Nature and Information Engineering Publishing

Human Resource Strategy and Practice

https://journals.niepublish.com/hrsp

REVIEW

AI-Driven Talent Management: Human-Centered, Competency-Based Recruitment

Viraj Tathavadekar [1*], *Nitin Mahankale* [2*]

[1] *Department of Management, Symbiosis International Deemed University, Pune 411051, India*

[2] *Symbiosis Centre for Management Studies, Symbiosis International Deemed University, Pune 411014, India*

ABSTRACT

The purpose of this perspective is to explore the potential of humanistic artificial intelligence (AI) to revolutionize talent management by emphasizing skills, emotional intelligence (EI), and cultural match through competency-based recruitment systems as opposed to the traditional, resume-centric selection processes. The methodological approach to this paper has been conceptually developed, presenting an interwoven review using available theory to delineate the weaknesses of automated applicant tracking, and introducing human-centered design principles for the next-generation talent management platform. No empirical investigation has been conducted. Conventional keyword-based recruitment practices fall short of addressing overlap in skills and fit in culture, nullifying their efficacy. AI models are competency-driven for the purpose of bias reduction, profiling behavioural indicators, and judging the proficiency of soft skills. A critical focus on human-centered design practices can make recruitment more inclusive while supporting the efficient use of technological resources. As a potential practical implication, a suggestion could be offered that should be further investigated. The AI recruitment systems may allow companies to go beyond parsing resumes to assess the EI of candidates and their transferable competencies, potentially fostering a truly diverse talent pool and resulting in better hiring practices. These AI-driven recruitment systems could have an impact on social justice as they weed out bias, creating more opportunities for fair access to candidates coming from non-traditional backgrounds, and all for the promotion of workplace diversity founded on meritocracy alone. Value/Originality: This paper occupies a unique niche in aligning human-centric design,

*CORRESPONDING AUTHOR:

Viraj Tathavadekar, Department of Management, Symbiosis International Deemed University, Pune 411051, India; Email: phdgrad.viraj.tathavadekar@siu.edu.in; Nitin Mahankale, Symbiosis Centre for Management Studies, Symbiosis International Deemed University, Pune 411014, India; Email: nitin.mahankale@scmspune.ac.in

ARTICLE INFO

Received: 12 January 2026 | Revised: 5 August 2026 | Accepted: 12 August 2026 | Published Online: 19 August 2026

DOI: https://doi.org/10.63385/hrsp.v2i2.101012

CITATION

Tathavadekar, V., Mahankale, N., 2026. AI-Driven Talent Management: Human-Centered, Competency-Based Recruitment. Human Resource Strategy and Practice. 2(2): 43–60. DOI: https://doi.org/10.63385/hrsp.v2i2.101012

artificial intelligence ethics frameworks, and competency-based recruitment structures, thereby ensuring a balance in human-technology convergence in ethical recruitment operations.

Keywords: AI-Powered Recruitment; Talent Management; Human-Centered Systems; Competency-Based Hiring; Diversity in Recruitment; Employee Experience Optimization

1. Introduction

Artificial intelligence (AI), applied to human capital management, is creating substantial change in present-day organizational practices. It is the obsolescence embodied in recruitment systems, which are typically based on keyword tracking, therefore excluding qualified people or even competent enough if their keyword is not deemed fit into a "whitelist" on one's resume. Rather, the age-old approaches place more emphasis on matching credentials against a genuine comprehension of competency. This approach actually reduces the focus on the skills deemed truly essential from a job perspective in today's world.

The rise of AI in Human Resources (HR) makes it possible to reshape recruiting around human-centered design, assessing abilities rather than merely matching text. Systems that scan a curriculum vitae (CV) for keywords, with no real analytics behind them, rarely identify the full universe of qualified candidates, because CV parsing attends only to surface-level terms. The shift from credential-based assessment to competency-based talent acquisition is instead aimed at identifying transferable competencies across diverse professional backgrounds.

Today's contemporary organizations are under growing pressure to advance diversity, equity, and inclusion while sustaining operational efficiency. The historical modes of recruitment undesirably soured candidates rooted in non-traditional backgrounds, coming career changers bearing transferable skills, and underrepresented groups whose lived experiences lie outside conventional resume templates. Human-centered AI-driven recruitment systems aim to pass the widespread exclusions.

Designing humane data is a process involving ethical considerations in creating AI-driven talent management systems. The decision must, in the end, approve a human sense of relevancy over the accuracy of the algorithm itself. The AI model to be developed is to be used in evaluating the "emotional intelligence," "adaptability," and "cultural fit" of potential employees. But their norms will be minimally accountable and transparent.

Human-centered AI recruitment has untold transformational possibilities for the future, as part of this paper. The theoretical background driving the practicalities and social impacts of competency-driven recruitment is detailed. Paradigmatic changes, discussed via **Table 1** in the paper, in view of the comparison between a traditional Applicant Tracking System (ATS) and an AI-driven competence-based approach, consist of another consideration.

Table 1. Comparative Analysis of Traditional ATS and AI-Enabled Competency-Based Hiring Systems.

Dimension	Traditional ATS	AI-Driven Competency-Based System
Primary Filter	Keyword/credential matching	Skills and behavioural competency assessment
Soft Skills	Not assessed; highly subjective	Natural language processing (NLP), video analytics, and simulation-based analysis
Bias Mitigation	Minimal; often perpetuates bias	Algorithmic fairness audits and diverse data curation
Candidate Experience	Opaque and impersonal	Transparent, feedback-oriented, and accessible
Diversity Outcomes	Credential filtering limits diversity	Skills-based inclusion broadens talent pools
Cultural Fit	Informal, subjective impression	Cultural contribution metrics
Transparency	Limited	Explainable AI with auditable criteria

Source: Authors' creation.

1.1. Theoretical Framework: Human-Centered AI in Talent Management

The AI selection criteria are always oriented towards human-oriented applications, cutting across human-computer interaction, organizational psychology, and machine learning ethics. Traditional automated recruiting software works on a framework derived from behaviorism, where a standard input yields standard outputs, apparently reduced to keyword frequencies to be matched to candidates' qualifications. This reductionist view does not dig very deep in its description of the varied potentialities of humans, thus making it futile in an explanation of an employment counterpart along with a corporation.

Human-centered design stands diametrically opposed to such notions since it prioritizes the user experience, the engagement of shareholders, and the consideration of ethical issues across all development stages of the system. From their research, Nguyen et al. pointed out that dimensioned design approaches do produce outcomes that are more responsive and inclusive [1]. In recruitment, human-centered design is when you dissect the candidate's experiences, the recruiter's workflows, and the dynamics of organizational culture in designing AI systems that would enhance and not replace human judgment. Comparable human-centered design approaches are documented across a wide range of applied domains, including building engineering, aviation, tourism, and smart-city planning, which together demonstrate the generalisability of the paradigm [2–5].

Competency-based assessment diverges significantly from credential-influenced evaluation by identifying and categorizing the capabilities that actually determine task performance, rather than relying on prior education and job designations. While determining competencies, the approach examines the willingness of the individual to do what it takes to get the job done. In short, the definition reflects an approach in line with employer needs in an age that prizes flexibility, creativity, and emotional intelligence.

The AI-based recruitment emotional intelligence assessment brings various difficulties and opportunities with it. As opposed to assessing technical skills, which are more easily gauged through standard tests, the evaluation of emotional intelligence involves behavioral cues, style of engagement, and other social clues. Therefore, it represents a major revolution in recruitment technologies to develop artificial-intelligence-based models that can assess emotional intelligence appropriately.

Achieving a fine balance through AI systems and deciding cultural fit via this system necessitates the recognition of cultural unity and diversity. It supports good morale in employees and promotes the retention of employees, too. If aligned on a much too anti-cultural ground, it may even actually be contributing toward cultural or corporate hegemony. Integration with AI talks about the importance of cultural influence more than that of cultural assimilation. It should matter most that a candidate can contribute to diverse perspectives that shape the culture of the company positively.

The integration of bias-reducing mechanisms in AI recruitment systems plays a major role in the field of social responsibility. Equally, the traditional hiring mechanism often demonstrates a reproduction of systemic bias through the decision-maker's personal arbitrary action, and the homogeneity of members in the selection committee. AI systems help this by doing hidden evaluations, well-curated datasets, and transparent algorithms. Most importantly, the necessity of continued review and ethical considerations remains essential.

1.2. Structural Constraints in Conventional Recruitment Models

A recruiter is an automated tracking system that is driven by speed over substance, systematically disqualifying first-class candidates and at the same time, failing to identify the candidates who might have the best matches for organizational matters. Keyword-filtering systems work with concepts that match candidates with keywords a certain number of exact words, e.g., in most cases, leading to their ignoring synonyms, changes in context, or lateral skills expressed through different wordings. That is why an equally skilled candidate from a different industry or speaking a different language will in all cases be left out, limiting diversity of talent pools, hence impeding organizational creativity.

The emphasis on credentials interferes with the non-traditional candidates' scope. All learners wishing to embrace new careers, self-taught learners, and underrepresented individuals find it rather challenging to fit into a credential-oriented evaluation system that looks more upon a catalog of facts and trivia details rather than a systemized human knowledge. The credentialism system exacerbates existing divides and prevents a truly diverse spectrum of real talents from shining. In any case, a biased interview assessment and some form of inconsistent interpretation become more subjective alternatives in evaluating traditional recruitment. Probably, some soft skills evaluation may have insufficiencies. These findings typically arrive through hypothetically unforeseen biases. Emotional, adaptive, and interactive capabilities are yet to be standardly measured, hence a haphazardly-determined selection process waits in store. Evidence from inclusive protocol design shows that deliberately structured, equity-oriented recruitment processes materially widen participation [6], while purpose-built technology platforms can open access for candidates who are routinely screened out, including individuals with intellectual disabilities [7].

Lack of transparency in traditional recruitment processes poses challenges for both sides of the spectrum, the potential candidates and the recruiters. Post-rejection, neither the reasons for rejection nor any specific criteria on the basis of which they were scored, are discussed with the candidates. The same is true for the organization that was in the dark about how to measure the effect of its internal recruitment arrangements, thus keeping it from treating the inherent issues. Evaluation of cultural fit in traditional systems usually revolves around subjective impressions, which will end up favoring those candidates who happen to come from backgrounds like sponsors, creating an organization of mixed identity and robbing it of the broad views that are essential for establishing more creativity and problem-solving.

1.3. Human-Centered Design Principles for AI Recruitment

Contreras-Cruz et al. show that human-centered design improves employee experience and user efficiency through solutions that meet the actual needs of users [8]. Human-centered design therefore requires that principles relating to the user, culture, technology, philosophy, and policy be meticulously observed and applied to AI systems, and that equality, diversity, and inclusion be embedded in usability testing rather than added afterwards [9]. Consequently, this extends to recruitment by ensuring that the perspective of the candidate, including candidates from underrepresented groups, is given due importance.

Inclusion and accessibility need to be core principles. These measures include alternative input methods for disabled candidates, multilingual support, and evaluation criteria free from indirect discrimination. Schoonderwoerd et al. describe frameworks for developing explainable AI systems that preserve human control while enhancing decision-making [10]. Systematic evidence from explainable medical imaging AI shows that explanations are useful only when they are designed around the people who must act on them [11], and evidence-based approaches to explainable AI provide empirical methods for testing whether an explanation actually improves decision quality [12]. To develop AI-powered recruitment systems, ensure continuous development of human-centered AI systems through feedback that can be zoomed in on, metrics on performance, and changing organizational objectives. Iterative development with continuous stakeholder input should ensure the system stays responsive, just, and effective.

1.4. Competency-Based Assessment Framework

Competency-based assessment frameworks rebase evaluation from title-based to candidate skills-based. Success in professional situations is judged more from the skill set exhibited rather than the formal qualifications, permitting the organization to have a wider scope for selecting talent alongside effectively predicting the quality of anticipatory hire outcomes.

Technical competency evaluation through the selection of tools that can be used to evaluate the candidate's quality. These include more mutual, general processes like person-preview, job-based testing, and task-specific assessments. An organization looking to acquire more competent creators may take a step further and combine developmental coaching into these processes.

The evaluation of soft skills happens to be a more complicated proposition due to its essential nature. Better off is where AI can model some acceptance of human relations like identifying communication styles, reaction consistencies, and other behavioral indicators. Blasco-Blasco et al. establish a structured relationship between competency-based questionnaire design and the range of capabilities that can be measured during hiring [13]. Simulation-based assessment of technical skill offers a well-documented precedent for structured, observable competency evaluation [14], and systematic reviews of skill-level classification supply criteria and performance indicators that can be adapted to recruitment [15]. Digitized, task-based instruments [16] and virtual skills-based assessments focused on communication [17] further demonstrate that competency can be measured reliably outside the traditional interview.

Problem-solving evaluation within the competency-based framework pops out as a systematic way to examine candidates' analytical thinking capability, their creativity, and their capacity to cope in a controlled testing situation.

Therefore, such a system operating along these lines may bring forth scenario tasks standardized to a certain extent, which enable the AI system to gauge the relationship between facilitating tasks and solution path, decision-making process, and learning fullness. Evaluation, as contributing to the evaluation of cultural contribution, presses on evaluating the contribution a candidate can make to the culture, apart from simply conforming to the presently available standard or requirement. This means the evaluation of alignment of values, collaboration and innovation and the promotion of diversity and academic excellence.

Transferable skills recognition AI helps organizations to accurately identify and transplant competencies such that the definition of the current profile requirements gets widened to attract candidates of different backgrounds; AI links competencies across various job contexts and helps in identifying non-traditional skills carried by a job candidate via disciplines like healthcare, education, or military service.

Figure 1 depicts an all-encompassing competency assessment matrix that merges within one common evaluation framework technical skills, soft skills, problem-solving skills, and cultural contribution metrics. This multidimensional approach renders holistic candidate profiles, thereby enabling more informed hiring decisions and removing reliance on traditional credential indicators. On the left vertical axis are the competency dimensions that have been identified as relevant to be assessed: technical skills, soft skills, problem solving skills and cultural contribution. On the upper horizontal axis are the five types of instruments that would be used by an AI system to assess each of those dimensions: portfolio analysis, behavioral assessment, simulation tests, communication analysis and value alignment test. Each cell indicates whether a certain instrument is a suggested primary or secondary source of evidence for the corresponding dimension. As this is a conceptual paper with no empirical study conducted, there are no numerical values assigned to any of the instruments listed in the matrix.

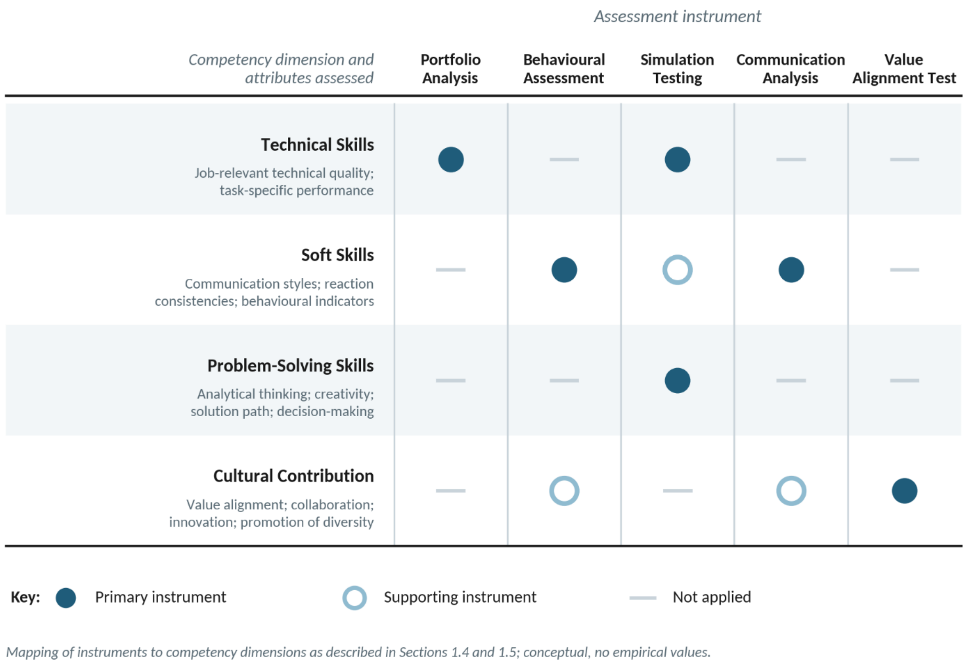

Figure 1. Competency-Based Assessment Matrix.

Note: The assessment matrix is illustrative only. Attributes of competency dimensions and linking instruments with dimensions are stated according to the description provided in Sections 1.4–1.5. Actual numbers of scores and percentages are not presented.

Source: Authors' creation.

1.5. Emotional Intelligence and Interpersonal Skills Assessment

Assessing emotional intelligence (EI) within competency-based talent management is a difficult but essential field. Where technical skills should be judged by standardized tests, emotional intelligence requires that individuals evaluate behavioral signals, communication modes, and interpersonal behavior dynamics.

Emotional intelligence encompasses self-awareness, of which touch aspects concerning work performance and team relationships (**Table 2**). These features can be assessed by AI through different tools such as the natural language processing of written responses, video analysis of nonverbal cues or observation of isolation in human interaction scenarios. These methods have made possible the measurement self-regulation, motivation, empathy, and social skills, all of quantifiable performance in qualities that were, hitherto, qualitative, and provided for more even assessments across candidate pools irrespective of their diversity.

Table 2. Emotional Intelligence Assessment Framework.

Competency Area	Assessment Method	Measurement Criteria	Scoring Weight
Self-Awareness	Reflection Analysis	Insight depth, accuracy	20%
Self-Regulation	Scenario Response	Emotional control, adaptability	20%
Motivation	Goal-Setting Exercise	Ambition, persistence	15%
Empathy	Perspective-Taking Task	Understanding, sensitivity	25%
Social Skills	Collaboration Simulation	Communication, influence	20%

Source: Authors' creation.

There is an evaluation of Communication effectiveness in both spoken and written forms concerning the clarity, persuasiveness, and style of communication. Therefore, natural language processing algorithms will evaluate the user's language, argumentation structure, and emotion, bearing in mind even more the cultural and language differences. This would counteract any accent or regional bias.

Empathy Behavioral-based Assessment for Adaptability is a dynamic simulation assessment that forces a candidate to change strategies and reassess priorities in their continuity of operation planning scenarios. Group communication activities also assist in a review of individual communication styles, conflict resolution styles, and leadership potentials. Work on pattern recognition of human behavioural and physiological signals in other interaction-intensive settings demonstrates the technical feasibility of inferring adaptive states from continuous behavioural data; while also underlining the interpretive caution such inference demands [18].

2. Methodology

This current text is a conceptual review paper that synthesizes the current theory to establish a foundation for a reflection on shortcomings of automated performance monitoring systems while proposing alternative human-centered designs for future management HR systems, which are yet to be tested.

Its foundation is conceptual and draws from existing conceptualizations of other fields such as Human-Computer Interaction (HCI), Organizational Psychology, AI ethics, and Competency-based Assessment literature. These frameworks, charts, and figures are constructed by the author; expansions of theoretical models put forth in the theoretical synthesis, they communicate and orchestrate conceptual understandings rather than empirical findings. This process is akin to the Viewpoint article format, representing the laying out of conceptual argumentation, and calls for further empirical validation in a wide variety of applied settings.

3. Bias Reduction and Inclusive Design

AI recruitment systems have been largely touted for their potential to obfuscate bias through measures that have introduced conversational ethics into the full design, production, and distribution of these systems, which is a far cry from old-fashioned and storied recruitment practices tainted as they are by bias consciously left within human-made decisions based on much subjective judgment, one-world-view interviews, and the use of standardized assessments that unintentionally overlook or disadvantage certain social groups in the hunt for the right candidate.

Algorithmic bias mitigation requires intense scrutiny of the training data, feature selection, and model validation (**Table 3**). Addressing the past data in hiring that leads AI systems to potential biases, therefore, should involve employing multiple training data, setting fairness standards, and conducting ongoing audits for bias. Aryasinghe et al. provide more ideas about the implementation of AI methods in the evaluation of inclusive HR practices and the enhancement of diverse corporate leadership, which further distinguishes them from the rest of the studies to date [19].

Table 3. Bias Reduction Framework for AI Recruitment Systems.

Development Stage	Bias Type	Mitigation Strategy	Implementation Method
Data Collection	Historical Bias	Diverse Dataset Curation	Multi-source sampling
Algorithm Design	Feature Bias	Objective Criteria Focus	Skills-based weighting
Testing Phase	Cultural Bias	Multi-demographic Validation	Representative testing
Deployment Stage	Outcome Bias	Continuous Monitoring	Regular bias audits
Iteration Cycle	Systemic Bias	Stakeholder Feedback	Inclusive design panels

Source: Authors' creation.

Algorithms and methods must be designed with particular caution when addressing gender bias. More proof demonstrates the agony of women who face gendered words written in job descriptions, and unconscious bias compounds the problem during interviews. This is ripe for assistance, to be rendered by AI through the mitigation of bias. This might be achieved by adopting a gender-neutral language or by using unbiased metrics, albeit still in a dysfunctional state, much of the research.

Racial and ethnic bias mitigation requires sensitive approaches in the appraisal design of any kind of culture; cultural backgrounds can influence communication styles and problem-solving approaches in ways that impact AI appraisal accuracy. Identifying these biases calls for stakeholder input, cultural competence testing, and continuous monitoring of outcomes by target groups.

Bias reduction strategies geared toward socioeconomic status attempt to remediate systematic disadvantage experienced by disadvantaged persons with lesser financial income, devoid of entry dues in prestigious schools or possession of technological resources. By basing its assessment on competence rather than identification, AI is minimally discriminatory. Coleman et al. provide a review pertaining to opportunities and challenges on this topic to aid the establishment of high-performance, diverse teams [20]. Case evidence from digital health equity work shows that human-centered design methods can be used explicitly to surface and reduce structural inequity in access to services, a lesson that transfers directly to recruitment technology [21]. Preventing discrimination requires an accessible system to design the AI recruitment system with a balance that accepts any further output and allots the set time for interpretation while also ensuring that evaluation criteria are void of discriminatory measures toward some persons with disabilities (**Table 4**).

Table 4. Human-Centered AI Design Principles and Expected HR Outcomes.

Human-Centered AI Principle	Design Feature	Expected HR Outcome
Transparency	Explainable AI scoring with clear criteria	Increased candidate trust and completion rates
Inclusivity	Multiple assessment pathways and accessibility options	Broader, more diverse talent pools
Fairness	Bias audits and diverse training data curation	Reduced discrimination in shortlisting
Accountability	Human review protocols on all final decisions	Ethical responsibility and legal compliance
Continuous Improvement	Feedback loops and regular stakeholder reviews	Adaptive, improving recruitment quality
Competency Focus	Skills-based scoring over credential matching	Better job-person fit and lower turnover

Source: Authors' creation.

4. Technology Infrastructure and Implementation

Putting into place a humane approach through refined and interconnected HRIS (Human Resources Information System) is highly dependent on robust technology setups that depend on various sources like high Cognitive methodologies, with some data being extracted from real-time candidate evaluation, mentorship, and meetings, ready with real-time data feeds on competent competency assessment systems. According to Kadir and Broberg, designing work systems by placing people at the center of transformation is informing technology adoption [22]. Those AI systems, so advanced, must exhibit high user friendliness of their displays and performance, guarantee data encryption, and reliability of systems.

The machine learning architecture is aimed to involve multiple assessments, including natural language processing, video analysis, behavioral pattern recognition, and performance simulation, among others, and all that requires potent computing resources. Because real-time feedback imposes significant computational demands, algorithms must be supplied with consolidated data streams through purpose-built pipelines. User-oriented implementation frameworks developed for conversational systems offer practical guidance on aligning such components with real user workflows [23].

Data infrastructures play an important role in ensuring the sustainability of an AI recruitment system carrying such private information. Records on applicants, including resumes, assessments, video interviews, and behavior analytics, would come with a promise of enterprise-level data storage facilities, access management, and a set of usage regulations. Technologies promoting privacy and data minimization policies guarantee that AI recruitment systems will always be operated to respect rather than exploit privacy rights. Systems are seamlessly integrated into existing HRISs to enable a seamless workflow. The system is cloud-native while remaining incredibly scalable and modular in design, rendering it fit for deployment within all sizes of organizations, regardless of the total scale or hiring volume (**Table 5**). Comparable human-centered work on clinical decision support [24] and on embedded machine-learning tools co-designed with frontline staff[25] shows that usability and trust depend on involving end users throughout development, as does research on cognitive assistance systems for industrial work [26].

Table 5. AI Recruitment System Technology Stack.

Layer	Component	Function	Requirements
Interface Layer	Candidate Portal	Application submission	Mobile-responsive design
	Recruiter Dashboard	Assessment management	Real-time updates
Processing Layer	NLP Engine	Text analysis	Multi-language support
	Video Analytics	Behavioural assessment	Real-time processing
Data Layer	Candidate Database	Profile storage	General Data Protection Regulation (GDPR) compliance
	Assessment Results	Performance tracking	Encrypted storage
Infrastructure	Cloud Computing	Scalable processing	99.9% uptime service level agreement (SLA)
	Security Framework	Data protection	Multi-factor authentication

Source: Authors' creation.

5. Organizational Implementation Strategies

Changing human-centric AI recruitment systems and transforming them into fully functioning operational products necessitates a complete reorganization across the entire technology infrastructure, human resources staff training, alignment of organizational cultures, and continuous participation of stakeholders. Organizations must ensure that the enhancement of the technology is supportive of recruitment effectiveness.

Change management strategies must address the possibility that recruitment professionals might feel threatened by the application of AI; rather, they could believe it to be infringing on their competency. Transparent communication and EI-informed change management are therefore essential. Such measures support rather than displace professional judgment, and they must be accompanied by educational programmes covering AI literacy, system operation, and result interpretation. Human-centered interface design for group-based training environments demonstrates how AI literacy can be built through structured, experiential learning [27], while studies of operator empowerment in assembly lines [28] and of human-centered design under reduced-workforce conditions [29] show that technology adoption succeeds when it visibly extends existing professional capability.

Pilot program design provides an organization that runs pilots for experimenting with AI recruiting systems in a controlled environment to see if such a system might be considered for an actual deployment. Here, the term "pilot" should be broadened to encompass varied roles, different types of candidates, and various organizational units. Fischer et al. promote human-centered, evidence-driven adaptive design concepts as realizable frameworks for organizational implementation strategy [30]. The implementation strategy holds stakeholder support to ensure that the modification of the recruitment strategy into AI functionality meets the needs and expectations of all individuals involved in hiring decisions. The continuous data collection and system reworking based on stakeholder input ensure the system, on one hand, is truly effective, and on the other, the organization buys into new recruitment methodologies.

Evaluation frameworks should be used to evaluate the efficacy of AI-integrated recruitment through a compound index consisting of candidate quality, hiring speed, diversity results, and cost efficiency compared with conventional methods and following long-term outcome indicators.

In **Figure 2**, a comprehensive organizational roadmap for the implementation of organized implementation and adoption of AI recruitment for human-centered work, hitherto organizational change in stratified organizational tiers and functional areas.

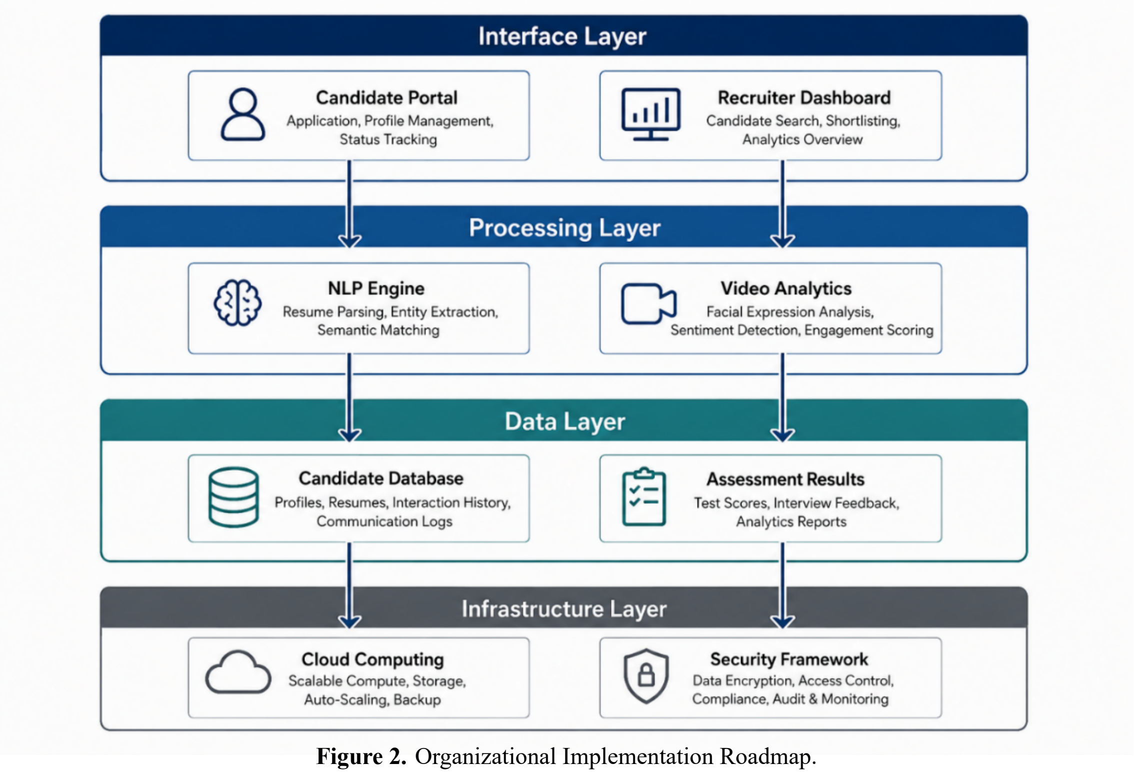

Figure 2. Organizational Implementation Roadmap.

Source: Authors' creation.

6. Ethical Considerations and Governance

The moral discourse of AI-based recruitment practices compels the setup of extensive governance structures to assert where AI can counter these rights of job seekers and to pressure organizational accountability (**Table 6**).

Transparency in algorithms means providing ethical transparency, for candidates to understand AI's decision-making processes for candidates and giving recruiters an insight into why a person could be considered or be overlooked. Trust follows from transparency and human supervision in making decisions for AI-guided recruitment. It was suggested that trust should be established, and, in addition, the balance in this respect has yet to be found, except for keeping some level of obfuscation over the methodological issues to sustain the integrity of the system on one hand, while gaming the system is mainly tied to transparency. Governance and accountability provide some semblance of human due diligence in the actual execution of the hiring process. Therefore, due protocols need to maintain the right proportion of human supervision over AI recommendations on final setting or rejection decisions and subsequent audits of these rationale justifications. Design guidance for explainable AI reinforces this requirement: explanations must be built for the people who act on them[11], and their effectiveness must be tested empirically rather than assumed[12].

AI recruitment systems will also have to consider constraints or restrictions in terms of data collection, consented usage, and retention schedules of candidates' submissions. In the context of unethical evaluations regarding interviews, implications of such considerations should be given continued review, modification, and enhancement. Regular statistical bias audits, eliciting inputs and reviews from a combination of various stakeholders, followed by appropriate actions, are important for addressing any area of discrimination and increasing the AI recruitment system's abilities to further diversity and the goal of inclusion. Embedding equality, diversity, and inclusion into usability testing provides a practical mechanism for operationalising these governance commitments [9].

Table 6. Ethical Governance Framework for AI Recruitment Systems.

Ethical Principle	Governance Mechanism	Implementation Strategy	Monitoring Method
Transparency	Algorithm Explainability	Clear result interpretation	Regular audits
Accountability	Human Oversight Protocols	Decision review processes	Appeal mechanisms
Privacy	Data Protection Policies	Encryption, access controls	Compliance assessments
Fairness	Bias Monitoring Systems	Regular bias audits	Outcome analysis
Autonomy	Informed Consent Procedures	Clear disclosure policies	Consent tracking
Justice	Equal Opportunity Measures	Inclusive design principles	Diversity metrics

Source: Authors' creation.

7. Industry Applications

AI-supported recruitment programs have been inherently executed across verticals very much associated with the onset of the human touch, technical capabilities, organizational challenges, and performance measures. As distinct domains indicate different ways in which machine intelligence and similar technologies boost recruitment performance, while considering sector implications.

Branding competencies required to specific skills, regulatory norms, and culture in health care can impede quality patient care. Thus, Carayon et al. have discussed at length how human-centered design technology solutions can improve the coordination of health care teams [31]. Human-centered work on clinical decision support [24] and on machine-learning tools developed together with nursing staff [25] indicates the level of clinical and interpersonal nuance such systems must accommodate. AI-powered healthcare recruitment solutions are responsible for assessing one's clinical know-how, social skills, and ethical decision-making while maintaining compliance with the licensing regulations of a state.

Recruiting for technology relies on gauging tech-savvy people, those with outstanding and innovative ideas, and those good at figuring out various ways to adjust to the volatile market trends. Initially, the recruitment procedure in such talent acquisition systems is powered by an AI-based system, consisting of an assortment of coding challenges that demonstrate learning agility following quick and adaptive assessments on the trial problem-solving platform during the meeting. Plus, technicality also involves meeting important balance sheets historically held over a lengthy time.

In the educational sector, pedagogical proficiency and cultural sensitivity are of top interest. Margolis et al. introduce longitudinal assessment of confidence development in varied professional contexts alongside skill development, both of which relate to cultural competency [32]. AI systems can also evaluate teaching effectiveness via simulated, practical exercises and test cultural proficiency via scenario-based appraisal. In manufacturing recruitment, no less ought to be expected than the safety diligence, technical skill, and cultural alignment that foster operational excellence; collaborative human-centered design of manufacturing tasks in multi-user immersive environments illustrates how such competencies can be observed directly rather than inferred from credentials [33]. In transport and highly automated operations, human-centered workplace design for the remote assistance of automated vehicles indicates the situational-awareness and vigilance competencies that AI-supported assessment would need to capture [34]. In financial services recruitment, further elaboration is given to the examination of analytical thinking, ethical reasoning, and regulatory ethics. Recruitment in the public sector should be fair, equitable, and transparent, supported by robust AI systems that leave ample room for candidates from different backgrounds while respecting the norms governing public employment; human-centered evaluation of public-sector digital services demonstrates the accessibility standards such systems must meet [35]. By so doing, the aim of achieving a representative workforce can also be advanced.

In **Figure 3**, the professional competencies that guide the customization of an AI recruitment system across various professional contexts are based mainly in the industry.

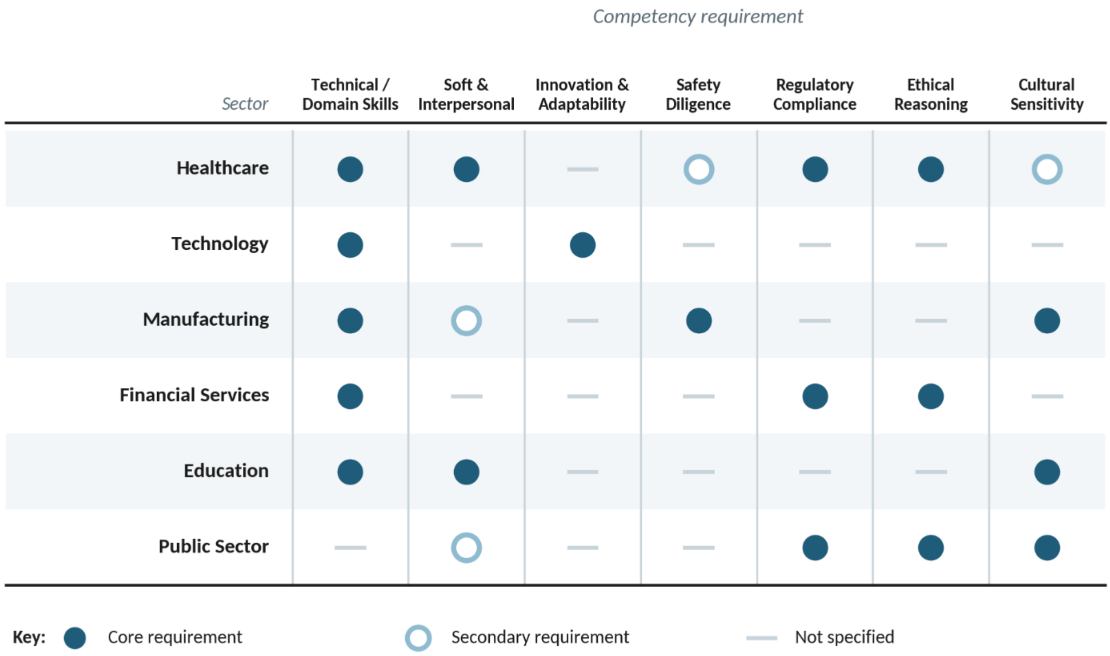

Figure 3. Industry-Specific Competency Requirements.

Note: Competency requirements per sector as described in Section 7; conceptual, no empirical values.
Source: Authors' creation.

8. Future Directions and Emerging Trends

Growth in the rate of development of AI as a tool for talent management derives from past technological advancement, changing workforce expectations, and the ways firms recognize that the essential strategic benefit will be autonomy for human beings and skill acquisition and altruism-driven behavior in recruitment.

Integration of virtual and augmented reality (VR/AR) in AI-based recruitment systems gives immersive assessment opportunities that realistically simulate workplace environments, along with job specifics to evaluate candidates (**Table 7**). Cucinella et al. have shown how fully customized immersive virtual reality applications can strengthen human-centered design in professional development contexts [36]. Related work on virtual and augmented reality in ergonomics and workspace design [37], on interface features that manage mental workload and spatial cognition during collaborative tasks [38], on augmented-reality interaction scenarios [39], and on machine-learning prediction of human experience in simulated environments [40] collectively indicates how immersive assessment could be designed and validated. These technologies help in enabling a more integrated assessment of spatial thinking, procedural knowledge, and human interactive skills.

Table 7. Future Technology Trends in AI Recruitment.

Technology	Timeline	Impact Level	Implementation Complexity	Adoption Likelihood
VR/AR Assessment	2–3 years	High	Medium	Medium
Predictive Analytics	1–2 years	High	Low	High
Blockchain Verification	3–5 years	Medium	High	Low
Advanced NLP	1–2 years	High	Medium	High
Continuous Learning AI	2–4 years	High	High	Medium
Cross-Cultural AI	3–5 years	Medium	High	Medium

Source: Authors' creation.

With their strong data analytics acumen, augmented AI systems can predict candidate readiness for success and potential to retain and develop the corresponding career path via scientific observation of patterns and fortnight-long data analysis. Among the potential solutions, integration with blockchain technology must verify qualifications and connect examination results to transparent artifacts, ideally on the verge of the decision-making stage.

The development of AI was fueled by advances in natural language understanding, letting AI interpret context, cultural references, and layers of meaning observed across various communication pathways used by humans. Possibly, the next step would be truly personalizing real-time conversation dialogue. AI could be able to learn by itself via algorithms that develop richer data concerning the performance, and without the necessity of manual updates, it certainly will continue to enhance its machine-learning abilities by continuously investigating an endless set of datasets. Research on adaptable automation cautions that such systems change human perception and behaviour, so adaptivity must itself be designed around the human operator [41].

Establishing a global presence and meeting the world's expectations seems to offer a very interesting platform for AI-driven recruiting frameworks to go global and outcompete others in global talent management. Singh et al. [42] further argue that health recommendation systems must be subjected to human-centered design fashioning to respond to diverse human needs and contexts. This sounds great for AI-based recruitment systems in the realm of cross-cultural offices. The next stage, therefore, must deal with linguistic as well as cross-cultural communication traits and regional legality to ensure consistent evaluation.

9. Challenges and Limitations

This section's problems are the outcome of a synthesis in the conceptual realm of existing literature without being empirically assessed. These are contemporary aids bestowed by scholars and practitioners on the undeniable claim of the AI recruitment challenge.

For measuring such intangible qualities as emotional intelligence, organizational culture fit, and leadership skills, assessing a candidate becomes significantly difficult, thanks to technical complications. Where there are observable and measurable hard skills that can be directly compared, we find subjective soft skills. Currently, many firms are working on developing and testing soft skills in artificial intelligence; at times, however, it might not acquire skill level precision.

AI recruiting tools face limitations and hurdles due to the quality and availability of features to manage new recruitment on AI constraints. The lack of historical recruitment data tempts AI algorithms more toward biases. This collateral they introduce will need a fair amount of editing and partiality in terms of data.

From country to country, the legal field ascends into a dynamic and budding affair, as with data processing and data storage, which have a very strict legal framework due to privacy laws like the GDPR. Thus, an effective compliance application for employment law calls for a well-rounded understanding based on discrimination laws and bias, where one thinks of protecting their business interests through hiring conventions under the duress of full compliance checks.

The resistance against technological advancements within the organization stands as the reason behind the non-acceptance, particularly with recruiters who are fearful that AI tools could take away their knowledge. Successful deployment follows all-encompassing change and management strategies, which present ways in which AI tools supplement the skills of human beings rather than taking them away.

To analyze AI evaluation, one must pursue consensus communication in a clear manner. If candidates belonging to the alternative stream have concerns about factors like biases and privacy, the tools will become void. Thus, importance is given to the operational requirements for clarification of the assessment and characteristics in general.

The geographic-cultural limitations often play a major role in navigating AI systems within the domain of the world. This can effectively shift the fairness and accuracy of AI judgment concerning the cultural diversity in communication styles, behavioral norms, and professional expectations. Gualtieri et al. set out to underline how transformational technology, heavily underlined by human-centered design principles, always puts human need ahead of anything else [43]; from this, the very essence of AI job recruitment systems is held in the balance for the professional world, be it in the West or non-Western countries.

Figure 4 illustrates that there are lots of dimensions in the challenge matrix that the organization must face for the successful adaptation of AI recruitment systems, including multi-faceted challenges across technical, organizational, and societal interfaces.

Challenge Category	Severity Level	Implementation Impact	Mitigation Complexity
Technical Limitations	Medium	High	High
Data Quality Issues	Medium	High	High
Regulatory Compliance	Low	Medium	High
Organizational Resistance	High	High	High
Cost Constraints	Medium	High	High
Candidate Acceptance	Low	Low	Medium
Cultural Adaptation	Low	High	High

Figure 4. AI Recruitment Implementation Challenge Matrix.

Source: Authors' creation.

10. Guidelines for Practical Implementation

Translating the preceding analysis into practice requires a structured implementation pathway. Very importantly, strategic planning includes a comprehensive analysis of the ability for an organization to successfully recruit from the labor market, circumventing various stages of the organizational and technological assimilation of AI. Organizations must move on to specify the recruitment peculiarities that AI is supposed to address against addressing issues like volume management, bias management, and process standardization over a period of time. When considering the indices of stakeholders and objectives, plans based on assessments and applications come into existence when the AI is brought up to tokenize and apply these systems (**Table 8**).

Table 8. AI Recruitment Implementation Checklist.

Phase	Activity	Responsible Party	Success Indicator
Planning	Needs assessment and objective setting	Senior Leadership	Clear goals documented
	Stakeholder consultation	HR Leadership	All stakeholders engaged
Vendor Selection	System capability and bias evaluation	Information Technology (IT) and HR	Scored shortlist produced
	Independent bias audit	Ethics Committee	Audit report completed
Pilot Design	Define pilot scope and roles	HR and Hiring Managers	Pilot plan approved
	Candidate transparency plan	HR Communications	Disclosure documents ready
Training	AI literacy program	Learning and Development (L&D) Team	100% team completion
	Ethical decision-making training	HR and Legal	Compliance certification
Deployment	System integration testing	IT	Zero critical failures
Monitoring	Quarterly bias audits	Ethics Committee	Audits on schedule
	Performance metrics review	HR Analytics	Monthly dashboards active
Iteration	Stakeholder feedback collection	HR	Improvement log maintained

Source: Authors' creation.

Technological capabilities, integration requirements, and reliability of the vendor are what need to be analyzed at the vendor-selection stage and system evaluation. The systematic review frameworks designed by Tonbul et al. could utilize this groundwork for an overview of AI-based evaluation systems that are explained in terms of various criteria and performance indicators or metrics [15]. The pilot program design affords multiple controlled environments wherein different role types, candidate pools, and assessment scenarios are mixed before the full deployment.

The course content should encompass performance analysis within the system, performance appraisal, detecting bias, and standard ethics for decision-making. In addition to the hard skills required for operating AI platforms, we also need the very soft skills reflected in assessing recommendations given by the algorithm and maintaining the professional conscience alongside the AI's inputs.

The whole integration program is required to address the technical qualifications to bring a recruitment AI system closer to what existed in the organizational previous: Before the date of AI implementation, performance monitoring must put into place apps that they use for performance assessing and data evaluation, given baseline measurements, benchmarks of the system, used soft metrics directed to quantitative sources of data, candidate quality, hiring velocity, divergence output related to these particular measures, and cost management.

10.1. Measuring Success and Return on Investment (ROI)

Measuring the effectiveness of AI-based recruitment systems demands models that capture all aspects of improvement in recruitment, such as efficiency gains, quality improvement, diversity outcomes, and cost optimization. Performance metrics inform the organization about efficiencies in the recruitment process, reduced time spent on recruitment, and streamlined process capture, key factors being a reduction in time-to-hire, acceleration in candidate screening, and automation of interview scheduling.

Quality metrics consider upgrades in the accuracy of hiring decisions, their fit to the job concerned, and the long-run success of an employee in terms of retention, performance appraisal, number of promotions, and cultural integration. In the context of quality, this encompasses gathering data over longitudinal progression that may take several months or years in order for consistent trends to increase and be of greater concern.

Diversity and inclusion metrics gauge the effectiveness of AI systems in terms of minimizing bias and promoting equal hiring across various demographic groups. Aryasinghe et al. lay down frameworks for the evaluation of inclusive recruiting methods applied by AI, which will aid in diversity metrics formulation [19]. Frameworks that integrate technology with human-centered design in order to enhance user well-being provide a useful model for treating candidate and employee well-being as a first-order success measure rather than a by-product [44]. Monetary measures track the financial benefits, such as the reduction of recruiting costs, improvements in the efficiency of hiring work, and overall improvements in the recruitment process. Candidate perception measures assess improvements in application processes, quality of communication, and satisfaction in general.

Figure 5 illustrates a comprehensive performance framework that not only measures the success of an organization but also integrates multiple performance indicators for different perspectives of stakeholders and objectives of an organization.

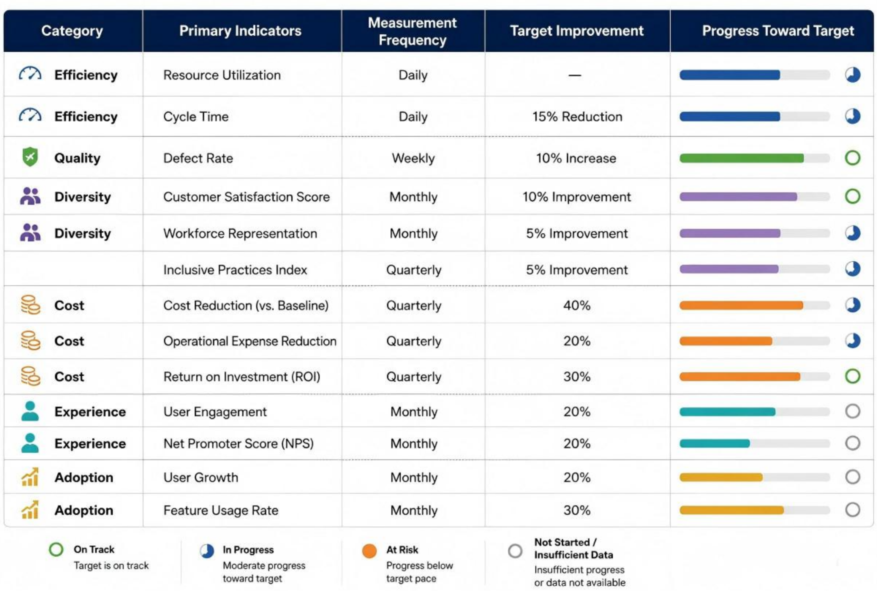

Figure 5. AI Recruitment Success Measurement Framework.

Note: Progress bars represent approximate achievement toward the target.
Source: Authors' creation.

10.2. Industry Impact and Transformation

In short, introducing AI-enabled human-centric hiring systems can change the game for HR in overcoming the biases, inefficiencies, and candidate carelessness entrenched in the manual talent acquisition. This can be essential to serve the good not just of organizations, as they are today relatively negligent toward their immediate labor-market dynamics, workforce development strategies, and social justice outcomes.

Improvements in labor market efficiency are related to the improved ability of AI systems to match candidates with job opportunities. Advanced matching algorithms connect between industries to transfer skills, creating pathways to careers, and reducing the time spent by laid-off workers seeking employment. Focusing on skills recruitment suppresses organizational focus from artifices to capabilities, giving way to nontypical candidates and counteracting the damaging effects of industry skill shortage (**Table 9**).

Workforce development alignment unfolds an AI recruitment system that provides insights into competencies and skill gaps demanded by education programs. Apparently, it will reduce the cost of turnover at the same rate that it fosters the increase in productivity. This could, in turn, lead to enhanced hiring choices because turnover due to training will be reduced, attributed to better performance ratings, and to the propitious production of novel ideas. In effect, human-centered momentum has proved to be a significant principle during technology transformations across a wide range of industries, from the built environment [45] and urban management [46] to the design of everyday public infrastructure [47]. The design insights generated in these fields are directly transferable to the engineering of AI recruitment products.

Hiring schemes are not fixed or permanently codified; they evolve with the times, shaping how organizations identify leading-edge talent through action items, policies, and strategies that work against historical inequity and support the inclusion of diverse candidates. In this way, AI systems can also facilitate cross-border mobility of talent assessed against a consistent competency standard.

Table 9. Multi-Sector Impact Analysis of AI Recruitment Transformation.

Sector	Efficiency Gain	Diversity Impact	Innovation Potential	Implementation Complexity
Technology	High	Medium	High	Medium
Healthcare	Medium	High	Medium	High
Financial Services	High	Medium–High	Medium	High
Education	Medium	High	Medium	Medium
Manufacturing	High	Medium	Low–Medium	Medium
Public Sector	Medium	High	Low	High

Source: Authors' creation.

11. Conclusions

The complement of AI with human-centered design in the talent management industry is far from just a technology shift but holds great promise for genuinely tackling problematic aspects of staffing and their obverse, i.e., fairness, for all. The pure screening of the processes for people with the right qualifications is better replaced today by moving into skill-based evaluations that promise to scale up the talent pool, bring in more diverse perspectives, and increase innovation.

The current paper makes new contributions in three significant areas: 1) linking human-centered design with AI ethics in recruiting, 2) embedding emotional intelligence and soft skills appraisal in the AI-driven framework, and 3) proposing a governance model for the responsible use of AI-driven recruiting systems. These points are still in concept and must be validated through empirical studies in different organizational environments to perceive their practical efficiency.

To adopt AI effectively, an organization must have the right technological backbone, a real commitment from the whole organization, and clear ethical standards. HR leaders should be authentic by blending transparency: trying to sell AI as an augmenter of human judgment rather than as a substitute for it. Policy makers should deliver regulation frameworks that will support and protect candidates' interests regarding data privacy, algorithmic accountability, and anti-discrimination, yet not kill competition.

Organizations should further conduct bias audits on a continuous basis as routine practice, cultivate diverse training datasets, and even craft procedures that actively integrate underrepresented communities. AI on skills will bring in non-traditional candidates and pave the way for addressing critical skills gaps as it connects economic growth with social equity. This is affiliated with a stronger way to scrutinize the avenues of virtual reality, predictive analytics, and blockchain. Ethical and consistent pursuit of these turns into a competitive edge and fairness within the scope of hiring in practice.

Author Contributions

Conceptualization, V.T. and N.M.; methodology (conceptual framework development), V.T.; writing—original draft preparation, V.T.; writing—review and editing, N.M.; supervision, N.M. Both authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Institutional Review Board Statement

Not applicable. This paper is a conceptual/viewpoint article and does not involve human participants, animal studies, or primary data collection.

Informed Consent Statement

Not applicable.

Data Availability Statement

No new data were created or analyzed in this study. Data sharing does not apply to this article.

Conflicts of Interest

The authors declare no conflict of interest.

AI Use Statement

AI tools were used solely for language editing, grammar correction, clarity, and formatting. The authors verified all content and accept full responsibility for manuscript accuracy and integrity throughout.

References

[1] Nguyen, H.N., Lasa, G., Iriarte, I., et al., 2022. Human-centered design for advanced services: A multidimensional design methodology. Advanced Engineering Informatics. 53, 101720. DOI: https://doi.org/10.1016/j.aei.2022.101720

[2] Zhang, Y., Chen, J., Liu, H., et al., 2024. Recent advancements of human-centered design in building engineering: A comprehensive review. Journal of Building Engineering. 84, 108529. DOI: https://doi.org/10.1016/j.jobe.2024.108529

[3] Wang, G., Li, M., Wang, M., et al., 2023. A systematic literature review of human-centered design approach in single pilot operations. Chinese Journal of Aeronautics. 36(11), 1–23. DOI: https://doi.org/10.1016/j.cja.2023.07.026

[4] Stankov, U., Gretzel, U., 2020. Tourism 4.0 technologies and tourist experiences: A human-centered design perspective. Information Technology and Tourism. 22(3), 477–488. DOI: https://doi.org/10.1007/s40558-020-00186-y

[5] Ahmadzai, P., 2025. Divergent and convergent thinking processes in smart cities: A systematic review of human-centered design practices. Cities. 159, 105744. DOI: https://doi.org/10.1016/j.cities.2025.105744

[6] Hayes, R., Smuk, M., Kasadha, B., et al., 2025. Achieving equitable recruitment through inclusive protocol design: Lessons learned from the ILANA study. Trials. 26(1), 229. DOI: https://doi.org/10.1186/s13063-025-08936-1

[7] Madan, S., Kumar, T., Bhagat, A., 2024. Inclusive hiring through technology: A recruitment platform for individuals with intellectual disabilities. Procedia CIRP. 128, 31–36. DOI: https://doi.org/10.1016/j.procir.2024.05.091

[8] Contreras-Cruz, A., Kirbac, A., Dennett, C., et al., 2023. Human-centered design as a tool to improve employee experience: The case of a US plant-based food manufacturer. Technology in Society. 73, 102248. DOI: https://doi.org/10.1016/j.techsoc.2023.102248

[9] Rutter, S., Zamani, E., McKenna-Aspell, J., et al., 2024. Embedding equality, diversity and inclusion in usability testing: Recommendations and a research agenda. International Journal of Human-Computer Studies. 188, 103278. DOI: https://doi.org/10.1016/j.ijhcs.2024.103278

[10] Schoonderwoerd, T.A.J., Jorritsma, W., Neerincx, M.A., et al., 2021. Human-centered XAI: Developing design patterns for explanations of clinical decision support systems. International Journal of Human-

Computer Studies. 154, 102684. DOI: https://doi.org/10.1016/j.ijhcs.2021.102684

[11] Chen, H., Gomez, C., Huang, C.-M., et al., 2022. Explainable medical imaging AI needs human-centered design: Guidelines and evidence from a systematic review. npj Digital Medicine. 5(1), 156. DOI: https://doi.org/10.1038/s41746-022-00699-2

[12] Famiglini, L., Campagner, A., Barandas, M., et al., 2024. Evidence-based XAI: An empirical approach to design more effective and explainable decision support systems. Computers in Biology and Medicine. 170, 108042. DOI: https://doi.org/10.1016/j.compbiomed.2024.108042

[13] Blasco-Blasco, O., Pinto-Delacadena, P.A., Vinueza-Cabezas, A., et al., 2025. Crafting a competency-based questionnaire based on Fuzzy Delphi: A proposal for enhanced hiring process. Quality and Quantity. 59, 3245–3269. DOI: https://doi.org/10.1007/s11135-025-02086-x

[14] Toale, C., Morris, M., Kavanagh, D., 2021. Perceptions and experiences of simulation-based assessment of technical skill in surgery: A scoping review. American Journal of Surgery. 222(4), 723–730. DOI: https://doi.org/10.1016/j.amjsurg.2021.03.035

[15] Tonbul, G., Topalli, D., Cagiltay, N.E., 2023. A systematic review on classification and assessment of surgical skill levels for simulation-based training programs. International Journal of Medical Informatics. 177, 105121. DOI: https://doi.org/10.1016/j.ijmedinf.2023.105121

[16] Valla, E., Toose, A.-J., Nõmm, S., et al., 2023. Transforming fatigue assessment: Smartphone-based system with digitized motor skill tests. International Journal of Medical Informatics. 177, 105152. DOI: https://doi.org/10.1016/j.ijmedinf.2023.105152

[17] VanLangen, K.M., Sahr, M.J., Salvati, L.A., et al., 2021. Viability of virtual skills-based assessments focused on communication. American Journal of Pharmaceutical Education. 85(7), 8378. DOI: https://doi.org/10.5688/ajpe8378

[18] Xing, Y., Lv, C., Zhao, Y., et al., 2020. Pattern recognition and characterization of upper limb neuromuscular dynamics during driver-vehicle interactions. iScience. 23(9), 101541. DOI: https://doi.org/10.1016/j.isci.2020.101541

[19] Aryasinghe, S., Carenzo, C., Barnett, K.-A., et al., 2025. Increasing the ethnic diversity of senior leadership within the English National Health Service: Using an artificial intelligence approach to evaluate inclusive recruitment strategies in hospital settings. Human Resources for Health. 23(1), 24. DOI: https://doi.org/10.1186/s12960-025-00991-8

[20] Coleman, D.M., Dossett, L.A., Dimick, J.B., 2021. Building high performing teams: Opportunities and challenges of inclusive recruitment practices. Journal of Vascular Surgery. 74(2), 86S–92S. DOI: https://doi.org/10.1016/j.jvs.2021.03.054

[21] Levander, X.A., VanDerSchaaf, H., Barragan, V.G., et al., 2023. The role of human-centered design in healthcare innovation: A digital health equity case study. Journal of General Internal Medicine. 39(4), 690–695. DOI: https://doi.org/10.1007/s11606-023-08500-0

[22] Kadir, B.A., Broberg, O., 2020. Human-centered design of work systems in the transition to industry 4.0. Applied Ergonomics. 92, 103334. DOI: https://doi.org/10.1016/j.apergo.2020.103334

[23] Janssen, A., Rodriguez Cardona, D., Passlick, J., et al., 2022. How to make chatbots productive—A user-oriented implementation framework. International Journal of Human-Computer Studies. 168, 102921. DOI: https://doi.org/10.1016/j.ijhcs.2022.102921

[24] Garabedian, P.M., Gannon, M.P., Aaron, S., et al., 2022. Human-centered design of clinical decision support for management of hypertension with chronic kidney disease. BMC Medical Informatics and Decision Making. 22(1), 127. DOI: https://doi.org/10.1186/s12911-022-01962-y

[25] Kaduwela, N.A., Horner, S., Dadar, P., et al., 2024. Application of a human-centered design for embedded machine learning model to develop data labeling software with nurses: Human-to-Artificial Intelligence (H2AI). International Journal of Medical Informatics. 183, 105337. DOI: https://doi.org/10.1016/j.ijmedinf.2023.105337

[26] Quandt, M., Stern, H., Zeitler, W., et al., 2022. Human-centered design of cognitive assistance systems for industrial work. Procedia CIRP. 107, 233–238. DOI: https://doi.org/10.1016/j.procir.2022.04.039

[27] Delvecchio, T., Zeijlemaker, S., De Bernardis, G., et al., 2025. Human-centered interface design for a dynamic cyber-risk group-based training game. Computer Standards and Interfaces. 95, 104030. DOI: https://doi.org/10.1016/j.csi.2025.104030

[28] Zysk, J., Florides, C., Werz, J.M., et al., 2024. Towards operator empowerment in assembly lines with human-centered design: A concept with application in the automotive industry. Procedia CIRP. 128, 490–495. DOI: https://doi.org/10.1016/j.procir.2024.04.013

[29] Khan, T.K., Schworm, P., Glatt, M.F., et al., 2024. Engaging human-centered design to maintain part manufacturing under reduced workforce restrictions. Production Engineering. 18(5), 733–750. DOI: https://doi.org/10.1007/s11740-024-01275-1

[30] Fischer, M., Safaeinili, N., Haverfield, M.C., et al., 2021. Approach to Human-Centered, Evidence-Driven Adaptive Design (AHEAD) for health care interventions: A proposed framework. Journal of General Internal Medicine. 36(4), 1041–1048. DOI: https://doi.org/10.1007/s11606-020-06451-4

[31] Carayon, P., Hose, B.-Z., Wooldridge, A., et al., 2022.

Human-centered design of team health IT for pediatric trauma care transitions. International Journal of Medical Informatics. 162, 104727. DOI: https://doi.org/10.1016/j.ijmedinf.2022.104727

[32] Margolis, A., Shah, S., Kraus, C., et al., 2020. Longitudinal assessment of pharmacy students' confidence and skill in providing evidence-based answers to clinical questions. American Journal of Pharmaceutical Education. 84(10), ajpe7884. DOI: https://doi.org/10.5688/ajpe7884

[33] Arkouli, Z., Tompoulidis, I., Kontos, M., et al., 2024. Collaborative human-centered design of manufacturing tasks: A multi-user immersive VR experience. Procedia CIRP. 128, 597–602. DOI: https://doi.org/10.1016/j.procir.2024.07.056

[34] Schrank, A., Walocha, F., Brandenburg, S., et al., 2024. Human-centered design and evaluation of a workplace for the remote assistance of highly automated vehicles. Cognition Technology and Work. 26(2), 183–206. DOI: https://doi.org/10.1007/s10111-024-00753-x

[35] Zahra, S.N.A., Suryatiningsih, S., 2024. Evaluation and improvement of user interface design of Bandung City APBD website using human centered design method. Procedia Computer Science. 234, 1791–1798. DOI: https://doi.org/10.1016/j.procs.2024.03.187

[36] Cucinella, S.L., de Winter, J.C.F., Grauwmeijer, E., et al., 2025. Towards personalized immersive virtual reality neurorehabilitation: A human-centered design. Journal of NeuroEngineering and Rehabilitation. 22(1), 7. DOI: https://doi.org/10.1186/s12984-024-01489-5

[37] Singh, A.K., 2025. VR/AR in ergonomics and workspace design: A dual-perspective analysis of applications and implications. Applied Ergonomics. 129, 104612. DOI: https://doi.org/10.1016/j.apergo.2025.104612

[38] Cao, H., Rivera, F.G., Soderlund, H., et al., 2025. Human-centered design of VR interface features to support mental workload and spatial cognition during collaboration tasks in manufacturing. Cognition Technology and Work. 27, 467–485. DOI: https://doi.org/10.1007/s10111-025-00809-6

[39] Liu, W., Zhu, Y., Huang, R., et al., 2023. Designing interactive glazing through an engineering psychology approach: Six augmented reality scenarios that envision future car human-machine interface. Virtual Reality and Intelligent Hardware. 5(2), 157–170. DOI: https://doi.org/10.1016/j.vrih.2022.07.004

[40] Zhang, Y., Xiao, B., Al-Hussein, M., et al., 2022. Prediction of human restorative experience for human-centered residential architecture design: A non-immersive VR-DOE-based machine learning method. Automation in Construction. 136, 104189. DOI: https://doi.org/10.1016/j.autcon.2022.104189

[41] Rieth, M., Onnasch, L., Hagemann, V., 2024. Adaptable automation for a more human-centered work design? Effects on human perception and behavior. International Journal of Human-Computer Studies. 186, 103246. DOI: https://doi.org/10.1016/j.ijhcs.2024.103246

[42] Singh, A., Schooley, B., Mobley, J., et al., 2025. Human-centered design of a health recommender system for orthopaedic shoulder treatment. BMC Medical Informatics and Decision Making. 25(1), 17. DOI: https://doi.org/10.1186/s12911-025-02850-x

[43] Gualtieri, L., Fraboni, F., Brendel, H., et al., 2023. Guidelines for the integration of cognitive ergonomics in the design of human-centered and collaborative robotics applications. Procedia CIRP. 120, 374–379. DOI: https://doi.org/10.1016/j.procir.2023.09.005

[44] Monteriu, A., Freddi, A., Longhi, S., 2024. Special issue on advancements in ambient assisted living: Integrating technology and human-centered design for enhancing user well-being and care. Journal of Ambient Intelligence and Humanized Computing. 15(5), 2659–2660. DOI: https://doi.org/10.1007/s12652-024-04799-7

[45] Javid Khan, R.A., Lucas, J.D., 2025. Building for human experiences: An in-depth exploration of human-centric design. Journal of Building Engineering. 106, 112493. DOI: https://doi.org/10.1016/j.jobe.2025.112493

[46] Jiang, B., 2024. The status quo of architecture and its impact on urban management: Christopher Alexander's insights. Journal of Urban Management. 13(4), 557–564. DOI: https://doi.org/10.1016/j.jum.2024.09.003

[47] Zhang, X., Ludwig, F., 2025. Shade for pedestrians: A novel approach to calculate the spatio-temporal shade benefits of street trees considering pedestrian flow. Building and Environment. 272, 112662. DOI: https://doi.org/10.1016/j.buildenv.2025.112662