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# Digital Transformation and Algorithmic Hiring: Evaluating AI Recruitment Failures in Biotechnology Talent Acquisition

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**Abstract**: The rapid adoption of artificial intelligence (AI) in recruitment marks a significant transformation in how organizations identify, evaluate, and select talent. Although AI-driven hiring systems offer efficiency, cost reduction, and standardized decision-making, their implementation may introduce organizational risks if technological capabilities do not align with complex workforce requirements. This case study analyzes a global biotechnology company that adopted an AI-based applicant screening system as part of a broader digital transformation initiative. The investigation reveals that algorithmic screening tools inadvertently excluded highly qualified candidates for specialized research and development positions, thereby narrowing the candidate pool despite ongoing staffing shortages. Drawing on peer-reviewed literature from databases such as Google Scholar and ProQuest, the analysis employs a narrative literature review to assess the organizational drivers, benefits, and risks of AI-enabled recruitment. The findings demonstrate that keyword-based screening models, limitations in training data, and insufficient human oversight contributed to algorithmic bias and false-negative screening errors. These results show that automated hiring systems can undermine strategic talent acquisition in knowledge-intensive industries when organizational processes and technological tools are not effectively integrated. The study applies strategic and change management frameworks, including the McKinsey 7S model and Kotter's change model, to interpret the organizational dynamics underlying the technology failure. The results underscore the importance of sociotechnical integration, governance structures, and leadership oversight to ensure that AI recruitment systems support rather than replace human judgment. The study concludes with practical recommendations for organizations seeking to implement AI-enabled hiring technologies responsibly while maintaining access to diverse, highly specialized talent in scientific and innovation-driven sectors.

**Keywords:** Algorithmic Bias, Algorithmic Hiring, Artificial Intelligence, Biotechnology Recruitment, Digital Transformation, Human Resource Management, Keyword Screening, Talent Acquisition, Automation Bias, Sociotechnical Systems, McKinsey 7S Model

## Introduction

The adoption of artificial intelligence (AI) in recruitment and talent acquisition has accelerated across industries, fundamentally altering how organizations screen, evaluate, and select job candidates. Organizations increasingly use AI-driven systems to process large volumes of applications, automate résumé screening, rank candidates, and improve the

speed and consistency of hiring decisions. Although these technologies offer notable gains in efficiency and cost reduction, recent research identifies substantial risks, such as algorithmic bias, lack of transparency, and the inadvertent exclusion of qualified candidates whose skills may not be readily identified by automated systems (Upadhyay & Khandelwal, 2022; SHRM, 2022). These risks are especially pronounced in knowledge-intensive sectors, where complex competencies and nontraditional career trajectories are difficult to assess with standardized, data-driven models.

These challenges are exemplified by the experience of a global biotechnology company undergoing rapid digital transformation. In response to increasing application volumes and the need to reduce recruitment costs, the company implemented an AI-driven applicant screening system to automate candidate evaluation and expedite hiring. Within several months of deployment, department leaders noted a reduction in the number of candidates progressing to the interview stage, including for essential research and development positions facing ongoing staffing shortages. An internal audit determined that the AI system relied predominantly on narrow keyword matching and historical hiring data, systematically excluding highly qualified candidates with interdisciplinary backgrounds, regulatory expertise, and transferable laboratory skills. Consequently, the organization encountered delays in filling critical roles and lost competitive talent to other firms.

The challenges identified in this case mirror broader trends documented in the literature on AI-enabled recruitment, where algorithmic systems frequently fail to capture evolving skill requirements and may perpetuate outdated hiring criteria (Chamorro-Premuzic et al., 2021). These findings underscore the need to align technological solutions with organizational objectives, incorporate human oversight, and regularly assess algorithmic performance to mitigate unintended consequences. This paper contends that the AI recruitment system's failure in this instance stems from a fundamental misalignment between algorithmic screening models and the complex, dynamic talent requirements of biotechnology roles. This case demonstrates that, in the absence of appropriate design, governance, and human integration, AI-driven hiring systems can impede rather than advance organizational performance.

## Problem Statement

The central issue in this case concerns the tension between the biotechnology organization’s pursuit of operational efficiency through artificial intelligence (AI)-enabled recruitment and the necessity of accurately identifying candidates with complex, interdisciplinary competencies. The organization adopted an AI-driven applicant screening system as part of a broader digital transformation strategy to reduce recruitment costs, accelerate hiring timelines, and standardize candidate evaluation. Although AI-enabled systems are widely implemented across industries to process large volumes of applications and improve administrative efficiency (Upadhyay & Khandelwal, 2022), empirical evidence indicates that such systems may yield unintended consequences if their design does not accommodate nuanced professional qualifications or human judgment (Chamorro-Premuzic et al., 2021; Jarrahi, 2018).

In this scenario, the AI system relied predominantly on rigid keyword matching and historical hiring patterns, which led to the systematic exclusion of highly qualified candidates with interdisciplinary skills, regulatory expertise, or transferable laboratory experience. Department leaders noted a significant decline in the number of candidates advancing to interviews for critical research and development roles, despite ongoing staffing shortages. Internal audits revealed that the algorithm did not capture diverse indicators of scientific competence, echoing a broader concern in the literature: inadequately designed or insufficiently supervised AI tools risk generating false negatives

and perpetuating inequities present in historical data (Köchling & Wehner, 2020; Raghavan et al., 2020). These outcomes compromise recruitment effectiveness, diminish organizational agility, impede innovation, and may erode workforce morale.

Theoretical perspectives on sociotechnical systems emphasize that technology implementation must align with human expertise and organizational workflows to achieve desired outcomes (Bostrom & Heinen, 1977; Pasmore, 1988). Within the biotechnology sector, misalignment between AI-driven recruitment processes and the complex requirements of scientific roles demonstrates the consequences of failing to integrate algorithmic systems with human oversight, domain expertise, and organizational norms. Research suggests that leaders may overestimate the objectivity of AI systems, presuming automated recommendations are neutral and reliable, which can intensify strategic misalignment and talent shortages (Raisch & Krakowski, 2021; Vial, 2019). In this instance, leadership prioritized operational efficiency over thorough evaluation of algorithmic outputs, illustrating how insufficient governance and accountability can heighten the risks associated with AI adoption.

This issue is especially pronounced in knowledge-intensive industries such as biotechnology, where positions demand interdisciplinary collaboration, domain-specific expertise, and rapid adaptation to emerging scientific developments (Chamorro-Premuzic et al., 2021). Algorithmic screening processes that undervalue nontraditional career trajectories or nuanced competencies may restrict access to specialized talent, delay project timelines, and diminish competitive advantage. Addressing this challenge requires an integrative approach that incorporates refined algorithm design, representative training datasets, structured human oversight, and strong leadership governance (Meijerink & Bondarouk, 2021). By systematically evaluating the causes of AI screening failures and implementing evidence-based interventions, organizations can balance efficiency gains with the strategic imperative of identifying complex, high-value talent, thereby ensuring that digital transformation initiatives advance rather than undermine workforce objectives.

## Purpose Statement

The purpose of this study is to examine the implementation and outcomes of an AI-driven applicant screening system within a global biotechnology company undergoing digital transformation, with a focus on how algorithmic hiring tools affect talent acquisition for specialized research and development roles. Organizations across industries increasingly adopt AI-based recruitment technologies to improve efficiency, reduce administrative burdens, and manage large applicant pools (Upadhyay & Khandelwal, 2022). However, research suggests that algorithmic decision-making systems can produce unintended consequences when automated evaluation criteria fail to capture complex human competencies or rely on historical data that may not reflect evolving workforce needs (Jarrahi, 2018; Köchling & Wehner, 2020). Accordingly, this study aims to identify the underlying causes of the system's rejection of highly qualified candidates, evaluate the organizational risks associated with automated recruitment, and develop evidence-based strategies to align AI screening processes with the evolving competencies required in biotechnology. By analyzing the intersection of digital transformation, algorithmic decision-making, and human resource management, this study seeks to provide actionable insights for organizations seeking to leverage AI technologies in recruitment while mitigating unintended consequences such as talent loss, operational delays, and reduced hiring effectiveness (Meijerink & Bondarouk, 2021).

This study also addresses a gap in the literature by investigating how AI-driven recruitment systems affect hiring outcomes in highly specialized scientific industries, where interdisciplinary expertise, regulatory knowledge, and nontraditional career pathways may

not be adequately captured by traditional keyword- or data-driven algorithms. Existing research on algorithmic hiring has largely focused on general corporate or service-sector environments rather than highly specialized knowledge-intensive industries (Chamorro-Premuzic et al., 2021; Upadhyay & Khandelwal, 2022). In fields such as biotechnology, organizations rely on employees with complex interdisciplinary skills and emerging competencies that may not be reflected in historical recruitment datasets or standardized résumé terminology. As a result, automated screening technologies may inadvertently exclude qualified candidates whose expertise falls outside conventional patterns captured by algorithmic models (Raghavan et al., 2020). The findings of this study will inform both theory and practice by offering guidance on how organizations can integrate AI recruitment tools with structured human oversight to support effective, efficient, and equitable talent acquisition in knowledge-intensive organizations (Jarrahi, 2018; Meijerink & Bondarouk, 2021).

## Significance Statement

The issue of AI-driven recruitment failures in biotechnology companies represents a widespread challenge for organizations implementing digital transformation in complex, knowledge-intensive environments. Research demonstrates that inadequately designed or monitored algorithmic hiring systems can systematically exclude qualified candidates, resulting in prolonged vacancies, operational inefficiencies, and loss of competitive talent (Upadhyay & Khandelwal, 2022; SHRM, 2022). These outcomes impede organizations from achieving strategic objectives and diminish their capacity to innovate and respond to rapidly changing industry demands. The recurrence of such challenges across multiple organizations indicates that this issue is pervasive and reflects broader concerns about the responsible adoption of AI in human resource management.

Failure to address this issue affects multiple stakeholders, including employees, hiring managers, and the organization's research and development objectives. Persistent recruitment inefficiencies may intensify workforce shortages, lower employee morale, and perpetuate inequities for candidates with nontraditional backgrounds or interdisciplinary expertise. Additionally, delayed hiring and talent attrition can undermine organizational resilience, impede innovation, and erode competitive positioning within the biotechnology sector. Implementing research-informed strategies, such as refining algorithm design, increasing human oversight, and aligning AI tools with evolving role requirements, can improve organizational effectiveness, promote equitable talent acquisition, and establish best practices for integrating AI into strategic human resource management.

## Literature Review

### *Overview*

The integration of artificial intelligence (AI) into organizational processes marks a significant transformation in strategic human resource management, especially in recruitment and talent acquisition. Organizations frequently adopt AI-driven screening systems to enhance hiring efficiency, reduce costs, and standardize decision-making (Upadhyay & Khandelwal, 2022). Despite these advantages, such technologies introduce challenges, including algorithmic bias, data limitations, and misalignment between automated screening systems and evolving job competencies. These challenges are evident in the case study "Digital Transformation and Algorithmic Hiring: Evaluating AI Recruitment Failures in Biotechnology Talent Acquisition," which describes how an AI-based screening system inadvertently excluded qualified candidates for specialized research roles. This literature review synthesizes research on AI recruitment technologies, algorithmic decision-making, and screening limitations, evaluates their impacts on

organizational stakeholders, and applies the McKinsey 7S Model, Kotter's change model, and digital transformation theory to interpret the case.

### *Scholarly Research on Digital Transformation and Algorithmic Hiring*

#### *Organizational Drivers and Strategic Intent*

Organizations adopt AI technologies in recruitment as part of broader digital transformation initiatives to improve operational efficiency, reduce costs, and enable data-driven decision-making (Vial, 2019; Kane et al., 2019). The primary organizational drivers include labor market pressures, talent shortages, competitive hiring demands, and the need to accelerate recruitment cycles (Black & van Esch, 2021). Research demonstrates that organizations often prioritize efficiency and process automation over strategic alignment with workforce capabilities, particularly in knowledge-intensive sectors such as biotechnology (Raisch & Krakowski, 2021).

The biotechnology case exemplifies this tension. Organizational leadership implemented an AI-driven screening system to streamline candidate evaluation for specialized scientific roles, prioritizing throughput and reducing administrative workload. Although these operational objectives were met, the AI system inadvertently excluded highly qualified candidates with interdisciplinary or nontraditional expertise. Empirical studies confirm that when AI adoption emphasizes efficiency metrics over strategic alignment, organizations risk misaligning technology with complex talent requirements, resulting in a gap between strategic objectives and workforce outcomes (Chamorro-Premuzic et al., 2021).

This theme underscores the importance of understanding the organizational context and strategic intent underlying AI adoption. Without careful alignment between AI systems and human capital needs, technology may produce unintended consequences, including talent gaps or diminished organizational agility. The following theme examines the operation of AI recruitment tools and the mechanisms through which they influence hiring decisions.

#### *Artificial Intelligence in Recruitment and Talent Evaluation*

AI recruitment technologies include résumé screening, candidate ranking, video interview analysis, and predictive assessments, designed to automate repetitive tasks and identify patterns within large datasets (Davenport & Kirby, 2016; Upadhyay & Khandelwal, 2022). Empirical research indicates that organizations using AI in recruitment often reduce time-to-hire and administrative costs, making these tools appealing for handling high application volumes (Black & van Esch, 2021).

Despite these advantages, AI systems often struggle to evaluate complex competencies, particularly in knowledge-intensive fields. Biotechnology roles demand interdisciplinary knowledge, regulatory expertise, and research-specific skills that are challenging to encode into structured algorithmic criteria (Chamorro-Premuzic et al., 2021). In the case study, the AI screening tool accelerated operational workflows but reduced the progression of qualified candidates to interviews. The algorithm's reliance on quantifiable indicators rather than nuanced professional capabilities led to the inadvertent exclusion of applicants whose resumes did not match predefined patterns, a phenomenon supported by empirical studies on AI oversimplification of candidate evaluation (Köchling & Wehner, 2020). Algorithmic decision-making is central to this theme. Algorithms analyze candidate data using statistical models to predict job performance or the likelihood of similarity to past hires (Raghavan et al., 2020). While these models enhance consistency, they can obscure the rationale behind selection decisions. In biotechnology, this opacity led HR staff and hiring managers to initially trust AI outputs without questioning the exclusion of

candidates with interdisciplinary backgrounds. The integration of AI tools thus requires both operational efficiency and human oversight to maintain decision quality.

This analysis demonstrates that AI recruitment systems are most effective when combined with human judgment, particularly in specialized industries. The subsequent theme addresses the limitations and biases inherent in these automated systems.

*Algorithmic Bias, Data Limitations, and Screening Errors*

AI hiring systems are prone to bias and data limitations because they often rely on historical employment data to train models (Raghavan et al., 2020). Such datasets may reflect prior hiring decisions, organizational preferences, or unintended discriminatory patterns (Chen, 2023). Consequently, AI tools can replicate systemic biases, favoring certain candidate profiles while disadvantaging others, particularly those with nontraditional or interdisciplinary backgrounds (Köchling & Wehner, 2020).

The biotechnology case demonstrates these dynamics. The AI system relied heavily on historical hiring data, emphasizing traditional academic pathways, thereby systematically excluding candidates with industry experience or emerging skill sets. Keyword-based screening further compounded this problem. While keyword matching streamlines candidate evaluation, research shows that these algorithms often fail to interpret contextual nuances, leading to false negatives (Chamorro-Premuzic et al., 2021; Black & van Esch, 2021). For example, candidates with extensive laboratory or regulatory experience were filtered out because their resumes lacked exact keywords recognized by the algorithm.

These findings are consistent with broader research on algorithmic errors. AI systems may misinterpret qualifications or fail to recognize transferable skills, leading to outcomes that undermine recruitment effectiveness (Upadhyay & Khandelwal, 2022). In practice, this can result in narrowed candidate pools, delayed hiring, and reduced workforce diversity. Implementing human oversight, continuous model retraining, and feedback mechanisms are essential strategies to mitigate these risks and ensure that AI tools support rather than constrain. Recognizing AI's limitations enables organizations to design systems that balance efficiency with equitable talent evaluation. The following theme explores the broader organizational consequences of AI misalignment.

*Organizational Misalignment, Performance Consequences, and Automation Bias*

Digital transformation initiatives succeed only when AI systems are aligned with organizational goals, workforce strategies, and operational realities (Vial, 2019; Kane et al., 2019). Misalignment occurs when technology is implemented without redesigning governance structures, workflows, and decision-making processes. The biotechnology case illustrates this risk: while the AI system reduced administrative workload, it simultaneously hindered the organization’s ability to hire specialized talent, producing operational bottlenecks and delaying R&D projects.

Automation bias further amplifies these challenges. Employees may defer to AI recommendations, perceiving them as objective or authoritative, even when outputs conflict with human judgment (Parasuraman & Riley, 1997; Jarrahi, 2018). In the biotechnology organization, HR staff initially accepted algorithmic decisions without scrutiny, exacerbating the exclusion of qualified candidates. Literature indicates that excessive reliance on AI can reduce organizational learning, slow corrective action, and diminish agility in addressing critical workforce gaps (Raisch & Krakowski, 2021).

These systemic effects have significant implications for organizational performance. Flawed AI hiring processes can delay recruitment of critical personnel, reduce diversity, and compromise innovation capacity (Kellogg et al., 2020). In biotechnology, missed hires directly impact scientific productivity, project timelines, and competitive advantage. Integrating case-specific insights with the literature underscores that technological

efficiency gains must be balanced with human oversight, cultural alignment, and ongoing evaluation. Organizations that achieve this alignment are better positioned to leverage AI while sustaining strategic workforce outcomes.

Across these four themes, research demonstrates that AI recruitment tools can enhance efficiency but also pose substantial risks in knowledge-intensive sectors. The biotechnology case illustrates how organizational drivers, AI mechanisms, algorithmic limitations, and systemic misalignment interact to produce unintended consequences. The literature consistently indicates that combining AI efficiency with human judgment, robust governance, and continuous adaptation is essential for achieving strategic workforce alignment. This thematic analysis provides the foundation for Sections 2–5 of the literature review, which examine AI's impact on organizational constituencies, its integration with the McKinsey 7S Framework, its application of Kotter's change model, and its application of sociotechnical systems theory.

## *The Impact of AI Recruitment and Digital Transformation on Key Organizational Constituencies*

Artificial intelligence (AI) recruitment systems, as part of digital transformation initiatives, have profound implications and do not operate in a vacuum; they shape experiences, roles, and outcomes across multiple stakeholders within knowledge-intensive organizations. Research consistently shows that digital hiring reforms influence employees, leadership, organizational culture, broader institutional performance, and external stakeholders often in ways that mirror the issues documented in the biotechnology case. Also, studies indicate that these impacts are multidimensional, affecting efficiency, equity, transparency, and strategic human capital management across organizations (Upadhyay & Khandelwal, 2022; Black & van Esch, 2021). Understanding these effects is critical, particularly in high-skill, knowledge-intensive sectors like biotechnology, where talent acquisition directly influences organizational innovation and competitive advantage.

### *Employees, Job Applicants, and HR Practitioners*

AI-enabled recruitment systems fundamentally reshape the roles and experiences of employees, job applicants, and HR practitioners by introducing operational efficiencies while also creating unintended workforce challenges. Automated screening tools expedite hiring workflows, standardize candidate evaluations, and reduce administrative burdens, enabling HR teams to prioritize strategic initiatives such as talent development, employer branding, and employee engagement (Chamorro-Premuzic et al., 2019; Black & van Esch, 2021). Nevertheless, research demonstrates that rigid algorithmic criteria may inadvertently exclude qualified candidates whose résumés do not match predefined keywords or historical hiring patterns (Köchling & Wehner, 2020; Raghavan et al., 2020).

In the biotechnology case, the AI system efficiently processed large volumes of applications but systematically excluded candidates with interdisciplinary expertise, regulatory experience, and nontraditional career paths. This exclusion reduced the interview pool and, in turn, increased workloads for existing employees due to staffing gaps on critical research teams (Ahuchogu et al., 2025). Additionally, HR practitioners experienced tension between process efficiency and the necessity of human judgment, as algorithmic outputs frequently conflicted with professional expertise (Jarrahi, 2018; Kellogg et al., 2020). These dynamics indicate that although AI tools provide operational benefits, they may unintentionally compromise talent quality and employee engagement, underscoring the need for oversight and adaptation, which leadership must address.

*Leadership and Decision Authority*

Leadership is central to effective AI adoption; however, excessive reliance on automated systems can increase strategic risks in talent acquisition. Leaders often overestimate the neutrality and accuracy of AI systems, presuming that data-driven algorithms are inherently objective (Raisch & Krakowski, 2021; Kellogg et al., 2020). Research indicates that without ongoing monitoring and sufficient technical literacy, organizational leaders may deploy AI tools that do not align with workforce requirements (Meijerink & Bondarouk, 2021; Chen, 2023).

In the biotechnology case, leadership prioritized efficiency and cost reduction over strategic talent alignment. Consequently, the AI screening tool systematically excluded candidates with essential interdisciplinary skills. The resulting misalignment between leadership objectives and the technical system delayed corrective action, leading to prolonged vacancies in research and development roles and negatively impacting organizational performance (Vial, 2019; Kane et al., 2019). These outcomes demonstrate that decision authority must be supported by oversight mechanisms, employee feedback, and ethical evaluation criteria to prevent unintended consequences. Leadership decisions influence organizational culture and HR practices, underscoring the need for governance, training, and collaborative oversight to ensure AI adoption advances strategic objectives.

*Organizational Culture and Norms*

AI recruitment systems shape organizational culture by influencing perceptions of fairness, transparency, and trust, thereby affecting employee behavior and engagement. Sociotechnical systems research demonstrates that technology adoption transforms both formal structures and informal norms (Trist & Bamforth, 1951; Jarrahi, 2018). Algorithmic decision-making may suggest that human judgment is subordinate to technology, encouraging overreliance on automated outputs (Parasuraman & Riley, 1997). Furthermore, studies show that employees may perceive AI systems as biased if certain applicant profiles are consistently excluded, thereby eroding trust and perceptions of inclusivity (Meijerink & Bondarouk, 2021; Chamorro-Premuzic et al., 2019).

In the biotechnology case, rigid keyword matching and reliance on historical hiring patterns resulted in the exclusion of interdisciplinary and nontraditional candidates. This exclusion reinforced a cultural norm that prioritized efficiency over critical evaluation and inclusivity. HR staff relied excessively on AI outputs, which reinforced automation bias and diminished engagement with the hiring process (Kellogg et al., 2020; Black & van Esch, 2021). Over time, these dynamics can erode organizational trust, decrease commitment to HR processes, and foster resistance to future digital transformation initiatives (Chen, 2023; Meijerink & Bondarouk, 2021). Organizational culture should be deliberately aligned with AI practices to promote fairness, trust, and critical oversight, thereby balancing operational efficiency with human judgment.

*Organizational Performance and Human Resource Processes*

Although AI recruitment tools enhance operational efficiency, these gains may compromise strategic alignment and negatively impact organizational performance. AI systems reduce time-to-hire, automate high-volume tasks, and standardize candidate evaluations (Upadhyay & Khandelwal, 2022; Black & van Esch, 2021). However, inadequate model design, reliance on historical data, and insufficient human oversight can lead to mismatches between hired talent and evolving organizational requirements (Raghavan et al., 2020; Chamorro-Premuzic et al., 2019).

The biotechnology case demonstrates that algorithmic screening excluded candidates with specialized interdisciplinary competencies, which delayed critical research initiatives. These staffing gaps led to operational inefficiencies, diminished innovation capacity, and

increased project costs (Köchling & Wehner, 2020; Raisch & Krakowski, 2021). HR teams had to re-evaluate rejected applicants, modify recruitment strategies, and introduce manual oversight, thereby offsetting the operational gains AI provided. This case highlights that AI tools cannot substitute for the nuanced assessment skills of human practitioners in knowledge-intensive industries. Successful AI adoption requires integration with HR processes, feedback mechanisms, and ongoing human oversight to ensure that efficiency does not undermine talent quality or organizational performance.

*Customers and External Stakeholders*

AI-driven hiring decisions have implications that extend beyond internal operations, affecting external stakeholders and organizational reputation. Research shows that failing to hire specialized talent can delay product development, hinder innovation, and impact service delivery (Upadhyay & Khandelwal, 2022; Black & van Esch, 2021). Moreover, ethical AI practices, transparency, and fairness are subject to increasing scrutiny from regulators, investors, and industry partners (Chen, 2023; Meijerink & Bondarouk, 2021).

In the biotechnology sector, delayed recruitment for research and development positions directly impacted product timelines and research outcomes. The exclusion of candidates and lack of transparency in algorithmic decisions threatened employer branding and stakeholder trust. Applicants viewed automated rejection outcomes as impersonal or unfair, potentially diminishing the quality of future applicant pools and challenging organizational legitimacy (Chamorro-Premuzic et al., 2019; Black & van Esch, 2021). These effects indicate that failures in AI recruitment have strategic consequences beyond internal HR performance, influencing market competitiveness and organizational credibility. Organizations should design AI recruitment systems that balance internal efficiency, human oversight, and external stakeholder expectations to ensure that technological adoption advances long-term strategic objectives.

This analysis demonstrates that AI adoption influences multiple organizational constituencies and exposes systemic challenges related to operational efficiency, workforce alignment, organizational culture, and external relationships. Section 3 will examine strategic and planning frameworks, such as the McKinsey 7S model, to address these multidimensional impacts and guide AI integration in knowledge-intensive environments.

## *Relevant Strategy/Planning Model: McKinsey 7S Framework*

The McKinsey 7S Framework provides an integrative strategy model that explains how misalignment across organizational elements can undermine strategic objectives, as seen in the biotechnology case. It is particularly relevant because digital transformation rarely involves technology alone; it involves strategy, structure, systems, shared values, skills, style, and staff aligning to support strategic goals (Waterman et al., 1980; Appelbaum et al., 2012) . In the context of the biotechnology case, where an AI-driven applicant screening system failed to deliver on strategic talent acquisition goals, the 7S Framework serves as both an analytical and corrective tool, helping to identify gaps between technological implementation and organizational objectives.

### *1. Strategy*

An organization's strategy defines its long-term objectives and the approaches to achieve them. In this case, the biotechnology firm's digital transformation strategy prioritized efficiency, scalability, and cost reduction by implementing an AI screening tool. However, research on strategic alignment indicates that focusing exclusively on operational metrics, such as throughput and cost, at the expense of human capital objectives like interdisciplinary expertise, can undermine competitive capabilities (Venkatraman, 1989; Raghavan et al., 2020). Such misalignment may result in operational efficiencies that

ultimately hinder broader talent and innovation goals. Application of the 7S Framework reveals that an effective strategy must balance efficiency with the complex requirements of specialized talent, ensuring that automation does not diminish workforce quality or innovation capacity.

***2. Structure***

The 7S model's structural element concerns how teams and reporting hierarchies are configured. In this case, automation shifted the focus of decision authority from human recruiters to algorithmic systems. Research on algorithmic management shows that when technology becomes the primary decision agent, it can disrupt traditional organizational roles and workflows, often without clear governance mechanisms (Kellogg et al., 2020). Structural redesign is needed to integrate human oversight and ensure that human evaluators remain central to decisions involving complex competencies. The framework highlights that structure must be adapted to integrate technology while preserving collaborative decision-making, ensuring that AI serves as a tool rather than a gatekeeper. Thus, clear structural integration would enable faster resolution of algorithmic recommendations.

***3. Systems***

Systems include formal procedures and processes such as recruitment workflows, candidate evaluation protocols, and feedback loops. The AI recruitment system functioned as a critical organizational system; however, its overreliance on keyword matching and historical hiring data revealed weaknesses in system design. The deployed AI system lacked robust monitoring, retraining mechanisms, and performance evaluation criteria that reflected evolving job requirements, collectively contributing to the exclusion of highly qualified candidates (Köchling & Wehner, 2020). Systems theory suggests that without feedback and adaptive capacity, technological systems degrade performance over time as the environment changes (Senge, 1990). In knowledge-intensive settings, adaptive systems incorporating human feedback outperform rigid ones (Davenport & Kirby, 2016). From a 7S perspective, systems must be designed to capture evolving role requirements and enable continuous adaptation, aligning technology with strategic talent needs. Thus, integrating human review loops addresses errors and preserves organizational knowledge.

***4. Shared values***

Shared values constitute the foundational beliefs of an organization. In this case, the biotechnology company's shared values emphasized data-driven objectivity and efficiency. Although these values facilitate technological adoption, they inadvertently diminish the role of human judgment and the evaluation of nontraditional competencies (Raisch & Krakowski, 2021). Research indicates that organizational cultures prioritizing technological objectivity without critically examining underlying assumptions may obscure biases and perpetuate exclusionary outcomes (Pasmore, 1988; Meijerink & Bondarouk, 2021). Adjusting shared values to prioritize ethical technology use, fairness, and human-AI collaboration is essential. The 7S Framework highlights that shared values should inform both human and technological decision-making, fostering ethical, equitable, and inclusive hiring practices. Reinforcing shared values in AI design encourages bias mitigation.

***5. Skills***

Skills are the capabilities that employees bring to their roles. In this case, HR staff lacked the analytical and algorithmic literacy required to critically evaluate screening outputs (Jarrahi, 2018). Scholarship on digital transformation underscores that technical adoption must be accompanied by capacity building, enabling employees to interpret, challenge, and supplement automated systems (Brynjolfsson & McAfee, 2014; Tarafdar et al., 2019). The 7S perspective indicates that organizations should cultivate employee skills that complement technological tools, empowering staff to monitor, adjust, and enhance AI

performance rather than relying passively on automation. Thus, training programs improve understanding and reduce reliance on automated recommendations alone.

***6. Style***

Leadership style encompasses decision-making behaviors and communication norms. In this case, a directive approach that prioritized technology adoption without inclusive consultation with HR teams or technical experts resulted in insufficient oversight (Upadhyay & Khandelwal, 2022). This top-down style reinforced excessive reliance on technology and delayed the identification of recruitment gaps. Research on change leadership demonstrates that collaborative styles facilitate more effective technology integration by engaging stakeholders in sense-making and co-creation of change agendas (Kotter & Cohen, 2002). The 7S Framework underscores the value of a collaborative leadership style that promotes review, feedback, and iterative improvement in the use of AI systems. A proactive management style ensures continuous monitoring and correction.

***7. Staff***

Staff encompasses human resources and talent deployment. In this case, AI screening displaced elements of human judgment, a phenomenon that workforce digitalization literature identifies as potentially leading to 'deskilling' in specific HR competencies unless roles are redefined (Autor, 2015; Susskind & Susskind, 2015). Aligning staff roles with technology, for example by designating 'AI overseers' or data interpreters, ensures that automation augments rather than replaces human expertise (Black & van Esch, 2021).

The application of the McKinsey 7S Framework to the biotechnology case demonstrates that failures in AI recruitment primarily result from systemic misalignment across strategy, structure, systems, shared values, skills, style, and staff, rather than from technological limitations alone. Examination of each element within the framework clarifies how organizations can realign these components to ensure that AI-driven systems facilitate, rather than hinder, talent acquisition and contribute to a cohesive and effective recruitment strategy. Incorporating human oversight into AI decision-making, fostering a culture of continuous learning, and training human resources personnel to interpret algorithmic outputs can collectively address the root causes of candidate exclusion and align digital transformation initiatives with strategic workforce objectives. Section 4 will examine change management models, such as Kotter's 8-Step model, to demonstrate that technological adoption must be integrated with behavioral and cultural alignment to achieve maximum impact.

## *Change Management Model: Kotter's 8-Step Change Model*

Kotter's 8-Step Change Model (Kotter, 1996) offers a structured framework for addressing AI-driven recruitment failures in biotechnology organizations. This model is widely recognized in organizational research and practice for its emphasis on leadership engagement and employee involvement, both of which are essential for the successful adoption of digital and technological innovations (Appelbaum et al., 2012). Its sequential steps guide organizations through creating urgency, building coalitions, developing a vision, and embedding change into organizational culture, directly aligning with the challenges identified in this case.

***1. Establish a Sense of Urgency***

The initial phase of Kotter's model requires establishing awareness of the need for change. Within the biotechnology sector, the AI recruitment system's inability to advance qualified candidates has led to operational bottlenecks, talent shortages, and diminished competitive advantage. Immediate attention to talent shortages in specialized biotech fields became necessary when the organization failed to communicate the urgency of the issue, resulting in low engagement and passive acceptance of AI-generated outcomes. Leaders can address

these risks by presenting data from internal audits and human resources performance metrics to stakeholders, thereby underscoring the urgency of correcting AI misalignment (Kotter, 1996). Research demonstrates that emphasizing tangible consequences encourages employees to participate actively in the change process (Hiatt & Creasey, 2012).

***2. Form a Guiding Coalition***

Effective organizational change requires a cross-functional team possessing both authority and credibility. In this context, the absence of a guiding coalition comprising HR leaders, technical experts, hiring managers, and AI specialists resulted in fragmented oversight. Collaborative decision-making ensures that both human judgment and algorithmic performance are considered during the redesign of the recruitment system (Appelbaum et al., 2012). Empirical studies indicate that diverse coalitions improve the quality of change initiatives by integrating multiple perspectives and areas of expertise (Kane et al., 2019).

***3. Develop a Vision and Strategy***

A clear vision should articulate how AI is intended to complement, rather than replace, human recruitment processes. For biotechnology organizations, this vision may emphasize equitable talent acquisition, interdisciplinary expertise, and improved efficiency. Strategy development should incorporate insights from the McKinsey 7S Framework to ensure alignment across structure, systems, skills, and shared values (Waterman et al., 1980). Empirical research demonstrates that organizations with a coherent vision and strategy are more successful in implementing technology-driven change (Kotter & Schlesinger, 2008). Ultimately, a clear vision linking AI adoption to both efficiency and equitable hiring would align stakeholders and clarify priorities.

***4. Communicate the Change Vision***

Kotter underscores the importance of consistent, repeated communication to ensure understanding and organizational buy-in. In this context, employees were unclear on AI's purpose, causing mistrust. Leaders should clearly articulate the limitations of the current AI system, outline the intended improvements, and define the HR staff's role in overseeing recruitment. Transparent communication reduces resistance to change and reinforces the shared values required to support both human oversight and algorithmic decision-making (Kotter, 1996; Armenakis et al., 2011).

***5. Empower Broad-Based Action***

Employees must be equipped with the necessary tools, training, and authority to act in accordance with the change vision. For instance, HR professionals should receive training to interpret AI outputs, identify false negatives, and make informed exceptions when candidate qualifications are not fully captured by the system. Thus, managers needed authority to override flawed algorithmic recommendations. Research demonstrates that empowerment facilitates the adoption of new systems, particularly when automation intersects with professional expertise (Jarrahi, 2018; Upadhyay & Khandelwal, 2022). Empowerment allows swift correction of errors and reinforces human judgment.

***6. Generate Short-Term Wins***

Short-term successes serve to demonstrate the benefits of change and reinforce organizational momentum. In the biotechnology context, this may involve piloting revised AI models for specific roles, measuring improvements in the progression of qualified candidates to interviews, and communicating these successes throughout the organization. Empirical evidence indicates that recognizing early wins enhances employee engagement and reduces resistance in technology-driven change initiatives (Kotter & Cohen, 2002). Highlighting early successes, such as improved placement of candidates with rare skill, sets reinforces AI benefits.

### *7. Consolidate Gains and Produce More Change*

Kotter's model emphasizes the importance of leveraging early successes to drive broader organizational transformation. In this scenario, continuous monitoring of AI screening outcomes, iterative algorithmic adjustments, and the integration of human oversight mechanisms would reinforce system reliability and address issues such as bias and false negatives. Studies highlight that consolidation is essential for sustaining performance improvements in complex, knowledge-intensive organizations (Kotter, 1996; Raghavan et al., 2020). Thus, feedback loops refine AI algorithms, embedding continuous improvement into HR processes.

### *8. Anchor New Approaches in the Culture*

Successful change ultimately requires embedding new practices within the organizational culture. For biotechnology organizations, this involves establishing human-AI collaboration, interdisciplinary assessment, and algorithmic transparency as core cultural norms. Institutionalizing these practices ensures that AI adoption aligns with organizational strategy, shared values, and long-term talent acquisition objectives (Raisch & Krakowski, 2021; Appelbaum et al., 2012).

Kotter's model is particularly well-suited to this case, as it offers a stepwise approach to integrating AI technology into organizational processes, emphasizing human oversight, cultural alignment, and strategic vision. When combined with the McKinsey 7S analysis, this model enables organizations to systematically address the root causes of AI recruitment failures, such as misaligned strategy, insufficient HR skills, and an organizational culture that prioritizes automation over informed judgment. Section 5 examines digital transformation theory, such as Sociotechnical theory, to demonstrate that AI systems require human involvement for effective error detection, contextual interpretation, and ethical oversight.

## *Digital Transformation Theory: Sociotechnical Systems Theory*

The implementation of AI-driven recruitment systems in biotechnology organizations can be examined using Sociotechnical Systems (STS) Theory. Originating from the work of Trist and Bamforth (1951) and further developed by Emery and Trist (1960), STS theory emphasizes the interdependence between social and technical subsystems within organizations. According to this theory, optimal organizational performance results from the joint design and alignment of technology, processes, human skills, and social structures, rather than viewing technological adoption as separate from human and organizational contexts (Pasmore, 1988; Cherns, 1976).

## *Key Components of Sociotechnical Systems Theory*

### *1. Technical Subsystem*

The technical subsystem includes the tools, processes, and infrastructure required to perform organizational tasks. In this context, the AI-driven applicant screening system constitutes the technical component. Although designed to accelerate hiring and reduce costs, the system's strict reliance on keyword matching and historical hiring patterns resulted in the systematic exclusion of qualified candidates with interdisciplinary or nontraditional backgrounds (Raghavan et al., 2020). Thus, the failure to include human judgment caused high-quality candidates to be overlooked. STS theory asserts that technology alone is insufficient for optimal performance; integration with human capabilities and process design is essential.

### *2. Social Subsystem*

The social subsystem comprises the individuals, relationships, roles, and cultural norms present within an organization. In the biotechnology example, HR staff, hiring managers, and leadership constitute the social subsystem. Their expertise in assessing specialized scientific competencies was diminished by algorithmic decision-making, resulting in a misalignment between human judgment and automated processes (Jarrahi, 2018; Upadhyay & Khandelwal, 2022). STS theory emphasizes that the social subsystem must actively engage with technical systems to sustain organizational effectiveness.

### *3. Joint Optimization*

STS theory emphasizes joint optimization, which requires that neither the technical nor social subsystem dominates; both must be designed to reinforce each other (Pasmore, 1988). In the biotechnology case, joint optimization was lacking, as AI systems prioritized efficiency over human expertise, leading to false negatives and the loss of talent. Empirical research indicates that organizations implementing AI with robust human oversight are more likely to achieve performance improvements and greater stakeholder satisfaction (Raisch & Krakowski, 2021; Kellogg et al., 2020).

### *4. Adaptation and Continuous Learning*

Effective sociotechnical design necessitates iterative adaptation, feedback mechanisms, and continuous learning. In this case, the AI model lacked processes for retraining or integrating feedback from hiring managers, which prevented adaptation to evolving role requirements (Köchling & Wehner, 2020). STS theory maintains that continuous learning and system adaptability are essential for sustaining performance in dynamic, knowledge-intensive sectors such as biotechnology.

### *5. Organizational Context and Performance Outcomes*

STS theory positions technical and social subsystems within the broader organizational context, highlighting the impact of misalignment on performance, culture, and stakeholder experience. In this instance, the disconnect between AI algorithms and human expertise led to delays in filling critical R&D positions, diminished hiring effectiveness, and potential competitive disadvantages. Empirical studies in digital transformation contexts demonstrate that organizations applying sociotechnical principles achieve higher adoption success, enhanced employee engagement, and more consistent performance outcomes (Henderson & Venkatraman, 1993; Ly, 2021).

STS theory is especially relevant in this context, as it offers a comprehensive framework for analyzing AI adoption. The shortcomings of the AI recruitment system stemmed not solely from technological limitations but from misalignment among technical algorithms, human judgment, organizational culture, and process design. Applying STS principles enables organizations to develop AI recruitment systems that balance automation with human oversight, integrate continuous feedback, and ensure that talent acquisition processes achieve both efficiency and quality objectives.

## Methodology

### *Type of Literature Review*

A narrative literature review was conducted to examine scholarly research on digital transformation, artificial intelligence (AI) recruitment systems, algorithmic decision-making, and their organizational implications. Narrative reviews are well-suited for synthesizing findings from diverse scholarly sources, interpreting complex organizational phenomena, and linking theoretical constructs to real-world contexts (Baumeister & Leary, 1997; Green et al., 2006). In this case study, this approach enabled the integration of interdisciplinary literature from management, human resource management, information systems, and organizational behavior. This facilitated an examination of how previous

studies have documented the adoption, benefits, and limitations of AI-driven hiring systems, as well as the relationship of these findings to organizational dynamics in the biotechnology sector. Synthesizing research across multiple academic domains, the review offers a comprehensive understanding of the influence of algorithmic hiring technologies on organizational decision-making, workforce outcomes, and digital transformation processes (Jarrahi, 2018; Upadhyay & Khandelwal, 2022).

***Search Strategy and Databases***

Peer-reviewed literature was identified through multiple academic databases to ensure comprehensive coverage across disciplines. The primary databases included Google Scholar, ProQuest, including ABI/INFORM, and Business Source Complete, each providing access to journals in management, human resource management, and information systems. The search was limited to publications from 2010 to 2024 to maintain relevance to contemporary digital transformation trends.

***Keywords and Boolean Operators***

A comprehensive set of keywords was used to guide the search process, focusing on the central constructs of artificial intelligence, recruitment systems, algorithmic decision-making, and organizational outcomes. The primary keywords included: "artificial intelligence in recruitment," "algorithmic hiring," "AI recruitment systems," "digital transformation in human resource management," "automated recruitment systems," "algorithmic bias in hiring," "recruitment automation," "talent acquisition technology," "human–AI decision-making," and "algorithmic management." Boolean operators such as AND, OR, and NOT were applied to refine the searches and ensure relevance. Example search strings included: "artificial intelligence" AND recruitment, "algorithmic bias" AND hiring, "digital transformation" AND human resource management, and "AI screening" AND hiring outcomes.

***Inclusion and Exclusion Criteria***

Articles were included if they were peer-reviewed, focused on AI recruitment or algorithmic decision-making in organizational contexts, addressed workforce impacts or ethical considerations, and were published within the last 10 to 15 years. Both empirical studies and theoretical papers were considered to provide a comprehensive understanding of organizational technology adoption (Chamorro-Premuzic et al., 2021; Raghavan et al., 2020). Articles were excluded if they were not peer-reviewed, focused exclusively on technical AI development, addressed unrelated AI applications such as healthcare diagnostics, or lacked methodological rigor.

***Thematic Grouping and Synthesis***

Over 30 articles were reviewed and organized into key themes for synthesis: (1) AI recruitment technologies and operational efficiency, (2) algorithmic bias and fairness, (3) human–AI decision-making and oversight, (4) leadership and governance in digital transformation, and (5) ethical and organizational implications of automated hiring. Thematic grouping enabled a structured comparison of findings and supported the integration of literature with the biotechnology case study, highlighting broader trends and risks associated with AI adoption in recruitment processes (Köchling & Wehner, 2020; Meijerink & Bondarouk, 2021).

Employing a narrative review methodology with systematic search strategies, defined inclusion criteria, and thematic synthesis situates the biotechnology case within a broader scholarly context. This approach offers insights into the challenges and opportunities presented by AI-driven recruitment technologies in knowledge-intensive organizations.

## Recommendations

The failure of the AI-driven recruitment system in the biotechnology organization reflects a broader pattern identified in the literature, where algorithmic hiring tools produce unintended consequences when misaligned with organizational needs, poorly governed, or implemented without sufficient human oversight (Köchling & Wehner, 2020; Raghavan et al., 2020). Addressing these issues requires a structured, evidence-based approach that moves beyond general recommendations to actionable, context-specific strategies. The following nine recommendations are organized across immediate, medium-term, and long-term priorities, each grounded in scholarly research and directly tied to the challenges observed in the case.

### *Immediate Actions (0–3 Months): Stabilizing Hiring Outcomes*

#### *1. Introduce Human Review for Rejected Candidates*

To mitigate the immediate exclusion of qualified candidates, the organization should establish a structured human review process for applicants rejected by the AI screening system. Human resource (HR) recruiters and research and development (R&D) hiring managers should conduct regular audits of rejected applications, with particular emphasis on critical roles experiencing persistent staffing shortages. This approach ensures that the AI system does not serve as the sole decision-maker in early-stage recruitment.

This recommendation is critical because research demonstrates that algorithmic screening systems frequently produce false negatives, especially when using rigid filtering criteria such as keyword matching (Köchling & Wehner, 2020). In the biotechnology context, these errors have led to the systematic exclusion of candidates with interdisciplinary expertise, thereby contributing to prolonged vacancies and operational inefficiencies. From a sociotechnical perspective, human oversight restores contextual judgment to decision-making processes, thereby enhancing accuracy and addressing algorithmic limitations (Jarrahi, 2018).

Responsibility for implementation should reside with HR leadership, while execution should be undertaken by recruiters in collaboration with R&D managers. These stakeholders possess the domain expertise required to identify overlooked competencies and to evaluate candidates comprehensively.

Success should be measured by an increase in the number of qualified candidates advancing to interviews, a reduction in time-to-fill for critical positions, and higher hiring manager satisfaction with candidate quality.

#### *2. Adjust Screening Thresholds and Keyword Sensitivity*

The organization should recalibrate the AI system's screening thresholds to minimize reliance on narrow keyword matching and to better recognize transferable, contextually relevant skills. Recommended measures include expanding keyword libraries, incorporating synonym recognition, and applying natural language processing techniques to interpret candidate qualifications more comprehensively.

This adjustment is warranted as research indicates that keyword-based screening models frequently overlook equivalent competencies articulated with alternative terminology, resulting in the systematic exclusion of qualified applicants (Chamorro-Premuzic et al., 2021). In the referenced case study, the AI system's rigid criteria failed to identify candidates with relevant laboratory and regulatory expertise, underscoring a misalignment between the algorithm's logic and the actual skill set.

The data science and HR analytics teams are responsible for implementing these adjustments. These teams must collaborate to refine model parameters and validate modifications using historical recruitment outcomes.

Success should be evaluated by increased diversity among candidate profiles progressing through the recruitment pipeline, improved alignment between shortlisted candidates and job requirements, and reduced false-negative screening errors.

### *Medium-Term Improvements (3–9 Months): Redesigning the AI Recruitment System*

#### *3. Align AI Models With Role-Specific Competencies*

The organization should revise its AI recruitment model to address the specific competency requirements of biotechnology roles by integrating input from subject-matter experts. This process requires the involvement of senior scientists and R&D leaders to define the skills, experiences, and indicators of success relevant to research positions.

This recommendation is essential because generic or standardized AI models do not adequately address the demands of knowledge-intensive industries, where positions require complex combinations of technical, regulatory, and interdisciplinary expertise (Kane et al., 2019). The case illustrates that the current system fails to account for these nuances, leading to suboptimal candidate selection and talent misalignment.

Responsibility for this initiative should be distributed among HR leadership, data scientists, and R&D managers to ensure that both technical and domain-specific perspectives inform the model design. Success should be evaluated by improved hiring outcomes, such as enhanced alignment between candidate qualifications and job performance, shorter vacancy durations, and higher retention rates among newly hired employees.

#### *4. Improve and Diversify Training Data*

The organization should expand and refine the datasets used to train its AI recruitment system to include diverse employee profiles, particularly those representing nontraditional and interdisciplinary career pathways. This process involves auditing existing data, identifying gaps, and incorporating additional sources that reflect evolving workforce needs.This recommendation is grounded in research showing that machine learning models replicate patterns present in their training data, which can perpetuate historical biases and limit adaptability (Raghavan et al., 2020). In the biotechnology case, reliance on outdated hiring data contributed to the exclusion of candidates with emerging skill sets and interdisciplinary expertise.

Responsibility for this effort lies with the data science team, with oversight from HR to ensure alignment with organizational talent strategies. Success should be measured through reductions in bias indicators, increased representation of diverse candidate profiles, and improved predictive accuracy of the AI system.

#### *5. Redesign AI as a Decision-Support Tool (Sociotechnical Integration)*

The organization should transition from a fully automated screening model to a hybrid system in which artificial intelligence serves as a decision-support tool rather than an autonomous decision-maker. This transition requires redesigning workflows to ensure that human judgment remains central to recruitment decisions, especially for complex or nontraditional candidate profiles. Sociotechnical systems theory supports this approach, emphasizing that optimal outcomes are achieved when technological systems are integrated with human expertise (Bostrom & Heinen, 1977; Jarrahi, 2018). In the case study, insufficient integration resulted in overreliance on algorithmic outputs and the exclusion of qualified candidates.

Human resources leadership and system designers are responsible for implementing this change. They must redefine recruitment workflows and establish clear decision checkpoints. Success should be measured by improved hiring quality, increased recruiter

engagement, and greater alignment between artificial intelligence recommendations and human evaluations.

### *Long-Term Organizational Changes (9–18 Months): Governance, Culture, and Sustainability*

#### *6. Establish AI Governance and Oversight Structures*

A critical long-term priority for the biotechnology organization is to establish formal AI governance and oversight structures to ensure that the recruitment system aligns with organizational goals, ethical standards, and workforce requirements. The case illustrates that the absence of structured oversight enabled the AI system to operate as an unmonitored decision-making authority, leading to persistent screening errors, exclusion of qualified candidates, and delayed corrective action. This outcome is consistent with broader literature findings indicating that algorithmic systems can obscure accountability and shift decision authority when governance mechanisms are weak or absent (Kellogg et al., 2020; Newell & Marabelli, 2015).

To address this issue, the organization should establish a cross-functional AI governance committee to oversee the design, implementation, and ongoing performance of the AI recruitment system. The committee should include representatives from human resources, data science, legal and compliance, and research and development leadership. Including R&D leaders is particularly important, as they provide domain-specific expertise necessary to assess whether the algorithm accurately reflects the interdisciplinary competencies required for biotechnology roles. This recommendation is supported by research demonstrating that cross-functional governance enhances algorithmic accountability and aligns technical systems with organizational objectives (Davenport et al., 2020).

This governance structure is essential because the failure observed in the case was not solely a technical issue but an organizational one, specifically a breakdown in oversight, accountability, and alignment between the AI system and workforce needs. In the absence of governance, the organization assumed the algorithm was functioning effectively, despite clear evidence of declining candidate flow and ongoing staffing shortages. Research on AI and organizational decision-making indicates that overreliance on automated systems can lead to strategic misalignment and reduced performance when leaders fail to critically evaluate algorithmic outputs (Raisch & Krakowski, 2021). Establishing formal governance addresses this gap by reintroducing accountability and structured evaluation into the recruitment process.

Responsibility for implementing this governance framework should reside with senior leadership, specifically the Chief Human Resources Officer (CHRO), in collaboration with the Chief Data Officer (CDO) or equivalent technology leadership. These leaders are accountable for establishing the governance committee, defining its authority, and integrating it into organizational decision-making processes. Committee members from HR, data science, legal, and R&D should contribute domain-specific insights, review recruitment outcomes, and recommend adjustments to the AI system. This shared responsibility ensures that governance is not siloed and reflects the interdisciplinary nature of AI-enabled decision-making.

As part of its oversight function, the governance committee should conduct regular algorithm audits and performance monitoring. These audits should assess both technical performance and organizational outcomes, including false-negative screening rates, diversity of candidate pools, time-to-fill for critical positions, and alignment between candidate qualifications and job requirements. This action is essential because research indicates that AI systems can perpetuate bias or decline in effectiveness over time if not

continuously monitored (Raghavan et al., 2020; Chen, 2023). In the biotechnology case, the absence of such monitoring allowed exclusionary patterns to persist, contributing to talent shortages and operational inefficiencies.

The success of this recommendation can be measured through several concrete indicators. First, reducing false-negative screening errors should increase the proportion of qualified candidates advancing to interview stages. Second, decreased time-to-fill metrics for critical R&D roles would indicate improved alignment between the recruitment system and organizational needs. Third, increased diversity and interdisciplinarity in candidate pools would demonstrate that the system is effectively identifying a broader range of qualified applicants. Finally, regular audit reports and documented system adjustments should provide evidence of ongoing oversight and continuous improvement.

### *7. Implement Continuous Monitoring and Algorithm Audits*

The organization should implement ongoing monitoring processes and conduct systematic audits of the AI recruitment system to assess performance, identify potential bias, and ensure alignment with organizational objectives. Key metrics, including false-negative rates, time-to-fill, and candidate diversity, should be consistently tracked and analyzed.

This recommendation is critical, as AI systems may degrade over time or generate unintended outcomes if not actively monitored (Chen, 2023). In this case, the lack of monitoring allowed screening errors to persist, contributing to ongoing talent shortages.

Responsibility for monitoring should be jointly assigned to the data analytics team and the AI governance committee. Success should be evaluated based on sustained improvements in hiring metrics, timely identification of system issues, and documented modifications to algorithm parameters. Over time, these indicators should collectively reflect improved recruitment outcomes and stronger organizational performance.

### *8. Provide Training to Reduce Automation Bias*

Targeted training programs for human resources staff and hiring managers are recommended to reduce automation bias and enhance critical evaluation of AI-generated outputs. These initiatives should emphasize the limitations of AI systems and underscore the essential role of human judgment in decision-making.

This recommendation is supported by research indicating that individuals frequently over-rely on automated systems, presuming their outputs are inherently accurate (Parasuraman & Riley, 1997). In the case study, such bias led to uncritical acceptance of flawed screening decisions.

Human resource leadership and learning and development teams are responsible for implementing training. Additionally, senior leadership should play a supportive role by endorsing the importance of training and reinforcing expectations that AI tools are to be used as decision-support systems rather than as authoritative decision-makers.

Success should be measured by increased human intervention, improved decision quality, and enhanced confidence in recruitment processes. Over time, these metrics are expected to indicate a transition from passive reliance on automation to active, informed engagement with AI tools.

### *9. Strengthen Leadership Accountability and Strategic Alignment*

The organizations should ensure that leadership evaluates AI recruitment systems based on their impact on hiring quality and organizational performance, rather than focusing solely on efficiency metrics. Achieving this objective requires integrating AI oversight into strategic planning and establishing accountability mechanisms for recruitment outcomes.

This recommendation is essential because the case illustrates that an initial leadership emphasis on efficiency led to misalignment between the AI system and workforce

requirements. Research on digital transformation underscores the significance of leadership in aligning technological adoption with organizational strategy (Vial, 2019).

Executive leadership, including the Chief Human Resources Officer and senior executives responsible for digital transformation initiatives, must champion strategic alignment and establish governance protocols.

Success should be measured by improved hiring outcomes, reduced vacancies, the frequency and effectiveness of algorithm audits, oversight committee reviews, and enhanced workforce capability.

The recommendations outlined in this section establish a comprehensive framework to address AI-driven recruitment challenges within the biotechnology organization. Implementing immediate corrective actions, redesigning the AI system, and instituting long-term governance and cultural practices will enable the organization to create a more effective and equitable recruitment process.

These recommendations are based on empirical research and directly address the root causes identified in the case, such as algorithmic bias, data limitations, and organizational misalignment. They underscore the importance of a sociotechnical approach that integrates human expertise with technological capabilities, ensuring that AI functions as a tool to enhance, rather than replace, human decision-making.

Adopting this structured approach will enable the organization to improve hiring outcomes, strengthen its competitive position within the biotechnology industry, and promote the responsible use of AI in organizational decision-making.

### *Organizational Risks and Tradeoffs Associated with AI-Enabled Recruitment*

The implementation of artificial intelligence (AI) in recruitment provides substantial efficiency gains but also introduces significant organizational risks and tradeoffs that require careful management. In the biotechnology case, adopting an AI-driven screening system increased the speed and scalability of applicant processing while diminishing the organization's capacity to accurately identify complex, interdisciplinary talent. This outcome exemplifies the broader tension in the literature between efficiency and decision quality in algorithmic systems (Raisch & Krakowski, 2021).

A primary trade-off concerns increased operational costs associated with system refinement and oversight. Although organizations often adopt AI systems to reduce recruitment costs, the case demonstrates that misaligned algorithms can lead to downstream costs, including prolonged vacancies, reduced productivity, and the need for corrective interventions. Research indicates that ongoing investments in system monitoring, training data updates, and human oversight mechanisms are essential to maintain effective performance (Raghavan et al., 2020). While these investments may offset initial cost savings, they are necessary to prevent more substantial strategic losses.

Another challenge is the potential for slower hiring processes when corrective measures are implemented. For instance, incorporating human review of AI-rejected candidates or conducting algorithm audits can extend recruitment timelines. However, the case demonstrates that prioritizing speed over accuracy led to missed talent and ongoing staffing shortages. Studies indicate that balancing automation with human judgment enhances long-term hiring outcomes, even if it introduces short-term inefficiencies (Jarrahi, 2018). Organizations can address this tradeoff by implementing targeted review processes, such as concentrating human oversight on high-priority roles rather than applying it uniformly to all applications.

A further significant risk is system complexity and the organization's dependency on AI technologies. As recruitment systems become more advanced, they may lose transparency and become increasingly difficult for HR professionals and leaders to

interpret. This complexity can foster greater reliance on algorithmic outputs and diminish critical evaluation, a phenomenon known as automation bias (Parasuraman & Riley, 1997). In the biotechnology case, this led to unchallenged screening decisions and delayed recognition of system failures. To address this risk, organizations should invest in training programs and governance structures that improve employees' understanding of AI systems and clarify their limitations (Kellogg et al., 2020).

There are also strategic and cultural trade-offs associated with AI adoption. Excessive reliance on standardized, data-driven evaluation can inadvertently discourage diversity in candidate profiles and limit the organization's capacity to identify nontraditional talent pathways. In knowledge-intensive sectors such as biotechnology, where innovation relies on interdisciplinary expertise, this may erode competitive advantage. Addressing this challenge requires aligning AI systems with organizational values and workforce strategies to ensure recruitment processes remain flexible and inclusive (Chamorro-Premuzic et al., 2021). Effective risk management requires a sociotechnical approach that integrates technological capabilities with human expertise and organizational oversight. This approach involves implementing governance frameworks, continuous monitoring systems, and structured points for human intervention within recruitment workflows. Such measures enable organizations to balance efficiency gains with the need for accurate, context-sensitive decision-making.

In summary, although AI-enabled recruitment systems offer clear benefits in efficiency and scalability, they also introduce trade-offs in cost, speed, complexity, and decision quality. The biotechnology case demonstrates that these challenges are both organizational and technical, requiring deliberate management strategies. Addressing these risks through targeted interventions allows organizations to leverage AI effectively, minimize unintended consequences, and align recruitment practices with long-term workforce objectives.

## Conclusion

This case study demonstrates that the implementation of artificial intelligence (AI) in recruitment, although intended to enhance efficiency and standardize decision-making, can introduce significant organizational challenges if not aligned with the complexity of workforce requirements. Drawing on interdisciplinary literature and the biotechnology case, the analysis indicates that AI-driven hiring systems are especially susceptible to algorithmic bias, screening errors, and misalignment with evolving skill demands. In this instance, the organization's dependence on keyword-based screening and historical data led to the systematic exclusion of highly qualified candidates, thereby undermining hiring effectiveness and contributing to talent shortages in critical research and development positions.

The findings of this study emphasize a central lesson: AI recruitment systems do not guarantee effectiveness solely through increased efficiency. Their success depends on integration with human expertise, organizational context, and strategic workforce requirements. The literature consistently demonstrates that, in the absence of appropriate governance, human oversight, and sociotechnical integration, AI systems may exacerbate existing limitations rather than enhance decision quality. In knowledge-intensive industries such as biotechnology, where positions demand interdisciplinary expertise and nuanced evaluation, the risks associated with excessive reliance on automated screening are especially significant.

This case further underscores the importance of leadership and organizational design in determining the outcomes of digital transformation initiatives. Effective implementation of AI in recruitment necessitates more than technological adoption; it requires ongoing

monitoring, alignment with organizational objectives, and active participation from domain experts. Organizations that do not establish these mechanisms risk undermining both operational performance and long-term competitive advantage.

Ultimately, this study demonstrates that the challenges associated with AI-enabled hiring are not solely technical but are fundamentally organizational. The biotechnology case illustrates that efficiency gains from automation must be balanced with the need for accurate, context-sensitive decision-making. As AI continues to transform human resource practices, organizations must ensure that these systems augment, rather than supplant, human judgment. The broader implication is that in complex fields where talent is critical to success, the effectiveness of AI in hiring will depend less on the extent of automation and more on the thoughtful integration of human and technological capabilities.

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