

Journal Article

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Recommended citation:

Prestini, D.K. (2026) 'Reframing AI-Driven Recruitment as a Socio-Technical Governance System: Integrating Operational Efficiency, Candidate Experience, and Organizational Legitimacy', *International Journal of Business and Management*, 21(3), pp. 130–144. Available at: <https://doi.org/10.5539/ijbm.v21n3p130>

Reframing AI-Driven Recruitment as a Socio-Technical Governance System: Integrating Operational Efficiency, Candidate Experience, and Organizational Legitimacy

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Received: April 3, 2026

Accepted: May 6, 2026

Online Published: May 23, 2026

doi:10.5539/ijbm.v21n3p130

URL: <https://doi.org/10.5539/ijbm.v21n3p130>

Abstract

Artificial intelligence (AI) is increasingly transforming recruitment processes, yet existing research remains fragmented across technical, operational, and behavioral perspectives. While prior studies emphasize efficiency gains and predictive accuracy, they often overlook the socio-organizational dimensions that shape the effectiveness and acceptance of AI-driven hiring systems.

This study addresses this gap by advancing a socio-technical governance framework that integrates operational efficiency, candidate perception, and organizational legitimacy into a unified analytical model. Drawing on legitimacy theory and interdisciplinary insights from human resource management, operations management, and marketing, the paper conceptualizes AI-driven recruitment as a dynamic and adaptive system.

The proposed model introduces causal relationships between core dimensions, highlighting the mediating role of candidate perception and the moderating function of governance mechanisms. Furthermore, it extends existing approaches by incorporating feedback loops that capture the temporal evolution of AI systems within organizational and institutional environments.

The study contributes to the literature by reframing AI recruitment from a purely technical tool to a governance-driven socio-technical system. It also contributes to interdisciplinary AI governance research by linking recruitment efficiency, candidate experience, and legitimacy within the emerging European regulatory context.

While conceptual in nature, the framework provides a foundation for future empirical research and offers practical insights for organizations seeking to balance efficiency, fairness, and legitimacy in AI-enabled recruitment processes.

Keywords: AI recruitment, algorithmic hiring, AI governance, socio-technical systems, legitimacy theory, HR analytics, feedback loops, EU AI Act

1. Introduction

Artificial intelligence (AI) is rapidly redefining how organizations identify, evaluate, and select talent, transforming recruitment into a data-driven and algorithmically mediated process. While these systems promise unprecedented gains in efficiency, scalability, and predictive accuracy, they simultaneously introduce a fundamental tension between technical optimization and socio-organizational legitimacy. This tension remains insufficiently theorized in existing research, which continues to privilege technocentric perspectives while underestimating the institutional and experiential dynamics shaping AI-driven hiring systems (Kellogg, Valentine, & Christin, 2020).

Despite these advancements, AI-driven recruitment systems are still predominantly conceptualized as neutral optimization tools, rather than as embedded socio-technical structures whose effectiveness is contingent upon organizational acceptance, perceived fairness, and institutional legitimacy (Lee, Kusbit, Metsky, & Dabbish, 2015).

These challenges are further intensified by the evolving regulatory landscape, particularly within the European context. Emerging frameworks such as the European Union AI Act emphasize the need for transparency, accountability, and ethical compliance in algorithmic decision-making (Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schafer, B., Valcke, P., & Vayena, E. 2018), reinforcing the importance of governance mechanisms that extend beyond purely technical considerations. Consequently, organizations face increasing pressure to balance efficiency with fairness and compliance when implementing AI-based recruitment systems.

A critical limitation of the existing literature lies in its fragmented treatment of AI-driven recruitment across disciplinary boundaries. Existing studies tend to isolate technical, behavioral, and governance dimensions, without adequately theorizing their interaction. As a result, AI recruitment systems are insufficiently understood as socio-technical entities shaped by both computational processes and institutional dynamics. In particular, the integration of operations management and marketing perspectives—capturing efficiency optimization and candidate experience remains largely underexplored within AI governance research.

In response to this gap, this study reframes AI-driven recruitment as a socio-technical governance system and proposes a cross-functional framework integrating three core dimensions: operational efficiency, candidate experience, and organizational legitimacy. By combining insights from operations management, marketing, and human resource governance, the paper conceptualizes recruitment systems as dynamic structures shaped by both technical processes and stakeholder perceptions.

The European context provides a particularly relevant setting for this analysis, given the increasing regulatory emphasis on AI governance through frameworks such as the EU AI Act. This institutional environment reinforces the importance of legitimacy and governance in shaping the adoption and effectiveness of AI-driven recruitment systems.

More specifically, this study extends legitimacy theory by embedding algorithmic decision-making within adaptive socio-technical governance structures, where organizational acceptance is continuously shaped by the interaction between technical outputs, candidate perception, and institutional pressures.

At the same time, the paper contributes to socio-technical systems theory by reconceptualizing governance not as an external control layer, but as an endogenous and dynamic component of AI-driven systems, actively influencing system behavior through feedback loops and policy mechanisms.

First, it reconceptualizes AI-driven recruitment as an adaptive socio-technical governance system, shifting the analytical focus from static algorithmic performance to dynamic interactions between technology, human perception, and institutional legitimacy.

Second, it develops a cross-functional theoretical framework that integrates operational efficiency, candidate experience, and organizational legitimacy—dimensions that have largely been examined in isolation—thereby advancing a more holistic understanding of algorithmic hiring systems.

Third, it introduces a dynamic governance perspective by embedding feedback loops and policy-driven adaptation mechanisms, positioning AI recruitment systems as evolving institutional structures rather than fixed decision-support tools.

Accordingly, this paper introduces a novel cross-functional governance framework for AI-driven recruitment systems, integrating operational efficiency, candidate experience, and organizational legitimacy within a unified socio-technical perspective.

This paper is primarily scoped to EU and OECD-regulated recruitment environments, where algorithmic hiring systems are increasingly shaped by formal data protection, non-discrimination, transparency, and accountability requirements. Although the proposed framework may offer conceptual relevance beyond Europe, its theoretical assumptions are grounded in institutional contexts where organizations face explicit regulatory pressure to justify, monitor, and document AI-enabled recruitment decisions. Therefore, the framework should not be interpreted as a universal model of AI recruitment governance, but as a socio-technical governance framework designed for comparatively regulated labour markets. In less formalised institutional contexts, including platform-mediated gig work, labour migration systems, or state-integrated algorithmic oversight regimes, the same governance mechanisms may require substantial adaptation.

2. Literature Review

The growing adoption of artificial intelligence (AI) in recruitment has generated a rapidly expanding body of literature across multiple disciplines, including human resource management, information systems, and

organizational studies. While existing research provides valuable insights into the technological and managerial implications of AI-driven recruitment, it remains fragmented and often lacks an integrated, cross-functional perspective. This section reviews the relevant literature across four key domains—AI in recruitment systems, operations management, marketing and candidate experience, and human resource governance—before identifying a critical research gap.

2.1 AI in Recruitment Systems

AI-driven recruitment systems are increasingly used to automate various stages of the hiring process (Cappelli, P., Tambe, P., & Yakubovich, V., 2019), including candidate sourcing, resume screening, and decision-making. Machine learning algorithms enable organizations to process large volumes of applicant data, identify patterns, and generate predictive assessments of candidate suitability. These systems promise significant improvements in efficiency, consistency, and scalability.

However, despite these advantages, the literature highlights several limitations. One of the most prominent concerns is the “black-box” nature of algorithmic decision-making (Burrell, J., 2016), which reduces transparency and makes it difficult for stakeholders to understand how decisions are generated. This opacity raises questions about accountability and fairness, particularly when algorithms replicate or amplify existing biases present in historical data (Raghavan, M., Barocas, S., Kleinberg, J., & Levy, K., 2020).

Recent algorithmic management scholarship is particularly relevant for understanding AI-enabled recruitment as more than a technical screening process. Algorithmic systems do not merely support decision-making; they can also structure visibility, ranking, evaluation, and control within organizational processes. Algorithmic management research shows that digital systems can reshape employment relations by mediating managerial control through data-driven infrastructures (Duggan, J., Sherman, U., Carbery, R., & McDonnell, A., 2020). The distinction between algorithmic matching and algorithmic control is particularly useful in this context, because AI hiring systems may simultaneously match candidates to vacancies, filter applicants, rank profiles, and shape access to employment opportunities (Möhlmann, M., Zalmanson, L., Henfridsson, O., & Gregory, R. W., 2021).

From this perspective, AI-driven recruitment should be understood as a managerial governance mechanism rather than as a neutral optimization tool. While such systems may improve speed and consistency, they may also redistribute decision-making authority from human recruiters to technical systems and external vendors. This reinforces the need for socio-technical governance mechanisms capable of monitoring not only recruitment outcomes, but also the forms of managerial power embedded in algorithmic processes.

Furthermore, AI-driven recruitment systems are often evaluated primarily in terms of predictive accuracy and efficiency, neglecting broader organizational and social implications. As a result, current approaches tend to treat recruitment as a purely technical optimization problem rather than a complex socio-organizational process.

However, this predominantly technocentric approach creates a critical limitation: it assumes that improved predictive accuracy inherently leads to better organizational outcomes, while overlooking the role of human interpretation and institutional acceptance in shaping the effectiveness of AI-driven decisions.

2.2 Operations Management Perspective

From an operations management perspective, recruitment can be conceptualized as a process optimization problem, where the objective is to improve efficiency, reduce costs, and enhance decision quality. AI technologies align well with this perspective, as they enable faster processing of applications, standardized evaluation criteria, and improved resource allocation.

Research in operations management emphasizes key dimensions such as process efficiency, cycle time reduction, and decision accuracy. In the context of AI recruitment, these dimensions translate into faster hiring processes, reduced administrative burden, and more consistent candidate evaluation.

However, this perspective has critical limitations. By focusing primarily on efficiency and optimization, it tends to overlook human and behavioral aspects of recruitment. The assumption that improved efficiency automatically leads to better outcomes does not always hold, particularly when candidate perceptions and organizational legitimacy are taken into account. Therefore, while the operations perspective provides essential insights into system performance, it remains insufficient for capturing the full complexity of AI-driven recruitment.

This perspective, however, implicitly assumes that efficiency gains translate into organizational effectiveness, neglecting the possibility that increased process optimization may generate negative perceptions among candidates, thereby undermining trust and legitimacy.

2.3 Marketing Perspective: Candidate Experience

The marketing literature offers a complementary perspective by focusing on the concept of candidate experience, which encompasses how applicants perceive and evaluate the recruitment process. This perspective highlights the importance of perceived fairness, transparency, and communication in shaping candidate attitudes and behaviors.

Candidate experience is closely linked to employer branding and organizational reputation. Even when AI systems are technically efficient, negative perceptions—such as a lack of transparency or perceived bias—can lead to dissatisfaction, reduced trust, and lower willingness to engage with the organization. This suggests that recruitment outcomes are not determined solely by algorithmic performance but are co-shaped by subjective evaluations.

A key insight from this literature is that perception does not necessarily align with objective outcomes. An algorithmically “optimal” decision may still be perceived as unfair or illegitimate by candidates, particularly when fairness is negotiated in practice rather than determined solely by technical accuracy (Van den Broek, E., Sergeeva, A., & Huysman, M., 2021; Cappelli, P., Tambe, P., & Yakubovich, V., 2019; Burrell, J., 2016; Dastin, J., 2018; Binns, R., 2018). This divergence underscores the need to incorporate behavioral and experiential dimensions into the design and governance of AI recruitment systems.

This argument can be strengthened through the lens of procedural justice (Lind, E. A., & Tyler, T. R., 1988). Procedural justice theory suggests that individuals are more likely to accept organizational decisions, including unfavourable outcomes, when the decision-making process is perceived as consistent, unbiased, transparent, and open to explanation. In AI-driven recruitment, this means that candidate acceptance depends not only on the accuracy of algorithmic recommendations, but also on whether the process is experienced as fair, respectful, and contestable.

Algorithm aversion further complicates the candidate experience. Applicants may distrust automated recruitment systems when they believe that human judgement has been replaced by opaque technical procedures. This distrust may emerge even when algorithmic systems are statistically efficient or accurate. Therefore, explainability, human oversight, and clear communication should not be treated as secondary design features, but as central governance mechanisms that reduce algorithm aversion (Dietvorst, B. J., Simmons, J. P., & Massey, C., 2015) and protect organizational legitimacy.

This creates a fundamental tension between objective algorithmic performance and subjective candidate evaluation, suggesting that technically optimal systems may still fail at the level of perceived fairness and legitimacy.

2.4 HR Governance and Organizational Legitimacy

The human resource management and governance literature emphasizes the importance of legitimacy, accountability, and ethical considerations in organizational decision-making. In the context of AI-driven recruitment, legitimacy refers to the extent to which stakeholders perceive the system as fair, transparent, and acceptable.

Recent developments in regulatory frameworks (Jobin, A., Ienca, M., & Vayena, E., 2019), particularly the European Union AI Act, have reinforced the importance of governance in AI systems. These frameworks require organizations to ensure transparency, mitigate bias, and implement accountability mechanisms, shifting the focus from purely technical performance to responsible and compliant use of AI.

The concept of legitimacy is particularly relevant in AI recruitment, as algorithmic decisions directly affect individuals’ employment opportunities. A lack of perceived legitimacy can lead to reputational risks, legal challenges, and reduced trust in organizational processes. Consequently, governance mechanisms such as audits, explainability, and bias mitigation are increasingly recognized as essential components of AI systems.

Organizational legitimacy is not produced by the mere existence of technical governance tools. Rather, it emerges when candidates, employees, regulators, and other stakeholders perceive recruitment decisions as desirable, appropriate, and consistent with accepted institutional norms (Jobin, A., Ienca, M., & Vayena, E., 2019). In this sense, governance mechanisms such as bias audits, human oversight, explainability protocols, and algorithmic impact assessments acquire legitimacy only when they reduce uncertainty about how decisions are made and why specific outcomes occur.

The link between AI governance and organizational legitimacy is therefore mediated by perceived procedural justice. Candidates are more likely to accept algorithmically supported decisions when they believe that the

process is transparent, consistent, contestable, and respectful. Conversely, an organization may formally comply with regulatory requirements while still losing legitimacy if candidates experience the system as opaque, impersonal, or biased. This distinction is central to the present framework, which treats legitimacy as a dynamic outcome of repeated interactions between technical system design, managerial oversight, and stakeholder perception.

To synthesize the different perspectives discussed above, Table 1 provides a comparative overview of the main approaches to AI-driven recruitment systems.

Table 1. Comparative perspectives on AI-driven recruitment systems

Perspective	Primary Focus	Key Advantages	Main Limitations	Key Concepts
AI / Technical Systems	Algorithmic performance and predictive accuracy	High scalability, automation, data-driven decision-making	Lack of transparency (“black-box”), risk of bias replication [3,9], limited interpretability	Machine learning, predictive analytics, automation
Operations Management	Process efficiency and optimization	Reduced hiring time, cost efficiency, standardized evaluation	Neglect of human and behavioral factors, overemphasis on efficiency	Process optimization, cycle time, decision quality
Marketing (Candidate Experience)	Candidate perception and experience	Improved employer branding, higher engagement, perception management	Subjectivity of perceptions, misalignment with objective outcomes	Candidate experience, perceived fairness, trust
HR Governance	Legitimacy, ethics, and compliance	Increased accountability, alignment with regulations, mitigation with risk	Implementation complexity, potential trade-offs with efficiency	Legitimacy, transparency, accountability, AI ethics
Integrated Approach (This Study)	Socio-technical governance system	Holistic understanding, balance between efficiency and fairness, adaptive systems	Higher conceptual complexity, requires cross-functional integration	Socio-technical systems, governance loops, cross-functional integration

Source. Author’s elaboration.

As shown in Table 1, existing perspectives provide valuable but partial insights, reinforcing the need for an integrated socio-technical approach that bridges efficiency, experience, and governance dimensions.

While governance frameworks emphasize transparency and accountability, they often treat AI systems as static entities, failing to account for the dynamic and adaptive nature of algorithmic decision-making processes.

This perspective aligns with legitimacy theory, where organizational acceptance is shaped by stakeholder perceptions and institutional conformity.

In this study, governance and management are treated as related but distinct concepts. Governance refers to the structural arrangements, accountability mechanisms, ethical principles, and institutional controls that define how AI recruitment systems should be designed, monitored, and justified. Management refers to the operational processes through which recruitment activities are implemented, including screening, ranking, communication, recruiter intervention, and system adjustment. This distinction is important because an organization may manage AI recruitment efficiently while governing it poorly. The present framework therefore focuses on governance as

the higher-level structure that shapes and constrains managerial action.

2.5 Research Gap

Despite the growing body of literature, a significant gap remains. Existing studies tend to analyze AI-driven recruitment from isolated perspectives—either as a technical system focused on efficiency, a behavioral process centered on candidate experience, or a governance issue related to compliance and ethics.

What is missing is an integrated framework that not only combines operational efficiency, candidate perception, and organizational legitimacy, but also models their dynamic interaction through governance mechanisms and feedback loops an aspect largely absent in existing AI governance and HRM literature. The lack of such a cross-functional perspective limits the ability to fully understand how AI recruitment systems operate in practice and how their outcomes are shaped by the interaction between technical performance and social acceptance.

Taken together, these perspectives reveal a fundamental theoretical fragmentation. Technical approaches prioritize efficiency and predictive accuracy, behavioral perspectives emphasize perception and experience, while governance frameworks focus on legitimacy and compliance. However, these perspectives remain conceptually disconnected and, in some cases, theoretically incompatible.

In particular, a key unresolved tension emerges between algorithmic optimization and socio-organizational acceptance: systems designed to maximize efficiency may simultaneously undermine perceived fairness and legitimacy. Existing research does not adequately explain how these dimensions interact, nor how organizations can manage the trade-offs between them.

This fragmentation highlights the absence of an integrated framework that captures the dynamic interaction between operational efficiency, candidate perception, and organizational legitimacy within AI-driven recruitment systems. Addressing this gap requires a socio-technical perspective that explicitly models these interdependencies and their evolution over time.

Previous applied studies have examined AI adoption and recruitment efficiency in European banking and AI-enabled workforce governance in Polish healthcare settings (Prestini, D. K., 2026). However, these contributions remain sector-specific and do not yet provide a general socio-technical governance framework for AI-driven recruitment. The present study extends this research line by developing a broader conceptual model that integrates operational efficiency, candidate experience, and organizational legitimacy.

3. Conceptual Framework: A Socio-Technical Governance Model of AI-Driven Recruitment

This study advances a cross-functional conceptual framework that reframes AI-driven recruitment as a socio-technical governance system. Rather than treating recruitment as a purely algorithmic optimization process, the framework integrates operational, behavioral, and institutional dimensions, reflecting the complex interaction between technology, human perception, and organizational legitimacy.

This interdisciplinary approach is informed by the integration of applied business perspectives, particularly operations management and marketing, which enable a combined analysis of efficiency-oriented and human-centered dimensions of recruitment systems.

Figure 1 illustrates the conceptual integration of the three core dimensions underlying the proposed socio-technical governance framework.

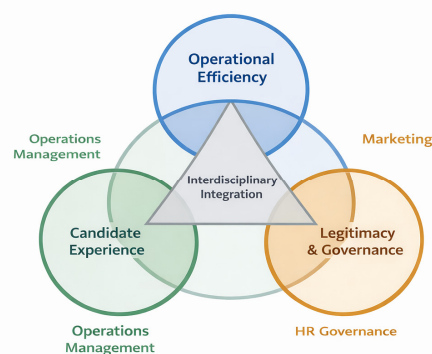


Figure 1. Triple integration of operational efficiency, candidate experience, and legitimacy in AI-driven recruitment systems

AI-driven recruitment systems can therefore be conceptualized as emergent structures resulting from the interaction of three core dimensions: operational efficiency, candidate experience, and organizational legitimacy. As shown in Figure 1, these dimensions are not independent but mutually reinforcing, requiring an integrated approach to system design and governance.

3.1 The Need for an Integrated Socio-Technical Perspective

Traditional approaches to AI in recruitment tend to isolate technical performance from its organizational and social implications. However, recruitment processes inherently involve both algorithmic decision-making and human evaluation, making them fundamentally socio-technical in nature.

A purely technocentric approach fails to capture how algorithmic outputs are interpreted, accepted, or contested by stakeholders. Conversely, a purely behavioral perspective neglects the structural constraints and capabilities of AI systems. Therefore, an integrated framework is necessary to bridge these dimensions and provide a more comprehensive understanding of AI-driven recruitment.

This need for integration is particularly evident in applied business education contexts, where operations management emphasizes efficiency and process optimization, while marketing highlights perception and experience. The combination of these perspectives, reinforced through international academic exposure, enables a more holistic conceptualization of recruitment systems.

3.2 Core Dimensions of the Framework

The proposed framework is structured around three interdependent dimensions, each rooted in a distinct but complementary disciplinary perspective.

3.2.1 Operational Efficiency

Operational efficiency reflects the extent to which AI systems optimize recruitment processes in terms of speed, scalability, and decision accuracy. Drawing on operations management principles, this dimension focuses on process standardization, cycle time reduction, and resource optimization. AI technologies enhance these capabilities by enabling rapid data processing and consistent evaluation criteria.

3.2.2 Candidate Experience

Candidate experience captures how applicants perceive and evaluate the recruitment process. Grounded in marketing theory and procedural justice, this dimension emphasizes perceived fairness, transparency, communication quality, and trust. However, candidate experience should not be understood only as an outcome of AI-enabled recruitment. In a dynamic governance system, it also functions as an input that informs system redesign. Candidate complaints, perceived fairness scores, drop-off rates, requests for explanation, and appeals against automated decisions provide signals about how the system is experienced by those subject to it. These signals can reveal opacity, exclusion, or procedural unfairness that may not be visible through internal efficiency metrics alone.

3.2.3 Organizational Legitimacy and Governance

Organizational legitimacy refers to the extent to which AI-driven recruitment systems are perceived as fair, accountable, and compliant with regulatory and ethical standards. This dimension is rooted in human resource governance and institutional theory, emphasizing the importance of transparency, explainability, and adherence to frameworks such as the European Union AI Act.

Together, these three dimensions form the foundation of a socio-technical governance system, where technical performance, human perception, and institutional acceptance interact dynamically.

3.3 Model Structure and Process Dynamics

The framework conceptualizes AI-driven recruitment as a sequential and iterative process that extends beyond algorithmic decision-making.

At a structural level, the system can be represented as a flow:

Input → Algorithmic Processing → Output → Candidate Perception → Legitimacy Outcome

However, this linear representation is insufficient to capture the dynamic nature of the system. In practice, recruitment processes operate through feedback loops, where outcomes influence future system behavior.

From an analytical perspective, the relationships between the core dimensions of the framework can be conceptualized as causal pathways.

Operational efficiency primarily influences system performance outcomes, but its impact on overall system

effectiveness is mediated by candidate perception. In particular, improvements in efficiency do not necessarily translate into positive outcomes unless they are perceived as fair and transparent by candidates.

Candidate perception acts as a central mediating variable, linking algorithmic outputs to organizational legitimacy. Positive perceptions of fairness and transparency enhance legitimacy, while negative perceptions can undermine trust regardless of technical performance.

Organizational legitimacy, in turn, functions as a system-level outcome that feeds back into governance mechanisms. Declining legitimacy triggers governance interventions, such as bias mitigation and audit processes, which subsequently influence future algorithmic design and decision-making.

Furthermore, governance mechanisms can be conceptualized as moderating variables that shape the strength and direction of the relationship between algorithmic outputs and legitimacy outcomes. Strong governance structures enhance trust and mitigate negative perceptions, while weak governance amplifies the risks associated with opacity and bias.

This causal structure reinforces the interpretation of AI-driven recruitment systems as dynamic and interdependent socio-technical systems, rather than linear decision-making pipelines.

Figure 2 presents the cross-functional structure of the proposed AI-driven recruitment framework.

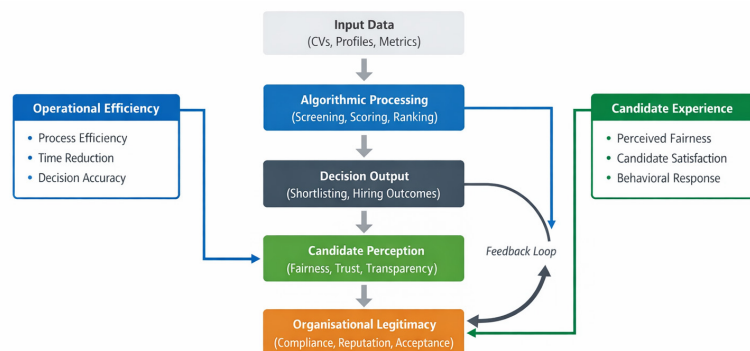


Figure 2. Cross-Functional Governance Framework for AI-Driven Recruitment Systems

Source. Author's elaboration.

As illustrated in Figure 2, algorithmic processes interact with candidate perception and organizational legitimacy, creating a system in which technical outputs are continuously evaluated through human and institutional lenses. This interaction highlights the necessity of balancing efficiency with experiential and governance considerations.

This figure represents not only a structural model but also a conceptual bridge between technical system design and socio-organizational interpretation.

3.4 Feedback Mechanisms and System Adaptation

A key contribution of this framework lies in its emphasis on feedback loops and adaptive dynamics. Candidate perceptions influence organizational legitimacy, which in turn shapes governance responses and policy interventions. These governance mechanisms subsequently affect how algorithms are designed, trained, and deployed.

This recursive process transforms AI-driven recruitment systems into adaptive socio-technical structures rather than static decision-making tools. The integration of feedback loops allows the system to evolve in response to both internal performance metrics and external regulatory pressures.

The extended governance dynamics of the framework are illustrated in Figure 3.

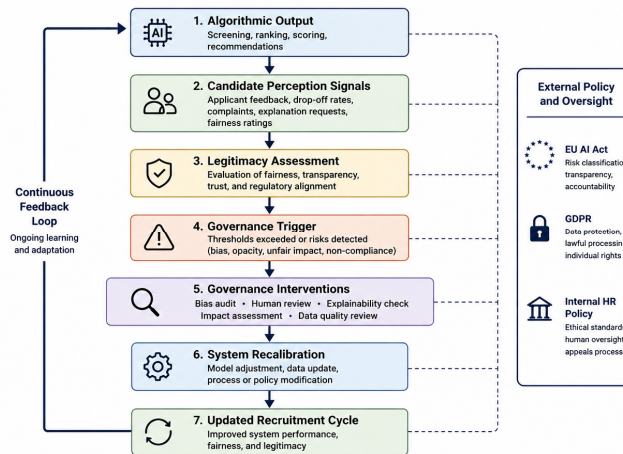


Figure 3. Dynamic feedback-loop governance model for AI-driven recruitment systems

Source. Author's elaboration.

Figure 3 illustrates the dynamic feedback-loop governance model proposed in this study. Unlike the structural model presented in Figure 2, this figure emphasizes the temporal sequence through which algorithmic outputs generate candidate perception signals, legitimacy assessments, governance triggers, governance interventions, system recalibration, and an updated recruitment cycle. External policy and oversight mechanisms, including the EU AI Act, GDPR, and internal HR policy, shape each stage of this process.

3.5 Theoretical Propositions

Building on the socio-technical governance framework developed in this study, a set of theoretical propositions can be derived to clarify the relationships between the core dimensions of AI-driven recruitment systems.

Proposition 1 (P1): Higher levels of algorithmic transparency are positively associated with improved candidate perception of fairness.

Proposition 2 (P2): Positive candidate perception of fairness enhances organizational legitimacy in AI-driven recruitment systems.

Proposition 3 (P3): Operational efficiency gains, when not accompanied by transparency and fairness mechanisms, may negatively affect perceived legitimacy.

Proposition 4 (P4): Governance mechanisms (e.g., bias mitigation, audit processes, and data protection) positively moderate the relationship between algorithmic outputs and organizational legitimacy.

These propositions provide a foundation for future empirical research and enable the conceptual framework to be operationalized and tested across different organizational and institutional contexts. P1 and P2 could be examined through candidate surveys or experimental vignette designs measuring perceived fairness, transparency, and trust in AI-supported hiring decisions. P3 could be tested through comparative case studies or field data comparing recruitment systems with different levels of automation and transparency. P4 could be investigated through longitudinal case studies assessing whether bias audits, explainability procedures, and human oversight mechanisms moderate the relationship between algorithmic outputs and perceived legitimacy over successive recruitment cycles.

3.6 Boundary Conditions of the Framework

The proposed framework is subject to several boundary conditions. First, it assumes that the organization has sufficient internal capacity to monitor, interpret, and adjust AI-enabled recruitment systems. In small firms or highly outsourced recruitment environments, governance may be weakened because technical decision-making is delegated to external vendors. Second, the model assumes a regulatory context in which transparency, explainability, and accountability are institutionally valued. In weakly regulated labour markets, organizations may have fewer incentives to convert candidate feedback into governance intervention. Third, the framework is more applicable to recruitment systems that involve repeated hiring cycles and measurable candidate interactions, such as high-volume screening, ranking, or interview-support tools. It is less applicable to one-off executive search processes where algorithmic decision-making is limited or informal. Finally, the framework may fail

when efficiency metrics dominate fairness and legitimacy considerations, leading organizations to treat governance as symbolic compliance rather than as a continuous socio-technical process.

4. Governance Expansion Model: From Static Framework to Adaptive Socio-Technical System

Section 4 extends the conceptual framework by moving from structural integration to temporal adaptation. While Section 3 defines the core architecture of the model, this section explains how AI-driven recruitment systems evolve through feedback loops, governance interventions, and regulatory pressures. The objective is to clarify how candidate perception, legitimacy signals, and operational data are translated into concrete system adjustments over time.

4.1 Operationalising Dynamic Feedback Loops

Dynamic governance in AI-enabled recruitment does not simply mean that the system changes over time. It refers to a structured cycle through which operational data, candidate perceptions, and legitimacy signals are continuously translated into governance interventions. For example, in a high-volume recruitment platform, a decline in candidate perception scores among a specific applicant group may function as an early warning signal. If this decline is accompanied by disproportionate rejection rates or unusually low progression rates, the organization should trigger a bias audit. The audit may then lead to adjustments in screening parameters, changes in the weighting of selection criteria, additional human review, or revision of candidate communication practices. The modified system is subsequently monitored through the next recruitment cycle to determine whether candidate trust, perceived fairness, and selection outcomes improve.

This process transforms candidate experience from a passive outcome into an active governance input. Feedback loops therefore operate as legitimacy-preserving mechanisms: they allow organizations to identify when efficiency-oriented automation begins to undermine fairness, transparency, or trust. Unlike static compliance models, which verify whether a system meets requirements at a single point in time, dynamic governance requires continuous monitoring, threshold-based intervention, and iterative recalibration.

The timing of feedback loops may vary according to the recruitment context. In high-volume recruitment, monitoring may occur weekly or monthly, while in lower-volume professional hiring it may occur at the end of each recruitment cycle. Governance intervention may be triggered by predefined thresholds, such as a statistically significant decline in candidate satisfaction, repeated complaints concerning opacity or unfairness, unexplained demographic disparities in screening outcomes, or divergence between algorithmic recommendations and human reviewer assessments. These thresholds should not be treated as purely technical indicators, but as socio-technical signals requiring joint interpretation by HR managers, data specialists, and compliance officers.

4.2 From Static Architecture to Dynamic Governance

Building on the static architecture defined in the previous section, this subsection introduces a dynamic interpretation of AI-driven recruitment systems, emphasizing continuous adaptation rather than fixed system design.

The initial framework conceptualizes recruitment as a cross-functional system, but it does not explicitly model how changes occur within the system. In practice, AI-driven recruitment operates in a dynamic environment where algorithmic decisions are constantly evaluated, challenged, and adjusted.

This dynamic perspective is particularly relevant in contemporary regulatory contexts, where organizations must continuously adapt to evolving legal and ethical standards. The transition from a static to a dynamic model therefore represents a critical step in understanding AI recruitment as an adaptive governance system.

This interpretation is consistent with the broader view of algorithmic systems as organizational infrastructures shaped by control, evaluation, and institutional accountability mechanisms [1, 11, 12].

This perspective reflects the growing importance of integrating operational, behavioral, and governance-oriented insights within a unified analytical framework for AI-driven systems.

4.3 Policy and Control Mechanisms in AI Recruitment Systems

The governance expansion model introduces three key mechanisms that actively shape the behavior of AI-driven recruitment systems:

4.3.1 Data Protection

Data protection mechanisms ensure compliance with privacy regulations and safeguard candidate information. These controls influence how data is collected, processed, and stored, directly affecting the design and

performance of AI systems. In the European context, regulatory frameworks such as GDPR impose strict requirements that constrain algorithmic decision-making processes.

4.3.2 Bias Mitigation

Bias mitigation mechanisms aim to identify and reduce discriminatory patterns in algorithmic outputs. These include techniques such as fairness auditing, dataset balancing, and algorithmic adjustments. While these mechanisms improve fairness, they may introduce trade-offs with predictive accuracy, highlighting the need for governance-aware system design.

4.3.3 Audit and Compliance Mechanisms

Audit processes and compliance frameworks ensure transparency and accountability in AI-driven decisions. These mechanisms include explainability requirements, internal and external audits, and documentation standards. They play a crucial role in aligning AI systems with regulatory expectations and organizational policies.

Together, these mechanisms represent active governance controls that transform AI recruitment systems from purely technical tools into regulated socio-technical infrastructures.

4.4 Feedback Loops and System Adaptation

A key advancement introduced in this extended model is the explicit incorporation of feedback loops as drivers of system evolution.

A defining feature of the governance expansion model is the introduction of feedback loops that connect system outputs to future system behavior.

Candidate perception plays a central role in this process. Negative perceptions—such as perceived bias or lack of transparency can reduce organizational legitimacy, triggering governance responses such as policy revisions, system audits, or algorithmic adjustments.

In turn, these governance interventions influence how algorithms are designed, trained, and deployed, creating a recursive cycle of adaptation.

This process can be summarized as follows:

Algorithmic Output → Candidate Perception → Legitimacy Assessment → Governance Intervention → System Adjustment

This feedback structure highlights that AI-driven recruitment systems are not only shaped by technical performance but also by social acceptance and institutional oversight.

Building on the adaptive dynamics illustrated in Figure 3, this section extends the framework by conceptualizing how policy mechanisms, institutional constraints, and organizational responses co-evolve with AI-driven recruitment systems over time.

4.5 Toward Adaptive Socio-Technical Governance

The integration of feedback loops and governance mechanisms transforms AI-driven recruitment from a static decision-making model into an adaptive socio-technical governance system.

This perspective has critical implications. It suggests that system effectiveness cannot be evaluated solely in terms of efficiency or predictive accuracy, but must also consider legitimacy, compliance, and stakeholder acceptance. Moreover, it highlights the need for organizations to adopt continuous monitoring and governance strategies rather than one-time system design approaches.

By introducing a temporal and adaptive dimension, this extended model moves beyond static representations of AI-driven recruitment and provides a more realistic conceptualization of how governance mechanisms, institutional pressures, and system performance co-evolve over time.

5. Discussion

To illustrate the practical relevance of the model, the framework can be applied to real-world recruitment scenarios where AI systems are implemented in high-stakes environments such as public sector hiring or large-scale corporate recruitment processes.

5.1 Theoretical Implications

This study contributes to the growing literature on AI governance by reframing AI-driven recruitment systems as adaptive socio-technical systems rather than static decision-support tools. By integrating legitimacy theory with

algorithmic management, the proposed framework advances the understanding of how AI systems interact with organizational and institutional environments.

The findings extend prior research by demonstrating that governance is not merely an external control layer but an endogenous and evolving component of AI systems. Through continuous feedback loops, AI-driven recruitment processes are shaped by candidate perceptions, regulatory pressures, and organizational responses, leading to ongoing system adaptation.

This perspective contributes to the literature in three main ways. First, it introduces a dynamic view of algorithmic governance, emphasizing co-evolution between technology and institutional context. Second, it expands evaluation criteria beyond predictive performance to include legitimacy, fairness, and compliance. Third, it bridges gaps between HRM, AI governance, and institutional theory, offering an integrated conceptual framework.

Table 2. Summary of theoretical and practical contributions of the proposed framework

Dimension	Traditional Approach	Proposed Framework (This Study)	Key Implications	Contribution Type
Nature of AI Systems	Static decision-support tools	Adaptive socio-technical systems	Systems evolve through feedback and interaction	Conceptual advancement
Role of Governance	External control mechanism	Endogenous and dynamic governance process	Governance embedded within system operations	Theoretical integration
Feedback Mechanisms	Limited or absent	Continuous multi-level feedback loops	Ongoing system adaptation and learning	Model innovation
Evaluation Criteria	Accuracy and efficiency	Legitimacy, compliance, stakeholder perception	Broader performance assessment beyond technical metrics	Expanded evaluation lens
Organizational Response	Reactive	Proactive adaptive	Organizations anticipate and manage risks dynamically	Managerial relevance
Policy Interaction	Peripheral	Central to system evolution	Regulatory frameworks shape system design and behavior	Policy contribution

Source. Author’s elaboration.

5.2 Managerial Implications

From a managerial perspective, the findings suggest that organizations should move beyond viewing AI-driven recruitment systems as purely technical tools and instead adopt a governance-oriented approach. Managers must recognize that system effectiveness depends not only on algorithmic accuracy but also on stakeholder trust and perceived fairness.

In practice, this implies that organizations should move toward governance-integrated recruitment architectures, where algorithmic decision systems are continuously monitored through candidate feedback analytics, audit trails, and regulatory compliance dashboards.

Organizations should implement continuous monitoring mechanisms, including candidate feedback systems and regular algorithmic audits, to ensure alignment with ethical and regulatory standards. Moreover, HR managers

should be actively involved in the governance of AI systems, collaborating with technical teams to interpret outcomes and adjust processes accordingly.

The framework also highlights the importance of proactive governance strategies. Rather than reacting to negative outcomes or external criticism, organizations should anticipate potential legitimacy challenges and embed governance mechanisms directly into system design and deployment.

5.3 Policy Implications

At the policy level, this study underscores the need for regulatory frameworks that account for the dynamic nature of AI-enabled recruitment systems. Traditional compliance models, which focus primarily on documentation before deployment, may be insufficient because recruitment algorithms operate in changing labour markets, interact with evolving candidate populations, and may generate new forms of bias after implementation.

Policy frameworks should therefore encourage dynamic accountability mechanisms rather than one-time compliance checks. These mechanisms may include continuous auditing requirements, algorithmic impact assessments treated as living documents, periodic bias monitoring, candidate-facing explanation procedures, and escalation pathways for contested automated decisions. Such tools would allow organizations to document not only how an AI recruitment system was approved, but also how it is monitored, challenged, and adjusted after deployment.

In practice, regulators and professional bodies could require organizations to maintain evidence of feedback-loop governance, including records of candidate complaints, audit triggers, human review interventions, bias mitigation actions, and system recalibrations. This would align AI recruitment governance with the logic of continuous risk management rather than static legal compliance. It would also strengthen the connection between regulatory compliance and organizational legitimacy by ensuring that governance remains responsive to candidate experience and institutional expectations over time.

6. Conclusion

This study has developed a conceptual framework that reframes AI-driven recruitment as an adaptive socio-technical governance system. By integrating AI governance with applied business disciplines—particularly human resource management, operations, and organizational theory—the research moves beyond purely technical interpretations of algorithmic hiring systems and highlights their embeddedness within broader institutional and social contexts.

The proposed model demonstrates that AI-driven recruitment systems evolve through continuous interactions between algorithmic outputs, candidate perceptions, and governance mechanisms. This dynamic perspective challenges static views of AI as a decision-support tool and instead positions it as part of an ongoing process shaped by legitimacy, regulatory pressures, and organizational responses. In doing so, the study offers a more comprehensive understanding of how AI systems operate in real-world organizational environments.

A key contribution of this research lies in its interdisciplinary approach. By bridging insights from AI governance, human resource management, and institutional theory, the framework provides a unified lens for analyzing the complexity of algorithmic recruitment systems. This integration not only advances theoretical understanding but also enhances the practical relevance of AI governance in organizational settings.

While the framework is conceptual, it is informed by interdisciplinary insights derived from European academic and regulatory contexts, including applied perspectives from operations management, marketing, and AI governance. This provides an initial empirical anchoring at the level of applied observation and contextual validation. As a theory-building study, this research deliberately focuses on conceptual development, positioning the proposed framework as a foundational structure for future empirical investigation. This approach enables the articulation of complex socio-technical dynamics that would be difficult to capture through immediate empirical testing alone.

Future research should focus on empirically testing the proposed framework through case studies, surveys, or experimental designs. In particular, comparative studies across industries and institutional environments—such as cross-country analyses within and beyond the European Union—would provide valuable insights into how governance mechanisms vary in practice. Additionally, longitudinal studies could examine how feedback loops and governance adaptations unfold over time, further refining the understanding of AI-driven recruitment as an evolving socio-technical system.

7. Limitations and Future Research

This study has several limitations that should be acknowledged. First, the conceptual nature of the model limits its immediate empirical generalizability, as the proposed relationships have not yet been tested through quantitative or qualitative data. Second, the framework does not fully account for industry-specific and organizational variations, which may influence how AI-driven recruitment systems are implemented and perceived in different contexts. Third, the model assumes a certain level of governance maturity and institutional awareness, which may not be present across all organizations.

These limitations open critical avenues for future research, particularly in terms of empirical validation, cross-industry comparison, and the exploration of context-specific governance mechanisms.

Overall, this study provides a foundation for future research and practice by offering a novel and integrative perspective on AI-driven recruitment, emphasizing the need for adaptive, governance-oriented approaches in the development and management of algorithmic hiring systems.

Informed consent

Obtained.

Ethics approval

The Publication Ethics Committee of the Canadian Center of Science and Education.

The journal and publisher adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

Provenance and peer review

Not commissioned; externally double-blind peer reviewed.

Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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