hiring and decisions made by managers in the field of human resource management (HRM). In order to do this, I will use evidence from industry benchmarking reports, market research on the HR-technology landscape, as well as scientific literature on algorithmic hiring, technology acceptance, and human-algorithm collaboration. It becomes evident from the evidence below that the application of GenAI provides quantifiable benefits in terms of efficiency improvements throughout the hiring process, including decreases in time-to-hire, cost-per-hire, and resume screening times, as well as increases in quality-of-hire and retention among early hires if used as part of a properly governed workflow. At the same time, the reviewed evidence also uncovers several consistent and even growing risks, including disparate impact created through algorithmic bias in the training datasets and algorithm itself, as well as human-in-the-loop studies suggesting high propensity to replicate the recommendations of biased algorithms. In this paper, I refer to the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and Structuration Theory as explanations for not only what causes adoption but also when the use of GenAI improves versus diminishes the quality of decision-making. The conclusion from this analysis is that the net impact of GenAI on recruitment quality depends on governance decisions made by people rather than the impact of the technology per se.

Keywords: *Generative artificial intelligence, human resource management, recruitment quality, algorithmic bias, decision-making, technology acceptance.*

1. INTRODUCTION

Artificial Intelligence (AI) that can generate human-like text, synthesize unstructured data, and recommend options—otherwise known as Generative Artificial Intelligence (GenAI)—has evolved over the last three years from a newfangled application in the realm of human resource management (HRM) to one of its fundamental capabilities. Adoption of AI for HR activities by organizations increased from 15 percent in 2023 to 26 percent in 2024, and further to 43 percent in 2025, according to SHRM. Recruiting was identified by 51 percent of adopters as the topmost use case [1], [18]. The global GenAI for HR market is set to grow from about USD 0.88 billion in 2026 to USD 1.7 billion in 2030 at a compound annual growth rate of about

17.8 percent [4]. This expansion is not limited to the large technological players as it is reported that 87 percent of all companies employ AI in recruiting, and 99 percent of the Fortune 500 companies utilize AI in their recruiting processes in some way or the other [22].

The extent and pace of GenAI adoption pose two linked but analytically separate questions which inform this paper. The first one pertains to recruitment efficiency and asks whether GenAI adoption improves the metrics that organizations care about – time to hire, cost per hire, match between candidates and jobs, as well as future retention – or simply speeds up the process without making it qualitatively better. The second and, perhaps, more important question is that of decision-making and asks how the use of GenAI recommendations, summaries and rankings changes the cognitive and procedural processes underlying human hiring decisions and under what circumstances the change enhances rather than degrades the decision-making process in terms of its quality, fairness and accountability. The answer to the latter question, provided by a 2025 University of Washington study, is stark and depressing: recruiters who used large language model tools embedded with bias followed the biased choices of the model in up to 90 percent of the cases, whereas working without such biases yielded unbiased outcomes for the recruiters [10].

It should not be taken lightly. Recruitment is more intimately tied to the personal experiences of people, and to laws related to non-discrimination, than any other HR process impacted by GenAI, which implies that the mistakes or biases made at this stage would affect the candidate personally, but would also have legal implications for the employer. On the other hand, the pressure for HRM departments to adopt AI in their recruitment efforts has never been stronger: the number of applicants for entry level positions has almost tripled since 2022 because the job seekers themselves start using AI technologies to produce job applications en masse, while recruiters face challenges in attracting high quality talent despite having increased access to the tools for doing so [21]. This specific situation – where job applicants use AI on one side and recruiters use AI on the other – reflects an entirely new labor market environment that current HRM theories do not take into account as they were mostly developed without the consideration of generative AI.

This paper is structured as follows. In Section 2, the literature on technology acceptance, algorithmic decision-making, and human-AI cooperation which informs the empirical research is reviewed. The methodology behind the paper is presented in Section 3. In Section 4, the scope and trend of GenAI adoption in HR are profiled. In Section 5, the impact of GenAI on the quality and efficiency of recruitment processes is assessed. In Section 6, the effect of GenAI on management decision-making processes, such as bias, automation bias, and human-AI complementarities is investigated.

LITERATURE REVIEW AND THEORETICAL FRAMEWORK

According to Technology Acceptance Model (TAM), derived from Theory of Reasoned Action, an individual's intention to adopt new technology depends on the perception of usefulness and ease of use of that technology, which affects adoption attitude [15], [23]. For the application to recruiter's behavior, TAM based studies reveal that the more the recruiters perceive GenAI technologies as time saving and effective, the better their attitudes become in relation to those technologies; however, TAM based studies also show conflicting factors such as loss of "human touch" due to the use of the technology, concerns over the possible algorithmic bias, and inability of the technology to measure soft skills or unconventional resumes that can affect the adoption intention despite their usefulness [15]. Another model, known as Unified Theory of Acceptance and Use of Technology (UTAUT), adds social influence and facilitating conditions as additional factors to the theory; and UTAUT based studies on adoption of AI in recruitment context, for instance one of the most cited case studies from Thailand, prove that organizational structure and social norms exert independent influences on adoption intention in addition to the usefulness and ease of use [14].

The second stream deals explicitly with issues around algorithmic decision making itself. The Throughput Model for Ethical Decision Making in Algorithmic HRM explains how the perception, judgement, and information processing abilities of individuals work together in deciding the ethical approach to take when making such decisions, and specifies the exact circumstances – those of high time pressure, high volume of data that cannot be manually analyzed and situations where predictability is more important than explanation – in which organizations are more likely to delegate the decision to algorithmic systems [13]. It is highly pertinent to recruitment which is precisely such a process.

A third, growing theoretical approach is structuration theory, which has been used to study recruitment enabled by GenAI by Dutta and Naveen, who posit that the adoption of discriminative and generative AI in recruitment and selection results in an interactive, recursive relationship between structure (official policies on hiring, role descriptions) and human agency (judgement of recruiters, presentation of candidates), where adoption of AI technology changes organizational structures of hiring and is, in turn, changed by the decisions of human actors [5]. Such an approach is especially helpful in avoiding a determinist perspective that would view GenAI in recruitment as an absolute boon or bane, shifting attention to the particular organizational and human decisions that intervene between the adoption of the technology and its effects, as adopted in this paper in Sections 5 and 6.

Finally, the literature on algorithmic bias and fairness in hiring serves as the empirical and normative balance to the literature above focused on adoption. An extensive literature base exists around the fact that algorithms commonly reproduce or reinforce biases already contained in the training data, resulting in disparate impacts based on gender, race, and other protected classes [8], [9], [11], [12]. A parallel yet newer body of literature studies the effects of human-AI complementarity and how the way an algorithmic recommendation is framed, the expertise level of the decision-maker, and how the algorithm is tuned affects the extent to which the human uses the information to improve his or her decision-making versus deferring to the recommendation entirely, an area that is tightly linked with automation bias; this paper applies insights from this literature in Section 6 with respect to the University of Washington bias-mirroring finding presented in Section 1 [10].

Finally, one more theoretical strand which could be mentioned here refers to the organizational justice theory in relation to algorithmic decision-making. Job candidates perceive the hiring process not only in terms of the outcomes but in terms of the perceived fairness of the process — procedural justice —

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as well, and there is a rich set of literature showing that the fairness of algorithmic hiring is determined by such factors as transparency of the decision criteria, an available option for appealing to the decision, and technological literacy of the candidate — HR-technology literacy [16]. This line of research seems to be especially important for interpretation of the candidate experience analysis provided in Section 5.3 insofar as it implies that reputational and employer branding aspects of AI-based hiring depend not only on the accuracy of technology used but also on the way in which this technology is presented to candidates.

Thus, all the listed theoretical perspectives allow considering the empirical results presented in Sections 4 to 7 from different angles in order to distinguish different types of the GenAI adoption and their distinct impact on the recruitment outcomes.

RESEARCH METHODOLOGY

The methodology used in this paper is a qualitative review based on a synthesis of secondary data in three broad source types. The first source type includes industry benchmarking studies based on large sample sizes, such as the SHRM State of AI in HR 2026 Report, LinkedIn Future of Recruiting report series, Gartner talent acquisition trends research, and recruitment technology analytics, such as Pin, InCruiter, and DataRefs [1]–[3], [18]–[22]. The second source type includes peer-reviewed academic literature on technology acceptance, algorithmic ethics, and audit of empirical biases from journals like Human Resource Management, Organizational Dynamics, Business Research, and Applied Sciences, as well as conference proceedings from the Hawaii International Conference on System Sciences and preprint archives related to computational fairness audits [5]–[17]. The third source type includes regulatory and policy sources that outline the development of the governance framework for algorithmic hiring, such as the EU AI Act and New York City's Local Law 144.

Quantitative indicators – adoption rates, efficiency statistics, and bias statistics – have been tabulated for comparison, as well as graphically displayed to show the trend patterns within each category. The reader must understand, however, that just like in the case of any summarization of a rapidly developing commercial field, the sources of adoption and efficiency statistics are predominantly the HR technology vendors themselves and their trade associations, which stand to gain from positive reports about themselves, whereas the sources of bias statistics are predominantly independent academic audits; this difference will be discussed explicitly in Section 6 and is something to keep in mind when reading the figures below, which are presented as industry results, not independent estimates.

In addition, there is a methodology issue associated with the issue of causality. The majority of the figures on efficiency and quality-of-hire that have been mentioned in this paper come from before-and-after studies and cross-sectional comparisons of companies that adopt and those that do not adopt AI. This creates the risk of companies that choose to adopt AI early and intensively being systematically different from companies that do not adopt in terms of factors that predict better hiring results, for instance, well-resourced HR departments, advanced data infrastructure, or higher levels of sophistication among company leaders. This means that some part of the benefits reported is actually due to selection and not to the technology itself. This paper focuses on studies with more controlled and quasi-experimental design, for instance, the University of Washington mirror-biasing study and debiasing experiments described in Section 6, precisely because they have more solid causal basis than the industry surveys that prevail in adoption and efficiency research.

THE RISE OF GENERATIVE AI IN HR: ADOPTION LANDSCAPE

Figure 1 traces the rapid rise in organizational AI adoption for HR tasks between 2023 and 2026, drawing on SHRM's annual Talent Trends surveys.

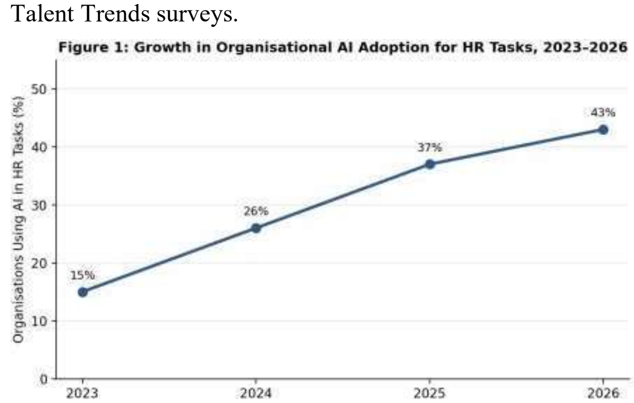

Fig -1: Growth in Organizational AI Adoption for HR Tasks, 2023–2026 (Source: SHRM Talent Trends Reports [1], [18])

This adoption varies in terms of organizational hierarchy. According to the 2026 State of AI in HR Report by SHRM, 73 percent of HR professionals at the director and above levels were using AI for work-related activities in 2025, while 66 percent of managers and supervisors and 65 percent of individual contributors were using AI in their work, with senior leaders starting to use AI in 2023 and 2024, while individual contributors started doing so later [1]. Figure 3 in Section 5 contextualizes this hierarchy against the efficiency metrics that are explained by it. Among those organizations that have

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adopted AI, its use is frequent and not occasional: 26 percent of HR professionals are using AI on a weekly basis, 20 percent on a daily basis, and another 9 percent more than once a day [1].

These particular applications for the technology are focused around a few high-volume tasks in recruitment. As per the SHRM 2025 Talent Trends Report, the most popular AI recruiting applications include creating job descriptions (66 percent of adopters), resume screening (44 percent), automating searches for candidates (32 percent), personalizing job listings (31 percent), and communicating with candidates (29 percent) [19], [20]. These applications have been described in Table 1 along with the rate of adoption and their function within the recruitment funnel. More importantly, in its slightly more conservative Future of Recruiting 2025 report, LinkedIn found that only 37 percent of organizations in talent acquisition have begun using generative AI (which is different from AI use in general), compared to 27 percent last year [2], [21].

Table -1: Leading GenAI Recruiting Use Cases, Adoption Share, and Funnel Stage

AI Recruiting Use Case	Adopter Share	Funnel Stage	Primary Reported Benefit
Writing job descriptions	66%	Sourcing (pre-posting)	Consistency, speed, reduced biased language
Resume/CV screening	44%	Screening	89–94% parsing accuracy; large time savings
Automating candidate search	32%	Sourcing	Access to passive candidates; faster shortlisting
Customising job postings	31%	Sourcing (pre-posting)	Higher-quality, targeted applica nt pools
Com muni catin g with appli cants	29%	Screening – Scheduling	Faster response; improved candidate satisfaction

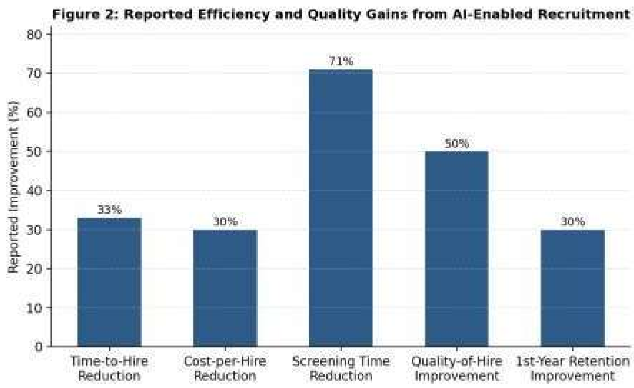
This competitive environment is interesting in its own right. According to the report by LinkedIn published in January 2026, over 90 percent of talent-acquisition professionals surveyed intended to increase their use of AI within the next year precisely in order to ensure meeting hiring objectives in the face of rising pressures, and 66 percent of those recruited indicated plans to expand AI use for conducting pre-screening interviews [24]. Such pressures are increased by the overall more competitive applicant environment: the number of applicants per opening position in the US has nearly doubled since spring 2022, and 66 percent of recruiters claim that finding good talent has become even harder amid – or, as some recruiters argue, partly due to – the rise of AI technologies being used by both sides of hiring [24]. However, despite such high levels of usage of AI tools, only 34 percent of talent-acquisition professionals described their teams as "AI power users," meaning they could effectively combine AI assistance with human judgment, while another 47 percent were learning how to use the tools in a strategic fashion [24].

EFFECTS ON RECRUITMENT QUALITY AND EFFICIENCY

1.1 Efficiency Gains Across the Hiring Funnel

The effect of GenAI implementation which has the highest level of consistency of documentation is the decrease of time and effort needed to process candidates throughout the recruitment process. According to the aggregated data for the industry, the average level of reduction of time-to-hire due to usage of AI solutions in recruiting reaches 25-50 percent with 70 percent reported in some cases for fully-automated enterprise implementations in case if AI is used for all stages - sourcing, screening and scheduling [19], [21]. In case if we speak about individual tasks, the time of resumes screening was estimated to be reduced from ten to two days while the time of interview scheduling was reduced from five to one day.

The reductions in the cost per hire reach an average of 30 percent, with 40 percent being reported in some North American implementations and nearly 78 percent of AI-recruiting users reporting cost reductions [19], [21]. Figure 2 presents the efficiency metrics together with the metrics related to the quality of hire and retention presented in Section 5.2.



1.1 Quality-of-Hire and Candidate Matching

In addition to speed, an increasing amount of industry research highlights how AI-assisted recruitment contributes to improved hiring outcomes in terms of their quality. According to the aggregated statistics from SHRM, there is a reported 50 percent improvement in quality of hire among organizations implementing AI, and the LinkedIn 2025 research reveals that companies utilizing AI-assisted candidate matching experience first-year retention rates which are 25 to 35 percent higher than in companies using only manual matching [19], [21]. Recruiters' messaging through the use of AI messaging tools proves to be important as well: the LinkedIn research shows that companies implementing AI-assisted messaging are 9 percent more likely to make a quality hire than those with low use of the technology [21]. The accuracy of resume parsing and skill identification by AI recruitment screening software is 89 to 94 percent now, which is a significant advance comparing to previous generations of purely keyword-based applicant tracking systems which often overlooked qualified applicants due to their different wording in resumes [21].

Alongside these improvements in the quality of hires, another trend that has been fueling them is the general move towards skills-based hiring that has become possible due to the use of AI technologies: the share of firms that use skills-based hiring methods has increased to 70 percent from 65 percent last year, while companies doing their best in terms of skills-based searches are believed to be 12 percent more likely to do a good job in terms of making a quality hire [21]. This trend can be traced through the diminishing importance of proxy measures: while in 2019, 73 percent of firms asked for a certain GPA, in 2025, this figure had dropped to 42 percent [21].

Even with such progress made, however, it should be noted that all findings are not entirely positive. Indeed, the statistics provided by SHRM themselves demonstrates an increase in the average cost-per-hire and time-to-hire in the last three years, despite the acceleration in the adoption of GenAI during the same period of time, a phenomenon well-explained by Gartner's October 2025 survey, where 88 percent of HR leaders say that their organization has not gained any significant business value through AI tools usage, despite the fact that 61 percent of organizations consider themselves to be in the advanced implementation stages of those tools [21]. The difference between tool use and value gained indicates that the improvements listed above do not come automatically with adoption of GenAI technologies, but are limited to organizations that have focused on implementation quality only, not just on the license purchase of AI tools, a question which will be addressed in Sections 7 and 8.

Indeed, the financial implications of making mistakes when it comes to quality of hire are substantial, giving an important background to understand why organizations still invest in AI recruitment solutions in spite of all the implementation problems mentioned above. According to SHRM, the average cost per hire amounts to around USD 4,700; however, the true cost of a hiring mistake is considerably higher, as organizations pay USD 17,000 in costs associated with training, lost production, and replacement on top of that. Moreover, according to the U.S. Department of Labor, the cost of a hiring mistake can amount to 30% of the annual salary of an incorrectly hired candidate, reaching around USD 24,000 for the position paid USD 80,000 a year [22]. Since AI-based quality of hire increases directly affect this cost structure, with each 50% improvement in quality of hire metrics meaning 50% less cases of costly mistakes in hiring decisions, even in organizations which have not yet achieved the efficiencies discussed further in the current section, there is a strong incentive for using such tools, explaining the continuing popularity of those tools despite Gartner's assertion that few organizations are benefiting from their use so far [21], [22].

1.1 Candidate Experience and Employer-Brand Effects

In terms of recruitment quality impact, GenAI influences not only the recruiting team but the job candidate experience as well. Quicker replies from companies facilitated by AI chatbots and scheduling features result in a noted 30% increase in candidate satisfaction with the recruitment process, thereby solving an ongoing problem where slow responses from employers were considered one of the major reasons for candidate dropout, especially in high-volume recruiting [22]. However, candidate views on AI-powered recruitment as a concept appear to be much more wary than those of recruiters: 44% of candidates stated that they avoid applying through AI-powered systems due to the lack of human touch in their process, and the general public's view is even less positive, with 71% of the general population rejecting the idea of an AI system making final decisions about hiring [22]. This mismatch between recruiter optimism about GenAI in recruiting and candidate wariness may present a separate risk for employer branding since companies overusing AI for communication

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with candidates may signal impersonality to exactly the target audience

— high-potential passive candidates receiving multiple job offers — that has no interest in being in the hiring process at all [8]. The indicators of candidate trust indicators alongside the bias and oversight findings that likely underpin them.

Moreover, this disconnect between recruiters' and candidates' perceptions of AI hiring technologies directly interacts with the skills-based hiring trend described in Section 5.2 in terms of its consequences for diversity of applicant pools. It turns out that procedural justice in algorithmic hiring is positively associated with applicants' perception of fairness when they receive an explanation about why they failed the initial screening stage, and do not receive any other kind of explanation or merely an automated rejection [16]. Since this type of transparency implies additional design effort above and beyond basic automation already widely adopted by firms, its prevalence in hiring practices appears to be quite low and likely contributes to relatively high levels of skepticism among candidates towards AI-driven recruiting technologies (44 percent avoid using such solutions, 71 percent oppose AI-made hiring decisions) despite growing level of satisfaction among recruiters [16], [22]. This mismatch between recruiters' and candidates' attitudes toward AI hiring tools poses another, less well recognized quality risk for recruitment: hiring process that appears to be efficient and fair to recruiters but seems to be opaque or impersonal to many applicants, systematically loses access to precisely the highly qualified, high-optionality candidates most likely to withdraw from a process they distrust, quietly degrading applicant-pool quality in a manner that standard AI-adoption metrics such as time-to-hire or cost-per-hire are not designed to capture.

EFFECTS ON MANAGERIAL DECISION-MAKING

1.2 Algorithmic Bias and Disparate Impact

The most critical and well-documented risk in the implementation of GenAI in HRM is the discrimination that occurs within the recommendations and rankings made by the technology. In audits of AI-powered resume screening, researchers have found discrimination on a gender and racial level: in one study in 2025, using large language models in automated resume assessment, gender and racial biases were found, whereas, in another Stanford study, in which it was established that the use of employer algorithms is used by approximately 90% of U.S. companies in some way, it was discovered that 26% of Black people and 15% of Asians applied for jobs in which the implemented algorithm discriminated against their racial groups based on a disparate impact standard in the same way that U.S. employment law Title VII does [9], [11]. The above findings have followed from previous and well-known instances, such as the Amazon internal resume-screening tool of 2018, which has found to downrate resumes of women. All of the above findings are in line with a systematic review that found that algorithmic HR recruitment and development have been discriminating repeatedly on various protected grounds if they were trained using historically discriminatory data [12].

The exact processes that cause this effect have been fairly well studied in the relevant technical literature: models trained using historical hiring results will reflect any demographics represented within those results; complex architectures obscure the exact reasons why a particular ranking is being done; and exclusionary selection criteria embedded into the prompt or in the process of training will discriminate against applicants with atypical career paths, periods without employment, or certain surnames which may be indicative of certain ethnicities or national origins [9], [11]. Fortunately, experimental research has found that the above problems are not inherent but, rather, solvable: it has been found that the use of structured debiasing measures on hiring algorithms leads to improved quality and demographic diversity of applicant pools in comparison to unbiased algorithms [8].

The very persistence of the biases in spite of so many years of proven cases is analytically meaningful in itself. The Amazon case of 2018 has now been around for more than seven years, and yet, in 2025-2026, auditors still find comparable disparate-impact patterns in currently deployed commercial hiring tools, implying that the mere awareness of the problem of bias has not been sufficient to solve the issue in the level of commercial tools [9], [11]. Part of the reason could be attributed to the transition from old rule-based and simple machine-learning classifiers to large-language-model-based GenAI tools: as LLMs use vast amounts of texts different from what the old resume-screening classifiers used, and because their output is created in ways that defy feature attribution, the technical challenge of auditing an LLM-based hiring tool for bias becomes harder than auditing the previous models, although adoption of GenAI tools has been accelerating [9], [12]. This is one of the main reasons why the mandatory, independent bias-audits proposed in Section 7 are necessary, as it seems that the voluntary and internal bias-testing would not be sufficient on its own because of the technical challenge of the matter.

1.1 Automation Bias and Human-AI Complementarity

However, an equally distinct and more recent form of risk does not arise from bias in the algorithm itself but instead is related to how having an AI recommendation alters human decision-making, a process which bears strong resemblance to what is termed "automation bias," which refers to the overreliance on recommendations made through automation even when human judgement suggests otherwise. The University of Washington

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2025 study discussed in Section 1 is the first piece of research to demonstrate this effect: in that study, reviewers who used large-language-model algorithms with inherent bias in their underlying model were seen to replicate those biases in between 80 and 90 percent of cases, while recruiters who did not use AI at all, or who used a debiased version of the AI algorithm, showed no significant difference in the probability of selecting white vs. non-white candidates [10]. According to the main author of this research, this study includes an undeniable "bright side," because since human decision-makers are seen to follow the AI's biases in this case, proper tuning of the underlying model toward increased fairness would be reflected in human judgement as well [10].

This can be explained by complementarity of humans and AI models literature where whether the human decision maker is going to use an algorithmic suggestion for improving his own judgement or simply rely on it without any criticism largely depends on decision maker's level of expertise, the presentation and confidence communication of the AI result and the nature of interface which can foster either critical thinking or blind acceptance [17]. In case of recruitment, it means that even though the 93 percent of hiring managers who believe that human involvement is crucial part of the hiring process cannot solve the problem of over-reliance on AI if the time-pressure workflow design of the recruitment process leads to fast acceptance of suggestions made by algorithms [13].

In light of the recruiter confidence results presented in section 4, the situation becomes even more worrying, since only 34 percent of talent acquisition specialists can call themselves true "AI power users" capable of seamlessly using AI tools in combination with their own judgment, whereas a substantially higher number of respondents is still learning how to use the tools operationally [17], [24]. In other words, the preconditions for such critical and expert interaction with the tool as the human-AI complementarity research suggests would be necessary to prevent automation bias are not necessarily met due to the low level of recruiting professionals' AI literacy [1], [10], [24]. Stated another way, the mirroring bias effect found by Wilson et al. might be most evident not among recruiters most knowledgeable about the technology who would be more likely to question the AI tool's recommendation, but among the larger group of recruiters using AI operationally rather than strategically, which happens to constitute, according to SHRM's research, the majority [1], [10], [24].

Figure 4 consolidates the trust, oversight, and bias-mirroring indicators discussed in this section and Section 5.3, illustrating the gap between recruiters' stated confidence in retaining human oversight and the empirical evidence on how that oversight functions in practice under AI influence.

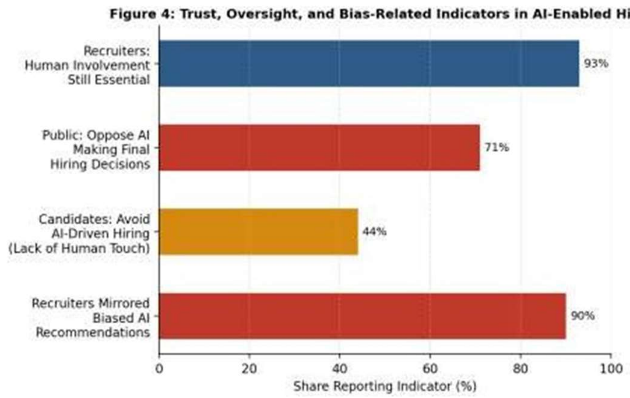

Fig -4: Trust, Oversight, and Bias-Related Indicators in AI-Enabled Hiring (Source: [10], [21], [22])

1.1 Explainability, Accountability, and the Limits of Predictive Accuracy

Yet another problem regarding decision making arises from explainability of GenAI recommendations. While the older rule-based Applicant Tracking Systems allowed a human recruiter to understand how certain decisions were reached, GenAI technologies that use large language models to analyze resumes or candidate profiles produce their recommendations via algorithms that are themselves hard to interpret even by the creators of the models in question, thus preventing the organization from offering a clear explanation for why it has decided to hire a particular candidate should it ever be required to do so. In fact, the ethical decision making framework proposed within the Throughput Model lists the situation "where prediction accuracy is more important than explanation" as one of those where organizations find it tempting to replace human reasoning with an algorithm's output [13]; hiring process, especially when it is done on a high scale, can fit into that category, but hiring itself is highly accountable procedure due to legal and reputational reasons. It means that there is a natural conflict between the need for an efficient algorithmic recommendation and the need for a defensible decision process, which is what drives the regulation efforts described in Section 7.

This aspect of the tensions discussed in this paper is not only about accountability in case of a single candidate but is also about organizational liability. Employment discrimination lawsuits usually require proof of disparate treatment (discrimination intentionally) or disparate impact (a practice that does not appear discriminatory at first glance but produces a discriminatory result). The latter approach is especially difficult to apply to GenAI systems as their decision-making processes are spread over billions of model parameters and cannot be expressed in the form of easily interpretable rules [11]. Modern legal scholars and HR compliance professionals

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argue that the inconsistency between the doctrine that has been developed with relatively simple hiring algorithms in mind and the complex nature of GenAI is a problem by itself and poses the risk of liability even without being discriminatory as the employer might fail to provide an explanation necessary in such cases. This problem, which Section 7 discusses, is to be resolved through the introduction of requirements for disclosure and auditing which, third-party-verified fairness assessment for the individual-decision explainability that the underlying model architecture cannot readily provide.

GOVERNANCE, REGULATION, AND ETHICAL GUARDRAILS

Responding regulatory frameworks have become increasingly active along with the increasing implementation. The EU's AI Act, which is coming into force with respect to hiring and recruitment algorithms starting August 2026, considers such algorithms high-risk technologies with requirements of accuracy, robustness, and cybersecurity, as well as a mandatory quality management system provided by the supplier [21], [44]. The AI Act follows a previous ban by the EU that came into effect in February 2025 and prohibited the use of emotion recognition technologies in hiring and employment, due to the lack of scientifically solid background of such technologies [21]. On the other side of the Atlantic, New York City's Local Law 144, which obliges employers to conduct independent audits of bias for "automated employment decision tools" prior to using them in hiring and to disclose audit results publicly, is one of the first binding requirements of its type in the United States, with many states of the US following [21].

All of these regulatory initiatives are directly relevant to the technical and behavioral research reviewed in Section 6 above. The mandatory bias audit requirement, for example, is directly responsive to the disparate impact risk noted in Section 6.1, and transparency and disclosure requirements can be seen as addressing some, although not all, of the explainability issues outlined in Section 6.3 — disclosure of audit results alone will not ensure the internal workings of a specific model are intelligible, but it will ensure some form of external accountability where internal governance is insufficient. In the UK Government's Responsible AI in Recruitment Guide, the assurance process for AI systems – defined as "a set of tools, process, and measures of system performance" [17] – is also framed as a way to help organizations measure performance, manage risk, and comply with regulation. Organizations operating in multiple jurisdictions will have to navigate a truly fragmented compliance environment, where a single recruiting algorithm might have to meet EU high-risk system requirements, US state and municipal bias audit requirements, and employment discrimination legislation requirements. — a compliance burden that itself may partly explain why 88 percent of HR leaders report not yet having realised significant value from their AI investments, since meaningful proportions of implementation effort are necessarily directed toward governance rather than pure capability deployment [21].

On top of regulatory efforts, another kind of self-regulation has taken shape via professional and industry standards. Model card disclosures and fairness testing have been increasingly provided voluntarily by

HR-technology vendors both in expectation of coming regulations and in line with procurement processes that increasingly incorporate questions around bias audits and explainability into due diligence procedures. It reflects a more general evolution in the approach to HR technology evaluation where the criteria for procurement in the initial stages of GenAI adoption had been driven mainly by promises of efficiency while today HR technology procurement sees governance capability as a key first-order procurement criteria in its own right and on par with data security. Indeed, this evolution is in line with the notion put forward in Sections 6 and 7 above that governance is no longer just a cost imposed on the efficiency benefits of GenAI but is becoming an integral part of its value proposition.

COMPARATIVE SYNTHESIS AND STRATEGIC IMPLICATIONS

Table 2 consolidates the effects of GenAI adoption discussed in Sections 5 through 7, organized by the primary theoretical lens through which each effect is best understood, alongside the practical governance implication each finding carries for HR leaders.

Table -2: Comparative Synthesis of GenAI's Effects on Recruitment Quality and Decision-Making

Effect Domain	Theoretical Lens	Key Empirical Finding	Governance Implication
Hiring-funnel efficiency	TAM / UTAUT (perceived usefulness)	25–70% time-to-hire reduction; 30% cost-per-hire reduction	Invest in workflow redesign, not licensing alone
Quality-of-hire & retention	Human capital / signalling theory	~50% quality-of-hire gain; 25–35% higher 1st-yr retention	Pair AI matching with skills-based criteria

Candidate trust & experience	Organisational justice / signalling theory	44% avoid AI hiring; 71% oppose AI final decisions	Preserve visible human contact at high-stakes stages
Algorithmic bias	Fairness & disparate-impact research	26% of Black, 15% of Asian applicants face biased screens	Independent, recurring bias audits (not one-off)
Automation bias in recruiters	Human-AI complementarity	Recruiters mirrored biased AI choices in ~90% of cases	Design workflows that slow decisions at key checkpoints
Explainability & accountability	Throughput Model of ethical decision-making	Low-explainability models complicate legal defensibility	Require audit trails and disclosure of decision criteria

The overarching pattern evident in Table 2 aligns with the structuration-theory lens outlined in Section 2: the net impact of GenAI on recruitment quality and decision-making is not dictated by the technology but depends significantly on the organizational and human decisions made in connection with it. Three important strategic implications arise as a result of this synthesis. Firstly, HR professionals need to resist the temptation of making an all-or-nothing licensing decision about implementing AI and instead understand that the 88 percent of organizations experiencing under-realization of value very likely include the companies that have invested insufficiently in the processes described in Section 5.2 – implementation, training, and redesign of workflows [21]. Secondly, in light of the bias mirroring findings in Section 6.2, organizations need to understand that "human-in-the-loop" is a design problem and not just a box to tick – the workflow interfaces need to be designed in such a way as to slow down decision-makers exactly at those points when independent judgement is necessary since speed and independent judgement are shown to trade off each other in the conditions identified by the Throughput Model [13]. Third, taking into account the stark effects on candidate trust found in Section 5.3, organizations need to balance the extent to which the use of AI in candidate communication is visible, limiting fully automated communication only to those truly low-risk, high-volume touchpoints, while ensuring that human interaction remains visible during critical candidate trust-building stages, like final interview and offer discussion [8],[22].

Taken together, these implications suggest that the organizations most likely to realize the substantial upside GenAI offers — with demonstrated efficiency gains between 25 and 70 percent and improvements in quality of hire in the 50 percent range — without the associated risks are those that adopt GenAI as a socio-technical governance programmed rather than a technology acquisition [19], [21].

The second implication that can be drawn relates to the move toward agentic AI workflows discussed in Section 5.1. With the shift in the automated recruiting process from human-triggered use of AI towards agentic systems that recruit, screen, and schedule with limited human triggering, the governance challenges discussed in Section 6 become amplified, as opposed to eliminated, by the fact that a self-enhancing agentic AI process provides even fewer opportunities for human intervention before the potentially erroneous pattern becomes deeply entrenched in the process. In their assessment of agentic AI recruitment tools, HR executives would, therefore, want to consider the availability and regularity of human checkpoints as one of the key criteria, along with the efficiency metrics that now prevail in the sales pitches, because the bias amplification evidence presented in Section 6.2 clearly demonstrates that regularity of checkpoints, and not just their presence, is what ultimately determines whether human oversight functions as a genuine safeguard or as a formality.

CONCLUSION

GenAI has gained widespread acceptance as a mainstream part of human resource management in an extremely short amount of time, with organizational usage of the technology in HR reaching from around 15 percent in 2023 to 43 percent in 2025, and with recruitment representing the single topmost use-case of GenAI. In this paper, we have analyzed the impact that GenAI adoption has on two separate but related outcomes – namely recruitment quality and managerial decision making. In terms of recruitment quality, the results are overwhelmingly positive but conditional: GenAI adoption leads to lower time-to-hire, cost-per-hire, and higher quality-of-hire and early retention, but these benefits are only achieved by companies that have invested in quality implementation of GenAI rather than being automatic after its adoption, as seen in the fact that a majority of HR professionals have yet to see tangible business benefits from their investments in AI.

The evidence on decision-making is decidedly more skeptical. The risks posed by algorithmic bias are longstanding and well-understood, both in terms of gender, race, and other protected categories, while recent studies on human-in-the-loop systems show that biased recommendations by algorithms are mimicked by human recruiters at extraordinarily high frequencies, undermining the common belief that having a "human in the loop" serves as a safety mechanism on its own right. The Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, the Throughput Model of algorithmic ethical decision-making, and the structuration theory imply that these are not inherent qualities of GenAI, but are rather products of the particular organisational context, governance decisions, and human behavior. In addition to that, the regulatory trends in the form of the European Union AI Act's designation of employment algorithms as high-risk applications, Local Law 144 of New York City requiring bias audit of algorithms, and the ban on emotion recognition technology in hiring in the EU serve as a binding external pressure on the governance domain, making some voluntary guidelines into legal necessities.

In sum, the relationship between GenAI and recruitment decision-making and quality can be characterized as conditional, not deterministic – the technology has proven itself capable of enhancing recruitment efficiency and recruitment decision-making quality and fairness in conditions of adequate governance, but at the same time has proven itself capable of reinforcing and magnifying bias and limiting human independent judgement when not accompanied by such governance measures. Those organizations, HR specialists, and policymakers who wish to leverage the benefits of GenAI technology and mitigate its potential risks should see responsible deployment, namely bias auditing, workflow design which preserves human independent judgement, transparency and adherence to regulations, as not an additional condition of AI implementation, but as the critical factor which determines whether this implementation will improve or undermine recruitment decision-making quality.

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BIOGRAPHIES (Optional, not mandatory)

Manohar is a Talent Acquisition Associate at Embark with a strong interest in talent acquisition, employee engagement, strategic workforce planning, and human resource management. With experience in recruitment, candidate sourcing, talent assessment, and hiring coordination, he focuses on identifying and attracting suitable talent while contributing to the development of an inclusive and employee-centric workplace.

His professional interests include employee retention, attrition management, workforce diversity, gender-neutral workplace practices, employee experience, performance management, and organizational culture. He is particularly interested in understanding how effective recruitment strategies, employee engagement initiatives, and people-centric HR practices can improve employee satisfaction, organizational commitment, workforce productivity, and long-term retention.

Manohar also explores emerging areas such as employer branding, talent analytics, diversity, equity and inclusion (DEI), employee well-being, competency-based hiring, learning and development, succession planning, and strategic talent management. His work emphasizes practical and inclusive approaches to addressing contemporary workforce challenges, particularly in areas such as employee motivation, retention strategies, workplace inclusivity, and sustainable human capital development.

Manohar aims to contribute to HR practices and research that bridge organizational objectives with employee expectations, supporting effective talent management, an inclusive workplace culture, enhanced employee engagement, and sustainable organizational growth in a dynamic and evolving business environment.